Macroeconomic Impact of the Remote Work Revolution

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Abstract

In recent years, remote work surged across the globe. We develop a novel macroeconomic model in which firms employ some workers remotely, trading-off potential productivity losses against savings on costs. Quantifying the model using U.S. data suggests that the surge in remote work (i) was primarily driven by workers' preferences, (ii) increased profitability and encouraged firm entry and (iii) shifted the firm distribution towards smaller businesses because they benefit relatively more from associated reductions in (fixed) costs. While increased entry sparks a boom, a larger share of small firms lowers aggregate productivity. Barriers to firm entry, therefore, emerge as a crucial margin determining the overall impact of the remote work revolution. Finally, we propose a novel identification strategy to estimate the firm-level effects of remote work, validating the model's key mechanisms and predictions.

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1 Introduction

The COVID-19 pandemic sparked an unprecedented adoption of remote work arrangements. Fueled by forced experimentation, changes in attitudes towards remote work and new technologies, about one quarter of workdays occur remotely in the U.S. since the pandemic ended – more than five times the pre-pandemic average (see Barrero et al., 2021, 2023). Similar values can also be found in other countries (see Aksoy et al., 2022). In this paper, we study the *macroeconomic* impact of this "remote work revolution."

Towards this end, we develop a novel macroeconomic model in which firms can choose to employ some of their workers remotely, optimally balancing the associated costs and benefits. On the one hand, remote work can reduce firms' production costs – e.g. because of a reduced need for production space (rent), or because workers prefer remote work and are willing to accept lower wages. On the other hand, remote work may come with decreased production efficiency (see e.g. Barrero et al., 2021, for a discussion).

To parameterize our model, we combine several U.S. (micro-)datasets on business dynamism, workers' time use and firm-level information on rental expenditures. In addition, we propose a novel identification strategy employing micro-data on firms' rental *commitments* prior to the pandemic with which we validate key model mechanisms and predictions. Using the parameterized model, we then study the main drivers and consequences of the remote work revolution. Two key messages stand out.

First, our model suggests that the dominant driver of the remote work revolution was a rise in preferences for working from home.[1] Second, our framework highlights that more favorable remote work conditions have two opposing macroeconomic effects. On the one hand, they raise overall firm profitability and, in turn, encourage business entry. This rationalizes the recently observed "surprising surge in applications for new businesses" (see Decker and Haltiwanger, 2024). On the other hand, however, the composition of firms shifts towards smaller businesses. This happens because smaller firms benefit relatively more from reductions in (fixed) costs brought about by cheaper remote work. While the former creates an economic boom, the latter lowers aggregate productivity.

The overall macroeconomic impact of the remote work revolution, therefore, crucially depends on the ease of firm entry. If a persistent rise in startups is hampered by financing or regulatory barriers, then weaker aggregate productivity can undo the individual (worker and firm) gains brought about by cheaper, more efficient and more preferred remote work. While recent U.S. data shows that firm entry has in fact remained persistently elevated since the pandemic, evidence from other countries is mixed. Therefore, the welfare impact of the remote work revolution may differ substantially across the globe, depending on country-specific (barriers to) business dynamism.

[1] This result may also be interpreted as a post-pandemic change in social norms which placed remote work into the mainstream (see e.g. Aksoy et al., 2022).

More concretely, we begin our analysis by developing a core theoretical framework which allows us to *analytically* show how changes in remote work conditions affect business dynamism. In this model, individual firms – which differ in their (permanent) productivity levels – have the option of letting their employees work remotely. They do so by optimally balancing the associated costs and benefits.

On the one hand, remote work reduces costs. We consider two distinct reasons for this. First, workers may prefer remote work and, in return, accept lower wages (see e.g., Mas and Pallais, 2017; He et al., 2021; Barrero et al., 2021). Second, remote work may lead to reductions in worker turnover and the associated training and hiring costs, or lower overhead costs because of a reduced need for production space (see e.g., Barrero et al., 2022, 2023; Bloom et al., 2024). On the other hand, remote work may lower productivity. This can occur because of less efficient communication, mentoring and training or through reductions in worker motivation and self-control (see e.g., Natalia et al., 2019; Battiston et al., 2021; Yang et al., 2022; Emanuel and Harrington, 2023; Gibbs et al., 2023).

Using our core model, we analytically show that more favorable remote work conditions have two opposing aggregate effects. Specifically, cheaper or more efficient remote work directly increases overall firm profitability. In the aggregate, this encourages firm entry. However, not all firms are affected equally. Small, less productive, businesses emerge as the "winners" of more favorable remote work conditions. For these firms, (fixed) costs represent a larger share of their expenditures and, therefore, they benefit relatively more when such costs are reduced through cheaper remote work.

To quantify which of these two effects eventually dominates, we generalize our core framework along several dimensions. First, we allow for fixed costs (heterogeneous across firms) of setting up remote work. This introduces an extensive margin, whereby only relatively productive (large) businesses can afford to start producing remotely. Note that this operates in the opposite direction to the intensive margin inherited from our core theory – *conditional* on producing remotely, smaller businesses tend to let more of their employees work from home. Second, we allow firm-level productivity to be affected by persistent idiosyncratic shocks and we *endogenize* the degree of long-run productivity differences across firms. Third, we introduce capital as a production factor and assume that its accumulation is subject to adjustment costs. Finally, we consider flexible labor supply, and explicitly model workers' preferences for remote work.

To parameterize the generalized model, we target (pre-pandemic) moments from several (micro-)datasets. First, we draw on the American Time Use Survey (ATUS) to compute remote work rates as the share of days worked from home among all work days. Second, we complement this information with the Current Population Survey (CPS) and its Annual Social and Economic Supplement (ASEC) in order to gain information on the size distribution of firms adopting remote work. Third, we use the Business Employment Dynamics (BED) data as a source of quarterly information on business entry, exit and size. Finally, we make use of firm-level information on rental expenses from Compustat to directly estimate one of the main cost margins intimately linked to remote work.

The parameterized model replicates salient features of the U.S. economy, with a particular focus on those pertaining to remote work. Specifically, our model matches average remote work rates overall and among large firms estimated from the ATUS and CPS. Moreover, the model does well in matching a range of *untargeted* empirical moments related to capital investment rates, firm-level productivity dynamics, the firm size distribution as well as the extent of productivity losses and cost savings associated with remote work.[2]

To quantitatively isolate the macroeconomic impact of the remote work revolution, we compare our baseline economy to a "remote economy" which is identical to the baseline but features more efficient, cheaper and more preferred remote work.[3] Recall from our core theory that all three of these forces incentivize firms to employ more workers remotely. However, savings on non-wage costs favor smaller firms relatively more. Therefore, to discipline the relative strength of (non-wage) cost reductions vs improvements in the efficiency of remote work, we require the remote economy to match the post-pandemic increase in work from home rates overall and over the firm size distribution. Finally, to discipline the importance of preferences for remote work, we makes use of existing estimates on the extent to which workers are willing to sacrifice wages in return for work flexibility (see e.g., Mas and Pallais, 2017; He et al., 2021).

As a first step in our quantitative analysis, we document that the dominant driver of the remote work revolution was a change in workers' preferences. In particular, our model suggests that stronger household preferences for working from home explain almost 2/3 of the surge in remote work rates following the pandemic. This result is consistent with recent evidence which also finds preferences to be key in understanding changes in remote work patterns (see e.g., Barrero et al., 2023; Bagga et al., 2024; Zarate et al., 2024).

Next, we use our model to study the aggregate impact of the remote work revolution. As highlighted by our core theory, more favorable remote work conditions come with increased profitability and, in turn, stronger incentives for firm entry. This is true also in the generalized model. Quantitatively, our model can explain almost 50 percent of the observed surge in firm entry. Importantly, however, increased firm entry raises labor demand and puts upward pressure on wages. This, in combination with reductions in the costs of remote work, creates winners and losers of the remote work revolution.

Specifically, the "winners" are smaller businesses conducting remote work which ben-

[2]Our parameterization implies only small efficiency losses and cost savings for the average firm employing a fraction of its workers remotely. This is consistent with evidence that hybrid work arrangements may come with little to no efficiency losses (see e.g., Barrero et al., 2023).

[3]We do not consider transition dynamics between the baseline and remote economies since we view the pandemic period and the associated lockdowns as truly extraordinary. Instead, we compare the two stationary steady states because a sustained increase in remote work rates must ultimately be supported by underlying changes in the associated costs and benefits.

efit relatively more from the associated (fixed) cost reductions. In contrast, the “losers” are larger firms operating only on-site. While these businesses do not directly benefit from more favorable remote work, they do feel the pain of a more competitive labor market. As a result, entry and exit decisions in the remote economy *endogenously* tilt the distribution of firms towards smaller businesses. Importantly, since small firms are on average less productive, this shift in the firm size distribution is also associated with lower aggregate productivity.[4]

Therefore, the boom driven by increased firm entry is slowed down by the endogenous shift of the economy towards smaller, less productive, firms. Which of these forces eventually prevails crucially depends on how strongly firm entry can increase. To highlight this, we consider a version of the remote economy in which barriers to entry (e.g., financial or regulatory frictions) mute the rise in startups. Our model suggests that, without a permanent surge in firm entry and associated economic boom, the welfare benefits of more favorable remote work can be entirely offset by a decline in aggregate productivity brought about by the endogenous shift towards smaller firms.[5] While recent data from the U.S. suggests that firm entry has in fact increased persistently since the pandemic, evidence from other countries is mixed. This suggests that the welfare impacts of the remote work revolution are likely to differ substantially across economies, depending on country-specific (barriers to) business dynamism.

As a final step in our analysis, we provide two pieces of empirical evidence in support of our key model predictions and mechanisms. First, we show that the model's predictions regarding firm entry, a shift in the size distribution of firms as well as changes in firm exit are all consistent with the data. This is true both qualitatively and quantitatively and both in the aggregate as well as across industries.

Second, we validate the key mechanisms of our model – i.e., we show that at the firm level, increases in remote work are associated with declines in firms' (rental) costs and labor productivity. A key empirical challenge is the lack of firm-level data on remote work. To overcome this, we propose a novel identification strategy utilizing Compustat data on firm-level *rental commitments*. In the data, some firms report having no rental commitments, while others report being committed several years into the future. To the extent that firms in 2019 did not predict the need for rental flexibility during the pandemic-induced surge in remote work, differences in rental commitments constitute exogenous variation in the *exposure* to the remote work revolution.

Intuitively, firms without rental commitments in 2019 were free to adjust their rental

[4]Not all small firms in our model are inefficient. Indeed, even productive firms start small and grow gradually over time. We discipline these firm-level dynamics by matching the life-cycle patterns of firm growth and exit observed in the data.

[5]While labor supply is flexible and workers have explicit preferences for remote work, we do not model additional benefits of remote work such as a decline in commuting time or benefits from home-production (see e.g., Barrero et al., 2023, for a discussion).

expenses during the pandemic if their workers (were forced to) work remotely. Moreover, because such firms could reap the cost-saving benefits of remote work, they were also more likely to *choose* higher remote work rates. Our model predicts that such firms should experience stronger post-pandemic declines in (rental) costs and labor productivity relative to firms with commitments. This is indeed borne out by the data. Moreover, a placebo treatment prior to the pandemic does not show any such effects. These results, therefore, provide additional independent validation of our model's key mechanisms.

Our paper is related to several strands of the literature. First, it contributes to research studying remote work (see e.g., Bloom et al., 2015), with several very recent papers analyzing the (post-)pandemic period and focusing on household trade-offs, income and wealth, real estate prices, agglomeration economies and city structures (see e.g., Aksoy et al., 2022; Barrero et al., 2022, 2023; Davis et al., 2024; Decker and Haltiwanger, 2024; Hansen et al., 2023; Liu and Su, 2024; Monte et al., 2023; Richard, 2024). In contrast, we study the implications of remote work for business dynamism and, in turn, its *macroeconomic* impact. Second, we connect to the literature on the macroeconomic importance of heterogeneous firms – especially the influence of entry and exit (see e.g., Hopenhayn and Rogerson, 1993; Clementi and Palazzo, 2016; Sedláček and Sterk, 2017; Sedláček, 2020). Finally, we also link to a broader set of studies investigating the role of entry barriers in determining aggregate outcomes (see e.g., Poschke, 2010; Boedo and Mukoyama, 2012; Peters, 2020). To the best of our knowledge, we are the first to study remote work in these settings.

The rest of the paper is structured as follows. The next section lays out our core model and presents key theoretical results. Sections 3, 4 and 5 describe the generalized model, parameterize it and lay out our main quantitative results. Section 6 provides empirical evidence in support of our key findings and model mechanisms and the final section concludes.

2 Core Theoretical Framework

The main purpose of this paper is to study the influence of work from home patterns on business dynamism and, in turn, on the macroeconomy. In this section, we develop a tractable theory allowing us to derive analytical predictions and to build intuition. The next section generalizes our framework along several dimensions and brings it to the data in order to quantitatively evaluate the impact of remote work on the macroeconomy.

2.1 Model

Consider a framework with heterogeneous firms, indexed by j, each producing a final good sold to the household for consumption. A key novelty that we introduce in this section is the possibility of firms optimally choosing to employ workers remotely.

To ease the notation, we omit the (discrete) time index where possible and use upper-case letters to denote aggregates and lower-case letters for firm-level variables. For the purpose of this section, we focus only on firms' optimal decisions and we defer the remainder of the model, including a formal definition of its equilibrium, to the Appendix.

Production. To produce output, businesses use a common production function and combine labor, n_j, with firm-specific productivity, $z_j > 0$:

$$y_j = z_j n_j^{\alpha}, \tag{1}$$

where $\alpha \in (0, 1)$ denotes returns to scale and where firm-level productivity is assumed to be constant throughout firms' life-cycles.

Costs. In order to produce, firms must pay wages to their employees and a per-period operational fixed cost, κ_o. In addition, businesses also pay non-wage labor costs, κ_n, for every worker. Put together, total non-wage costs are given by $\kappa_n n_j + \kappa_o$.

The primary interpretation of these costs is as a continuous approximation to (likely staggered) expenditures on office or production space.[6] More broadly, these costs may also represent expenditures on office or production equipment and supplies, worker training or hiring costs.

Work from home. We assume that all firms have the option of letting a fraction, $\omega_j \in [0, 1]$, of their employees work from home. This is associated with both costs and benefits, which we detail below and which the firm optimally balances.

Note that we abstract from the fixed costs of *setting up* remote work. We do so for tractability, but relax this assumption in the generalized model of Section 3. Therefore, the theoretical results in this section can be viewed as pertaining to the intensive margin of remote work, conditional on firms having paid a fixed setup cost.

Work from home: Wages. We assume that remote work directly helps alleviate wage pressures. This occurs because workers value time and location flexibility (see e.g., Mas and Pallais, 2017; Barrero et al., 2021, for experimental and survey evidence).

Therefore, we assume that a firm's wage bill falls as remote work rates increase. In particular, a firm's wage bill is given by $h(\omega_j)Wn_j$, where $h(\omega_j) \in (0, 1]$ with $h'(\omega_j) < 0$. W can then be viewed as the wage rate in firms that operate fully on site.

[6] If adjusting office space incurred a cost, firms would optimally decide to increase office space in a staggered manner at certain firm size thresholds. Our cost structure, $\kappa_n n_j + \kappa_o$, serves as a continuous approximation to such an underlying step function.

Work from home: Cost reductions. Aside from its impact on a firms' wage bill, remote work can also help reduce non-wage costs. This may occur because firms require less production or office space – see e.g., Barrero et al. (2023) for a discussion and Krause et al. (2024) for estimates of the post-pandemic decline in office space demand using German data.

In addition to production and office space expenditures, however, non-wage costs may also decline because remote work can reduce quit rates and the associated turnover and training costs (see e.g., Barrero et al., 2022). We model these effects by allowing (non-wage) labor and overhead costs to fall as remote work rates rise, $g(\omega_j)(\kappa_n n_j + \kappa_o)$, where $g(\omega_j) \in (0, 1]$, with $g'(\omega_j) < 0$.

Work from home: Productivity. While the previous two effects of remote work constitute benefits to the firm, work from home may also come with costs. In particular, we assume that producing with a larger fraction of remote workers can lower productivity.

Several studies show, in various settings, that fully remote work yields lower productivity than on-site work. These productivity losses of remote work occur because of impeded communication, less effective mentoring or management and reductions in worker motivation and self control (see e.g., Natalia et al., 2019; Battiston et al., 2021; Yang et al., 2022; Emanuel and Harrington, 2023; Gibbs et al., 2023; Liu and Su, 2024).[7] Therefore, we assume that firm productivity declines as remote work rates increase, $f(\omega_j)y_j$, where $f(\omega_j) \in (0, 1]$ with $f'(\omega_j) < 0$.

Combining the three effects of remote work on firms' operation – (i) wages, (ii) non-wage costs, and (iii) productivity – we can write firm profits as:[8]

$$\pi(z_j) = f(\omega_j)y_j - g(\omega_j)(\kappa_n n_j + \kappa_o) - h(\omega_j)Wn_j. \tag{2}$$

[7]Studies of hybrid arrangements, i.e., partial work from home setups, find either no productivity effects or slight gains (see e.g., Bloom et al., 2015; Choudhury et al., 2021; Angelici and Profeta, 2023). While in reality firm-level productivity may rise for lower levels of ω before declining, in what follows we assume a monotone negative impact of remote work on productivity. This omission does not affect our results because – as will become clear – firms would always optimally choose levels of ω which imply productivity losses that exactly balance associated cost savings.

[8]Note that the effects of remote work on firms' operations can be interpreted as those *perceived* by firms. Changes in $f(\omega)$, $g(\omega)$ and $h(\omega)$ can then be viewed as learning about the uncertain impact of remote work. Indeed, studies and anecdotal evidence suggest that the COVID-19 pandemic lead to forced experimentation allowing a quick reduction in the previously high levels of uncertainty about the impact of remote work (see e.g., Barrero et al., 2021, 2023).

Firm exit. All businesses are subject to an exogenous risk of shutting down, $\delta \in [0, 1)$.[9] Therefore, firm value is given by:

$$v(z_j) = \max_{n_j, \omega_j} \sum_{t=0}^{\infty} [\beta(1-\delta)]^t \pi(z_j) = \max_{n_j, \omega_j} \frac{\pi(z_j)}{1 - \beta(1-\delta)}, \tag{3}$$

where $\beta \in (0, 1)$ is a discount factor.

Firm entry. There is a continuum of potential entrants which are, ex-ante, identical. In order to enter the economy, potential startups must pay a fixed entry cost, κ_e, upon which they obtain a draw of their (fixed) idiosyncratic productivity. Firms draw their productivity from a common distribution described by a probability and cumulative distribution function $h_z(z)$ and $H_z(z)$, respectively. Assuming free entry gives rise to the following entry condition:

$$\kappa_e = v_e, \tag{4}$$

where $v_e = \int v(z)h(z)dz$ is the expected value of entry.

2.2 Theoretical Results

In what follows, we study analytically optimal work from home choices, ω^*. In doing so, we pay special attention to how remote work choices differ with firm size and how they impact firm entry. We defer all proofs to the Appendix.

Optimal work from home. The following proposition summarizes firms' optimal work from home decisions and their relation to firm productivity. For simplicity, we assume $g(\omega) = h(\omega)$, allowing these to differ in our generalized model.

Proposition 1 (Optimal work from home rates)
In the framework described above, for interior solutions and when $g(\omega) = h(\omega)$, optimal work from home rates, ω^*, satisfy the following

a) if $\kappa_o = 0$, then ω^* is common across firms and implicitly given by

$$\frac{f'(\omega^*)}{f(\omega^*)} \frac{g(\omega^*)}{g'(\omega^*)} = \alpha,$$

b) if $\kappa_o > 0$, then

$$\frac{\partial \omega^*}{\partial z} < 0.$$

[9] Implicitly, we assume that fixed costs of operation, κ_o, and the distribution of firm-level productivity, z_j, are such that firms never choose to shut down endogenously. We relax this assumption in our generalized model.

The first part of Proposition 1 states that without fixed overhead costs, all businesses optimally choose the same level of work from home rates. Intuitively, firms choose work from home rates to balance the associated marginal cost (productivity declines) and benefits (cost savings). When remote work reduces wage and non-wage costs in the same way (i.e., when $g(\omega) = h(\omega)$), this trade-off mimics optimal labor demand. Therefore, in the absence of fixed overhead costs, optimal remote work rates are constant and common across firms, governed by returns to scale in production, α.

The second part of Proposition 1 constitutes one of our key results which will be crucial for the aggregate effects discussed in the later part of the paper. In particular, it states that with positive overhead costs, optimal work from home rates decrease with firm productivity. Intuitively, for less productive (smaller) firms, fixed overhead costs represent a larger share of their overall costs. This provides small firms with greater incentives to save on such costs by shifting more of their workforce off-site.

Note that, as explained above, our results in this section pertain to the intensive margin of remote work. In our generalized model, we allow for an extensive margin by introducing fixed setup costs of work from home. As will become clear, the extensive margin will work in the opposite direction to the intensive one, since larger businesses will be more readily able to pay the fixed setup costs. We address the quantitative question of which of these two forces dominates in Section 5.

Changes in work from home conditions. We now analyze how changes in work from home conditions affect firm profits and, in turn, entry decisions. Towards this end, let us denote $\widetilde{f}$ and $\widetilde{g}$ as parameters of $f(\omega)$ and $g(\omega)$ which, respectively, affect the speed of productivity losses and cost savings accrued with remote work. For simplicity, we continue to assume that $h(\omega) = g(\omega)$, i.e., $\widetilde{h} = \widetilde{g}$.

Without loss of generality, we define these parameters such that their increase leads to a rise in work from home rates:

$$\frac{\partial f(\omega;\widetilde{f})}{\partial \widetilde{f}} > 0, \quad \frac{\partial^2 f(\omega;\widetilde{f})}{\partial \omega \partial \widetilde{f}} > 0 \quad \text{and} \quad \frac{\partial g(\omega;\widetilde{g})}{\partial \widetilde{g}} < 0, \quad \frac{\partial^2 g(\omega;\widetilde{g})}{\partial \omega \partial \widetilde{g}} < 0.$$

Proposition **2** (Changes in remote work conditions)
All else equal and assuming internal optimal work from home rates, ω^*, exogenous changes in $\widetilde{f}$ and $\widetilde{g}$ have the following impact on firm entry incentives:

$$\frac{\partial v_e}{\partial \widetilde{f}} > 0 \; \textit{and} \; \frac{\partial v_e}{\partial \widetilde{g}} > 0.$$

Proposition 2 constitutes our second key result. Specifically, it states that entry incentives (summarized by the expected value of starting up a business, v_e) strengthen when remote work becomes cheaper or more efficient. Intuitively, such productivity boosts or cost reductions lead to higher profits, since businesses can produce more or at lower costs. In turn, higher profits, and hence firm values (3), incentivize firms to enter (4).

Before moving on, let us summarize the key mechanisms present in our core theory. First, conditional on conducting remote work, less productive (smaller) businesses benefit relatively more from the possibility of letting a fraction of their employees work from home – Proposition 1. Second, improvements in remote work conditions strengthen firm entry incentives – Proposition 2. As will become clear in the next section, these two effects are opposing forces which play a key role in shaping the overall macroeconomic impact of the remote work revolution.

3 Generalized Model

In this section, we generalize our core model along several dimensions. The next two sections then parameterize this model to U.S. data and use it as a laboratory to *quantitatively* evaluate which drivers were most important for the remote work revolution and how they impacted the macroeconomy.

The generalized model retains the structure of our core framework, but extends it along five important dimensions. First, we endogenize heterogeneous wages through employees' flexible labor supply and preferences for remote work. Second, we introduce the fixed costs (heterogeneous across firms) of setting up remote work. Third, we allow for endogenous firm exit. Fourth, we generalize firm-level productivity by (i) allowing it to be affected by persistent shocks and (ii) endogenizing the degree of long-run productivity differences across firms. Finally, in addition to labor, we also introduce physical capital as a production factor, the accumulation of which is subject to adjustment costs.

All these extensions have important consequences for the model-implied distribution of firms which, in turn, is what drives the responsiveness of the economy to structural changes – including the remote work revolution. Indeed, a primary use of our model will be to study the aggregate consequences of the remote work revolution. At this stage, it is important to stress that we will not use our framework to study aggregate fluctuations. Instead, our approach will rest on comparing steady-state equilibria which differ in the prevalence of remote work.

3.1 Household

We assume a representative household which owns all businesses in the economy and optimally chooses aggregate consumption and labor in individual firms.

Preferences for remote work. A key feature of household's utility is the preference for remote work, consistent with experimental and survey evidence (see e.g., Mas and

Pallais, 2017; He et al., 2021; Barrero et al., 2021). Formally, we model the per-period household utility as:

$$\ln C - \sum_j \upsilon_j n_j, \tag{5}$$

where $\upsilon_j = \upsilon h(\omega_j) > 0$, with $h'(\omega) < 0$ as in our core model. In other words, while the household takes ω_j as given, its disutility of labor diminishes with if household members are allowed to work remotely.[10]

The representative household maximizes the expected present value of life-time utility subject to its budget constraint:

$$C = \sum_j W_j n_j + \Pi, \tag{6}$$

where, normalizing the aggregate price level $P = 1$, real aggregate profits are given by Π and firm-level real wages are given by W_j. Wages are heterogeneous across firms because businesses optimally choose different levels of remote work – partly driven by the fact that in return for flexibility workers are willing to accept lower wages according to the following labor supply condition:

$$W_j = \upsilon_j C. \tag{7}$$

3.2 Firms

In the absence of aggregate uncertainty, all aggregates will be fixed at their respective steady state values. However, firm-level variables will in general fluctuate over time, reflecting changes in firm-specific (endogenous and exogenous) state variables. Therefore, whenever necessary, we denote time with a subscript t.

Costs of setting up remote work. As in our stylized model, work from home is associated with efficiency losses in production, summarized by $f(\omega_{j,t})$, and reductions in non-wage costs, summarized by $g(\omega_{j,t})$.

An important novel feature of our generalized model is the presence of firm-level costs of *setting up* remote work. These setup costs may represent not only costs of hardware and software necessary for remote work, but also the costs associated with developing and implementing efficient protocols and procedures for remote communication. We denote these fixed costs as κ_j^ω and allow them to be heterogeneous across firms (but fixed over time).

Every period, firms decide whether or not to pay the fixed setup costs. If a business decides not to pay the setup cost, it cannot employ workers off-site and, therefore, $\omega_{j,t} = 0$. Once a business pays κ_j^ω, it has the option to employ workers remotely in all future

[10] We implicitly assume that all employees in a given firm work the same fraction, ω_j, of hours remotely.

periods, i.e., $\omega_{j,t} \in [0,1]$. We discuss all optimal firm decisions below.

Productivity process. We assume that firm-specific productivity, $z_{j,t}$, evolves according to the following law of motion:

$$\ln z_{j,t} = \underline{z}_j(1-\rho) + \rho \ln z_{j,t-1} + \epsilon_{j,t}, \tag{8}$$

where $\rho \in (0,1)$ is the persistence of firm-level productivity and ϵ_t are productivity shocks which are distributed identically and independently across firms and over time according to the distribution function H_z with zero mean and dispersion σ_z.

The parameter $\underline{z}_j$ represents the unconditional, long-run, mean of firm-level productivity. We assume that $\underline{z}_j$ is heterogeneous across firms but fixed over time.

Permanent heterogeneity. At this point, we highlight that firms in our model are characterized by *permanent* differences. These are governed by differences in firms' long-run productivity, $\underline{z}_j$, and remote work setup costs, κ_j^ω. In what follows, we will refer to these permanent differences as firm "types" and we will describe in detail how type heterogeneity is determined in our model.

It is important to note that different types of firms will make different decisions, even conditional on the same firm-level state variables. To ease the notation, we will not explicitly denote firm-level choices with $\underline{z}_j$ and κ_j^ω unless necessary for the clarity of our exposition. Instead, we will use the firm-level subscript j, implicitly understanding that each firm is characterized by its own pair of permanent characteristics $\underline{z}_j$ and κ_j^ω.

Production. Firms produce output using labor, $n_{j,t}$, and capital, $k_{j,t}$. They do so according to the following production function:

$$y_{j,t} = f(\omega_{j,t}) z_{j,t} \left(n_{j,t}^{\alpha} k_{j,t}^{1-\alpha} \right)^{\theta}, \tag{9}$$

where $\alpha \in (0,1)$ and $\theta \in (0,1)$ are common across all firms. As mentioned above, the efficiency of production is affected by firms' work from home decisions according to $f(\omega_{j,t})$.

Capital adjustment costs. We assume that firms accumulate capital subject to adjustment costs. In particular, investing $x_{j,t}$ into capital accumulation comes at a cost $\zeta(x_{j,t}, k_{j,t})$. The stock of firm-level capital then evolves according to the following law of motion:

$$k_{j,t+1} = x_{j,t} + (1-\delta_k) k_{j,t}, \tag{10}$$

where $\delta_k \in (0,1)$ is the capital depreciation rate and where we assume that capital becomes productive only in the next period.

Fixed operational costs. As in the core theoretical model, firms must pay a per-period fixed overhead cost, κ_o. However, in our generalized framework, we assume that these costs are stochastic, distributed identically and independently over time and across firms according to the cumulative distribution function H_κ with mean μ_κ and dispersion σ_κ. As will become clear, it will be convenient to denote the stochastic component of overhead costs as $\widetilde{\kappa}_o = \kappa_o - \mu_\kappa$, where $\widetilde{\kappa}_o$ is distributed according to H_κ with zero mean and dispersion σ_κ.

In contrast to the core model, our generalized framework allows for the possibility of endogenous firm exit. This happens whenever the firm value falls below zero. We next turn to describing all optimal firm decisions.

Optimal decisions of incumbent firms. Every period, incumbent firms choose whether or not to stay in operation and – if they decide to continue – how many workers to hire and what amount of resources to devote to capital accumulation. In addition, businesses in our framework must also choose what fraction of their employees to conduct remote work. Before being able to do so, however, they must first pay the fixed cost of setting up remote work.

Formally, businesses make their decisions to maximize the net present value of current and all future profits. In particular, the beginning-of-period value of a business in operation which has *not* yet paid the fixed setup cost of setting up remote work is given by

$$v_j(z_{j,t}, k_{j,t}) = \max_{n_{j,t}, x_{j,t}} \left\{ \pi_{j,t} + \beta(1-\delta) u_j(z_{j,t}, k_{j,t}) \right\}, \tag{11}$$

where $\pi_{j,t} = f(\omega_{j,t})y_{j,t} - W(\omega_j)n_{j,t} - g(\omega_{j,t})(\kappa_n n_{j,t} + \mu_\kappa) - x_{j,t} - \zeta(x_{j,t}, k_{j,t})$ are per-period profits and where we have made explicit that firm-specific wages depend on remote work. In particular, using the household's labor supply decision (7), we can write $W(\omega_j) = W_j = \upsilon h(\omega_j)C$. Recall that firms which have not yet paid the fixed setup cost of remote work cannot choose to have part of their employees work from home. Therefore, for these firms $\omega_{j,t} = 0$.

In the above, u_j is the continuation value of a business which is not yet doing remote work. This continuation value summarizes the optimal choice between three options: (i) shutting down, (ii) continuing purely on-site or (iii) paying the fixed setup cost and continuing as a firm which can produce remotely. Formally, the continuation value is given by

$$u_j(z_{j,t}, k_{j,t}) = \int \max \left[\begin{array}{c} v_j^x(k_{j,t+1}), \mathbb{E}_t v_j(z_{j,t+1}, k_{j,t+1}) - \widetilde{\kappa}_o, \\ \mathbb{E}_t v_j^\omega(z_{j,t+1}, k_{j,t+1}) - \widetilde{\kappa}_o - \kappa_j^\omega \end{array} \right] dH_\kappa(\widetilde{\kappa}_o), \tag{12}$$

where $\mathbb{E}$ is an expectation operator with respect to the evolution of firm-level productivity.

The exit value, v^x, is given by

$$v_j^x(z_{j,t}, k_{j,t}) = k_{j,t}(1-\delta_k) - \zeta(-k_{j,t}(1-\delta_k), k_{j,t}), \tag{13}$$

where firms obtain value from selling their stock of capital, but have to take into account the adjustment costs of doing so. The value of a firm which has paid the setup cost for remote work is given by

$$v_j^\omega(z_{j,t}, k_{j,t}) = \max_{n_{j,t},\omega_{j,t},x_{j,t}} \left\{\pi_{j,t} + \beta(1-\delta)u_j^\omega(z_{j,t}, k_{j,t})\right\}, \tag{14}$$

where the continuation value now contains only two options: (i) exit or (ii) stay in business with the possibility of doing remote work. Formally, the continuation value is given by:

$$u_j^\omega(z_{j,t}, k_{j,t}) = \int \max\left[v_j^x(k_{j,t+1}), \mathbb{E}_t v_j^\omega(z_{j,t+1}, k_{j,t+1}) - \widetilde{\kappa}_o\right] dH_\kappa(\widetilde{\kappa}_o). \tag{15}$$

Note that firms must pay the fixed setup cost of remote work only once. After it has been paid, firms do not have to pay it again even if they decide not to conduct remote work at times but "restart" again in later periods, that is, when $\omega_{j,t} = 0$ but $\omega_{j,t+s} > 0$ for $s > 0$.

Entry. Recall that there are permanent differences across firms, summarized by the subscript j. For the purpose of describing firm entry, however, we will make explicit the dependence of firms' decisions on the underlying parameters $\underline{z}_j$ and κ_j^ω. In particular, let $v^\omega(z, k; \underline{z}, \kappa^w)$ and $v(z, k; \underline{z}, \kappa^w)$ be the firm value of a business with productivity z, capital stock k, long-run productivity $\underline{z}$ and a remote work setup cost κ^ω which, respectively, has and has not paid the fixed setup cost.

For tractability, we assume a finite number of different productivity and fixed cost types. Specifically, let I be the number of different long-run productivity types and L the number of different setup cost types. The distribution of firm types is endogenous, modeled along the lines of Sedláček and Sterk (2017).

In particular, potential startups are free to choose which type of long-run productivity businesses they will *attempt* to start up. In order to do so, they must first pay an entry cost, κ^e, common across business types. This allows them to compete for a limited and time-invariant number of business opportunities of a given productivity type, denoted by Ψ_i.

Each business opportunity is exclusive, allowing for at most one producer. This means that not all potential startups succeed if multiple competitors attempt to seize a single opportunity. Specifically, the mass of successful startups of a given productivity type,

m_i, is determined by the following "entry function"

$$m_i = \Psi_i^{\phi} s_i^{1-\phi}, \tag{16}$$

where s_i is the mass of startup attempts of type i and $\phi \in (0, 1)$ determines the degree of crowding out which is common across productivity types.

Upon entry, firms are randomly (and independently from productivity types) assigned a fixed setup cost of remote work, κ_l^{ω}. We use p_l to denote the probability of a particular cost type, where $\sum_l p_l = 1$. Therefore, assuming free entry, we obtain the following entry conditions

$$\kappa_e = \frac{m_i}{s_i} \sum_l p_l \int_z \max \left[v(z, 0; \underline{z}_i, \kappa_l^{\omega}), v^{\omega}(z, 0; \underline{z}_i, \kappa_l^{\omega}) - \kappa_l^{\omega} \right] dH_z(z), \tag{17}$$

where we assume that firms enter with zero capital and an initial productivity draw from the distribution $H_z(z)$. The total mass of entrants is then given by $M = \sum_i m_i$. Notice that in equilibrium, potential startups are indifferent between business types. This happens because business types with high expected payoffs (firm values) attract more startup attempts which, in turn, lowers the chances of successfully starting up.

Finally, note that since firm entry is determined by expected firm values, the mass of entrants of any given type is constant in the absence of aggregate uncertainty. However, while constant in the stationary steady state, the distribution of firm types is *endogenous*. Importantly, for purposes of this paper, our model allows for the possibility that changes in work from home conditions will influence this distribution of startup types.

3.3 Aggregation

Let $\mu_{i,l}(z, k)$ denote the distribution of firms with long-run productivity $\underline{z}_i$ and setup costs κ_l^{ω} across productivity levels, z, and capital holdings, k. Then, the following expressions describe goods and labor market clearing:

$$Y = \sum_i \sum_l \int \int y \, \mu_{i,l}(z, k) dz dk, \tag{18}$$

$$N = \sum_i \sum_l \int \int n \, \mu_{i,l}(z, k) dz dk. \tag{19}$$

Finally, the aggregate resource constraint is given by

$$Y = C + S\kappa_e + \sum_i \sum_l \int \int \left[\zeta(x, k) + g(\omega)(\kappa_n n + \mu_\kappa) + \widehat{\kappa}_o + \kappa_l^{\omega} \mathbb{1}_{i,l}(z, k) \right] \mu_{i,l}(z, k) dz dk, \tag{20}$$

where $S = \sum_i s_i$ is the total mass of startup attempts and where aggregate output is used for consumption and all paid costs. The latter include costs of firm entry and capital adjustment, non-wage labor costs, overhead costs (where $\widehat{\kappa}_o$ indicates the *paid* overhead costs, conditional on firm survival) and setup costs of remote work. For the latter, $\mathbb{1}_{i,l}(z,k)$ is an indicator function which is equal to one if a firm with long-run productivity $\underline{z}_i$, setup costs κ_l^ω and productivity and capital z and k, respectively, decides to pay the setup cost and zero otherwise. We defer a formal definition of the equilibrium to the Appendix.

4 Taking the Model to the Data

In this section we bring our generalized model to the data. In doing so, we ensure that it is consistent with a range of salient features of the U.S. economy pertaining to business dynamism and remote work arrangements. Our baseline calibration uses a model period of one year and targets pre-pandemic (2003-2019) moments of the U.S. economy. The next section describes in detail how we quantitatively isolate the macroeconomic impact of the remote work revolution.

4.1 Data

To parameterize our model, we use information from five different data: (i) the Business Response Survey, (ii) the American Time Use Survey, (iii) the Annual Social and Economic Supplement of the Current Population Survey, (iv) Business Employment Dynamics and (v) Compustat. In what follows, we briefly describe each dataset and which set of targeted moments it is used for.

Work from home. When analyzing remote work, we focus on both the share of hours worked remotely and the share of establishments conducting remote work. To measure the latter, we rely on the Business Response Survey (BRS) of the Bureau of Labor Statistics (BLS) which started in 2020. The survey offers, among other things, information on the fraction of establishments conducting remote work, including just prior to the pandemic.

To measure the intensive margin, we rely on the American Time Use Survey (ATUS), also conducted by the BLS. The ATUS provides monthly information (starting in January 2003) on how individuals in the U.S. allocate their time among various activities. The sample of households is connected to the Current Population Survey (CPS) allowing us to link individuals' time allocation data to other information, such as the industry they work in.[11] In addition, utilizing the Annual Social and Economic Supplement (ASEC) of

[11]The ATUS targets households which have completed their final (eighth) month of the CPS. From each of the selected households, a random individual aged 15 and over is chosen to participate in ATUS. The questionnaire asks information about the respondent's previous day and is conducted only once for each individual. For more details on ATUS, see Hamermesh et al. (2005).

the CPS allows us to infer the size of establishments for which individuals in the ATUS report working remotely.

Business dynamism. To measure the entry and exit of businesses, we use the Business Employment Dynamics (BED) dataset of the Bureau of Labor Statistics. This dataset is generated from the Quarterly Census of Employment and Wages (QCEW) and offers quarterly information on employment at the establishment level covering approximately 98 percent of all employment in the U.S. economy.[12] A key advantage of this dataset is its relatively timely nature with the latest data – at the time of writing this paper – running all the way to Q4 2022 allowing us to analyze the post-pandemic period.

Establishment entry – formally called "births" in the BED – is defined as units which record positive employment for the first time in a given quarter and which exclude (seasonal) re-openings of businesses. Symmetrically, establishment exit – formally called "deaths" in the BED – is defined as units with zero employment which exclude temporary closings of businesses.[13]

Finally, the BED does not report overall establishment size at a quarterly frequency. However, for establishment births and deaths, it can be imputed using information on the number of entering or exiting establishments and their respective employment levels. Therefore, in our analysis we focus on the size of entrants and exiters instead of average size of all establishments.[14]

Non-wage labor costs. As already highlighted in our theory, firm-level costs play an important role for understanding the heterogeneous effects of changes in remote work conditions. Firms' rental expenses are one of the major costs directly affected by remote work choices. For this reason, we make use of Compustat which offers detailed information firms' rental expenses.

While Compustat is one of the main sources of U.S. firm-level information and has been used extensively in economic research it is well known that the Compustat sample

[12]The BED excludes self-employed individuals, government institutions and some non-profit organizations. An alternative popular data source for business dynamism is the Business Dynamic Statistics (BDS) of the Census Bureau. While there exist differences between the BDS and the BED, the numbers of establishments as well as their employment sizes typically co-move strongly across the two datasets (see e.g., Decker and Haltiwanger, 2024, for a discussion). In the Appendix, we provide a comparison between the BDS and the BED showing that for our purposes they are similar in the overlapping periods.

[13]To determine whether a shut down is a death or temporary closure, the BLS requires establishments to report zero employment for four consecutive quarters before it classifies it as a death. Such establishment deaths are then "back-dated" to the relevant quarter when they occurred. Moreover, the Appendix shows that our results are similar when using establishment openings and closings as opposed to the stricter births and deaths.

[14]The Appendix shows that our results are similar when using overall establishment size imputed from the QCEW – the underlying source for the BED which is available quarterly but is, however, based on a somewhat different sample (see `https://www.bls.gov/opub/hom/cew/concepts.htm`) – or *annual* establishment size taken from the BED.

of (publicly traded) firms is not representative. To address this issue, when computing model-generated moments with counterparts in Compustat, we use estimated size-based weights which align the Compustat and BED firm-size distributions (see the Appendix for details).

4.2 Parameterization

In what follows, we describe our parameterization strategy. This entails explaining our functional form choices and how we set parameter values in order to match key targets from our datasets. All model parameters are summarized in Table 1.

Functional forms and permanent firm heterogeneity. To bring our model to the data, we need to assume particular functional forms for the remote work productivity loss, non-wage cost saving functions and preferences for remote work, $f(\omega)$, $g(\omega)$ and $h(\omega)$. Towards this end, we follow León-Ledesma and Satchi (2019) in their analysis of technology adjustment and specify f, g and h as versions of exponential functions:

$$f(\omega) = \exp\left(\widetilde{f}\omega^2\right), \quad g(\omega) = \exp\left(-\widetilde{g}\omega\right), \quad h(\omega) = \exp\left(-\widetilde{h}\omega\right). \tag{21}$$

Note that, without loss of generality, the above specifications imply that increases in $\widetilde{f}$, $\widetilde{g}$ and $\widetilde{h}$ all result in remote work becoming more favorable or desirable.

Next, we follow Cooper and Haltiwanger (2006) and assume the following capital adjustment costs

$$\zeta(x,k) = \zeta_0(x)k + \frac{\zeta_1}{2}\left(\frac{x}{k}\right)^2 k, \tag{22}$$

where $\zeta_0(x) = \zeta_0$ whenever investment, x, is non-zero and $\zeta_0(x) = 0$ otherwise.

Recall that our generalized model features permanent firm heterogeneity in terms of long-run productivity and setup costs of remote work. Therefore, aside from the above functional form choices, we also need to make a stand on the parameterization of permanent firm-level differences.

For tractability, we assume two types of firms along each dimension, indexed by subscripts L and H to denote "low" and "high" types. Long-run differences across firms are then governed by seven parameters: four level parameters ($\underline{z}_L$, $\underline{z}_H$, κ_L^ω and κ_H^ω), two parameters controlling the masses of low and high productivity type startup opportunities ($\Psi_L > 0$ and $\Psi_H > 0$) and the share of low setup cost firms which we denote by $\Psi_\omega \in [0,1]$.

Common choices and normalizations. We set the discount factor to $\beta = 0.96$, reflecting a roughly 4% annual interest rate. The production function parameters are given by $\alpha = 0.65$ and $\theta = 0.9$. While the former mimics the observed labor share in income, the latter falls within the span of control values estimated in the data and commonly used in the literature (see e.g., Basu and Fernald, 1997; Clementi and Palazzo, 2016). We set the capital depreciation rate at 8% per year which lies in between values used in the literature (see e.g., Cooper and Haltiwanger, 2006; Clementi and Palazzo, 2016).

We set the disutility of labor υ such that the wage rate in on-site only firms is normalized to $W = 1$. Similarly, we assume the entry cost κ_e is such that the mass of entrants is normalized to $M = 1$. Following Sedláček and Sterk (2017), we set $\phi = 0.156$ and provide robustness exercises in the Appendix.

Indirect inference. The remainder of the parameters are set to match a range of business dynamism and work from home moments in the data. While all model parameters affect the behavior of the entire model, we discuss the targeted moments in relation to the parameters to which they are tied the most. Specifically, there are 17 remaining parameters: the persistence and dispersion of productivity shocks, the two long-run means and the respective masses of business opportunities (ρ, σ_z, $\underline{z}_L$, $\underline{z}_H$, Ψ_L, Ψ_H), the mean and dispersion of fixed overhead cost (μ_κ, σ_κ), capital adjustment cost parameters (ζ_0 and ζ_1), parameters controlling the impact of remote work on productivity, non-wage costs and preferences ($\widetilde{f}$, $\widetilde{g}$, $\widetilde{h}$), the level of non-wage labor costs (κ_n), the level of remote work setup costs (κ_L^ω, κ_H^ω) and the respective fraction of startups with low setup costs, Ψ_ω.

Practically, we compute the selected model-generated moments and compare them with their respective empirical counterparts and minimize the following loss function:

$$\min \sum_m \left(\frac{\text{model(m)} - \text{data(m)}}{\text{data(m)}} \right)^2 ,$$

where m indicates a given moment. Note that our model is over-identified as we are estimating 17 parameters using 26 moments described below. Details of the computational strategy are provided in the Appendix.

Indirect inference: Remote work setup costs. Recall that there are two types of firms when it comes to the costs of setting up remote work. The distribution of these firm types is governed by the share of low cost firm types (Ψ_ω) and the respective levels of setup costs (κ_L^ω and κ_H^ω).

First, we assume that the low remote work setup cost is $\kappa_L^\omega = 0$. This reflects the fact that for some businesses the necessary hardware and software for conducting remote work is part of their regular operations (i.e., subsumed in their capital stock) and that basic versions of remote work telecommunications services are often available free of charge.

Given κ_L^ω, we pin down κ_H^ω and Ψ_ω by targeting the pre-pandemic fraction of firms conducting remote overall and among large firms as reported in the Business Response Survey. Intuitively, since the minimum setup cost is $\kappa_L^w = 0$, all firms with such costs

Table 1: Parameter values and targeted moments

	Parameter	Value	Target/Source	Data	Model
β	Discount factor	0.96	Interest rate of approx. 4%		
α	Labor elasticity of output	0.65	Labor share in income of approx. 65%		
θ	Returns to scale	0.90	Basu, Fernald (1997) estimate		
δ_k	Capital depreciation	0.08	Cooper, Haltiwanger (2006)		
υ	Disutility of labor	0.017	Normalization, $W = 1$		
κ_e	Entry cost	0.67	Normalization, $s_H + s_L = 1$		
ϕ	Elasticity of entry function	0.156	Sedláček and Sterk (2017)		
κ_L^ω	"Low" remote work setup costs	0	Normalization, minimum remote work setup cost of 0		
$\widetilde{f}$	Speed of remote work productivity losses	-0.151	Average work from home rate, ATUS	4.1%	3.9%
$\widetilde{g}$	Speed of remote work cost savings	0.325	Work from home rates in 100+ over 100- firms, ATUS & ASEC	1.12	1.12
$\widetilde{h}$	Household preferences for remote work	0	Wages unresponsive to remote work	0	0
κ_n	Non-wage labor costs	0.255	Rental expenses - size coefficient, Compustat (see (24)	0.86	0.91
κ_H^ω	"High" remote work setup costs	5.3	Share of large firms conducting remote work, BRS	30%	29%
Ψ_ω	Share of "low" remote work setup costs	0.195	Share of firms conducting remote work, BRS	23%	23%
Ψ_L	Mass of "low" business opportunities	$1.1e-4$	Share of small (<50) businesses, BED	95%	94%
Ψ_H	Mass of "high" business opportunities	$9.2e-6$	Startup success rate, BED	21%	24%
$\underline{z}_H$	Mean "high" productivity	0.131	Average establishment size, BED	15.4	14.9
$\underline{z}_L$	Mean "low" productivity	0.104	Average establishment size of small (<50) businesses, BED	6.8	7.6
ρ	Productivity persistence	0.723	Establishment size life-cycle profile, BED	see Figure 2	
σ_z	Productivity shock dispersion	0.208	Establishment size life-cycle profile, BED	see Figure 2	
ζ_0	Capital adjustment costs, fixed	0.001	Establishment size life-cycle profile, BED	see Figure 2	
ζ_1	Capital adjustment costs, variable	0.61	Establishment size life-cycle profile, BED	see Figure 2	
δ	Exogenous exit rate	0	Establishment exit life-cycle profile, BED	see Figure 2	
μ_κ	Overhead costs, mean	0.795	Establishment exit life-cycle profile, BED	see Figure 2	
σ_κ	Overhead costs, dispersion	2.49	Establishment exit life-cycle profile, BED	see Figure 2	

Note: The table presents values for all model parameters. The first three columns describe each parameter and its parameterized value, while the last two columns indicate the most relevant target or data source.

will choose to "pay" them. Therefore, the fraction of firms conducting remote work is informative about Ψ_ω. In contrast, only relatively productive (large) firms are capable of affording non-negative ("high") setup costs, $\kappa_H^\omega > 0$. Therefore, the fraction of large firms conducting remote work is informative about the magnitude of κ_H^ω.

Indirect inference: Remote work and firm outcomes. There are three key parameters determining how remote work choices impact firm outcomes: $\widetilde{f}$, $\widetilde{f}$ and $\widetilde{h}$. To pin these down, we will require our model to match key moments of remote work in the (pre-pandemic) U.S. economy.

In order to measure the extent of remote work, we follow Barrero et al. (2023) and focus on individuals' time allocated to work and its location as reported in the American Time Use Survey. Specifically, we count working days of individual i, d_i, as those in which individuals devote at least 6 hours to work in their main job.[15] Analogously, we define days worked from home, d_i^{home}, as those in which individuals spend at least 6 hours working from home in their main job. The *work from home rate*, ω_t, is then defined as the number of days spent working at home, d_t^{home} as a fraction of all work days, d_t. We do so at the sector level, s, and quarterly frequency:

$$\omega_{s,t} = \frac{\sum_{i=1}^{I_{s,t}} d_{i,\tau}^{home}}{\sum_{i=1}^{I_{s,t}} d_{i,\tau}}, \tag{23}$$

where $I_{s,t}$ is the number of individuals reporting in sector s in quarter t.

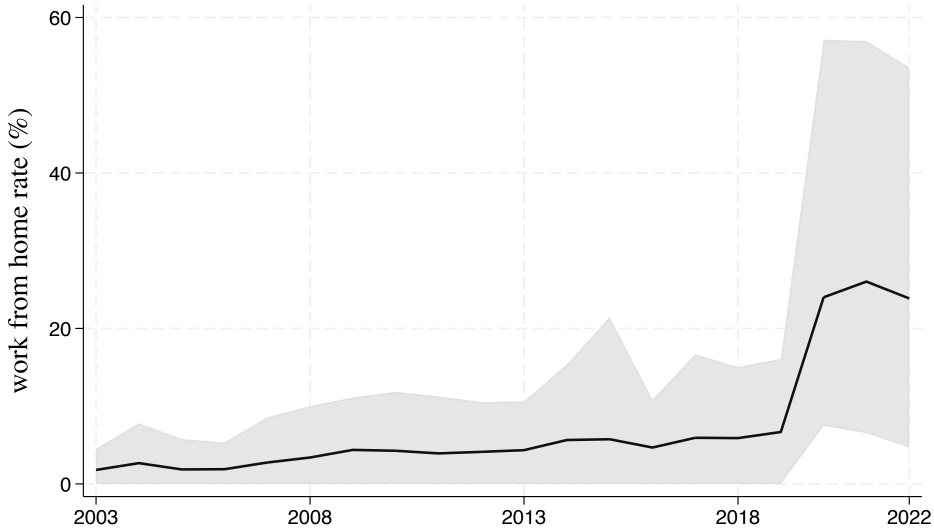
Figure 1 shows how work from home rates evolved over time. The solid black line depicts the *aggregate* work from home rate, while the shaded areas then indicate the range of work from home rates across industries (more details are presented in the Appendix). As is clear from the figure, work from home was very rare prior to the pandemic, albeit on an increasing trend. In particular, the average pre-pandemic remote work rate was 4%, increasing from about 1.8% in 2003 to 6.7% in 2019.

Note that with the help of ASEC and the CPS, we can obtain the same measure of remote work rates for different firm size bins. This reveals that on average remote work rates in large firms (with more than 100 workers) were 1.12 higher than those in all other businesses prior to the pandemic. In other words, larger businesses tended to conduct more of their production remotely.

Using the above information, we parameterize the key remote work parameters as follows. First, recall from Propositions 1 and 2 that all three factors – f, g and h –

[15] To define our baseline measure of working from home, we focus on workers with minimum real annual earnings of $20,000 (counted as 52 times average weekly earnings, deflated by the Personal Consumption Index). The Appendix shows that results are similar when considering "work-outside-workplace", i.e., anywhere but the respondent's workplace. Moreover, similar results are obtained when defining working from home as the fraction of hours worked from home *at the individual level*. Intuitively, this is because most individuals either spend entire days working at home or at their workplace.

Figure 1: Work from home rate



Note: The figure shows work from home rates – computed from ATUS as described in the main text – over time for the aggregate economy (solid black line) and the range of values across industries (shaded area).

impact firms' remote work choices. However, non-wage cost savings of remote work, g, induce heterogeneity in remote work rates across the firm size distribution. Therefore, to pin down f and g, we require our model to match the average remote work rate overall and among large firms. In the data, the average remote work rate was 4% prior to the pandemic and large firms had 12% higher remote work rates compared to small businesses.

The resulting parameterization implies that a business employing 4% of its workers remotely (the pre-pandemic average) would experience a 0.02% efficiency loss and a 1.3% lower non-wage cost. These results are broadly consistent with the empirical evidence that partial remote work arrangements come with little to no productivity or cost changes (see e.g., Barrero et al., 2023). Moreover, while detailed research in this area is still emerging, the few existing studies estimate that *fully remote* work is associated with productivity losses in the range of about $8-19\%$ (see Battiston et al., 2021; Yang et al., 2022; Emanuel and Harrington, 2023; Gibbs et al., 2023). Our baseline parameterization implies such costs to be about 14%, falling well within the empirical bounds.

Finally, while workers may have well preferred working from home even prior to the pandemic, we interpret the rare incidence of remote work prior to the pandemic as suggesting that working from home was not a significant factor in wage determination. Therefore, we set $\widetilde{h} = 0$ in the baseline (pre-pandemic) economy implying that firms' remote work decisions do not influence their wage bill.

Indirect inference: Permanent productivity differences. As with remote work setup costs, there are two types of firms when it comes to long-run productivity. To pin down the levels and respective masses of low- and high-productivity business opportunities, we target moments of the firm size distribution and the probability of starting up from the Business Employment Dynamics.

In particular, to discipline Ψ_L, Ψ_H, $\underline{z}_L$ and $\underline{z}_H$, we target the following four moments: (i) average size overall, (ii) average size of small firms (those with fewer than 50 workers), (iii) the share of small firms and (iv) the average startup probability ($M/(s_H + s_L)$). The first three targets are directly observable in the BED. To measure the last target, we interpret the model-implied startup probability as the *within first year* survival probability in the BED data.

Indirect inference: Non-wage labor costs. To parameterize non-wage labor costs, κ_n, we use information on firms' rental expenses from Compustat. Specifically, rental expenses in Compustat represent all costs for rental of land, space, buildings and/or equipment for continuing operations (see the Appendix for descriptive statistics). Through the lens of our model, the observed rental expenses are given by $g(\omega)\kappa_n n$. Therefore, to parameterize κ_n, we target the following reduced form relationship between rental expenses and employment in the cross-section of firms:

$$\ln(rent_{j,t}) = \alpha + \beta \ln n_{j,t} + \mathbf{X}'_{j,t}\theta + \epsilon_{j,t}, \tag{24}$$

where $rent_{j,t}$ are the rental expenses of firm j in period t and where the regression is estimated on pre-pandemic (2003-2019) data only. To account for potential differences across industries and for heterogeneous rental price developments across geographical locations, we include sector-year and city-year fixed effects in $\mathbf{X}_{j,t}$.

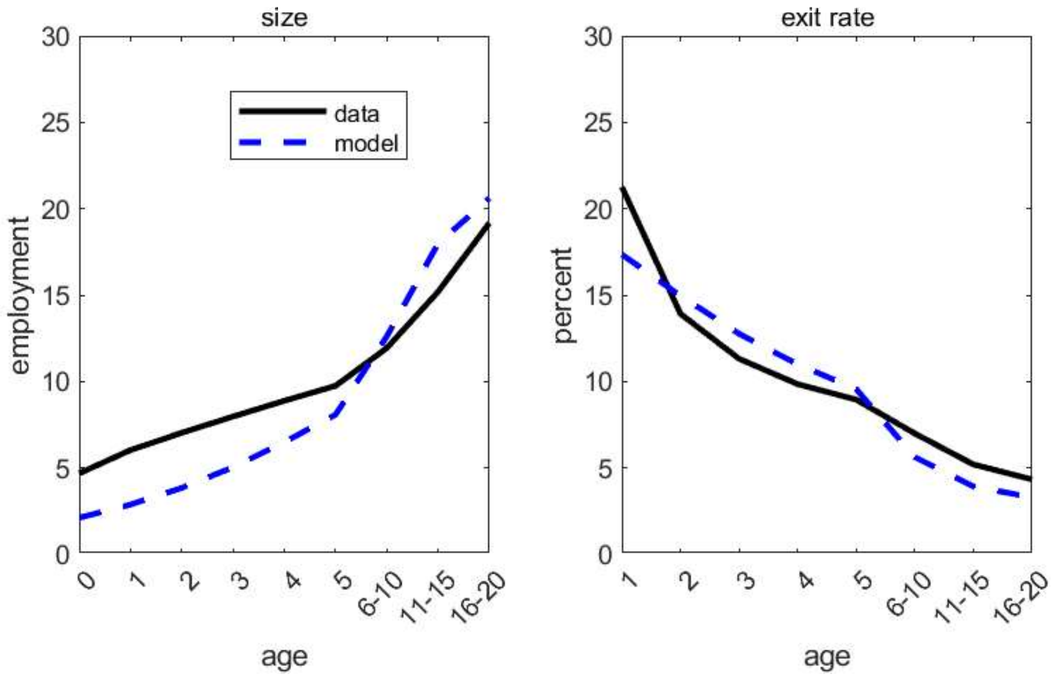
The coefficient of interest is estimated at $\beta = 0.861$ with a standard error of 0.0003. Using model-simulated data, and weights aligning the model-implied size distribution with that of Compustat as explained above, we replicate this reduced-form regression with $\kappa_n = 0.255$.

Indirect inference: Stochastic operational costs. Recall that firms in our model face an exogenous probability of shutting down, δ, as well as the option to exit the market endogenously. The latter occurs if the realization of stochastic fixed operational costs is high enough.

Therefore, to discipline the exogenous exit rate, the mean (μ_κ) and dispersion (σ_κ) of stochastic operation costs, we target the entire life-cycle profile of exit rates from age 1 to age 20 taken from the BED and averaged over the years 2003 to 2019.[16] Intuitively, the

[16] Since the BED starts in 1992, the life-cycle information for establishments in the age group of 6-10

Figure 2: Life-cycle profiles of size and exit rates: Data and model



Note: The left panel shows average establishment size (employment) by age, while the right panel shows average exit rates by age for the model and the data. The latter is taken from the BED, averaged over the years 2003-2019.

level of exit rates among young and old firms is informative about δ and μ_κ. Moreover, the speed at which exit rates decline with age is informative about σ_z. The right panel of Figure 2 shows the empirical and model-implied exit rates.

Indirect inference: Firm-level productivity and capital adjustment costs. The remaining parameters pertain to firm-level productivity shocks (persistence, ρ, and dispersion, σ_z) and to capital adjustment costs (ζ_0 and ζ_1). All four of these parameters are closely related to firm size and growth patterns.

Therefore, to pin these parameters down, we require our model to match the entire life-cycle profile of business size from startup (age 0) to age 20 as observed in the BED. The left panel of Figure 2 shows the empirical and model-implied size profiles.

4.3 Model Performance

Table 1 and Figure 2 show the targeted moments and their model counterparts. In addition, our model is consistent with a range of *untargeted* moments and estimates in the literature.

years is from 2004 to 2019, for ages 11-15 is from 2009 to 2019, and for the age group 16-20 it is from 2014 to 2019.

Investment, firm-level productivity and the firm-size distribution. First, our model is consistent with capital investment patterns. In particular, Cooper and Haltiwanger (2006) estimate average investment rates at around 12% and average inaction rates (investment rates between -1% and 1%) of about 8%. Our model predicts these values to be, respectively, 14% and 7%.

Second, in addition to matching average patterns, our model also does well in matching dispersion moments. Specifically, Cooper and Haltiwanger (2006) report the dispersion of investment rates to be 0.34. Our model predicts this value to be 0.36.

Third, the implied values of persistence and volatility of firm-specific productivity are close to empirical estimates in existing studies. For instance, Foster et al. (2008) estimate persistence of firm-specific TFP to lie between 0.75 and 0.81. The standard deviation of such productivity shocks is then estimated to fall within the range of 0.21 and 0.26. Our parameterization strategy yields a persistence parameter of 0.72 and a standard deviation of productivity shocks of 0.21. In addition, the implied firm-level growth process is also consistent with the evidence on high-growth firms. In particular, the share of gazelles – businesses with growth rates exceeding 25% – is about 9 percent, consistent with the U.S. data (see Haltiwanger et al., 2016).

Fourth, as will become clear, the share of small firms will be important for our quantitative results. While our model is designed to match the share of small businesses ($<$ 50 workers), it also does well at matching the share of very small businesses (with 1-4 workers). This is true both overall and among startups only. In particular, while in the data the share of very small establishments among all businesses (among startups) is 0.54 (0.89), in the model this share is 0.55 (0.89).

Additional work from home patterns. While we target the overall share of firms doing remote work and that among large firms (with more than 100 employees), our model also matches the extensive margin of work from home in other parts of the firm size distribution. In particular, while 24 percent of businesses with fewer than 20 workers report doing remote work in the data, this fraction is 23 percent in our model. On the other extreme, 44 percent of very large firms (with more than 500 workers) have some of their employees work remotely in the data. In our model, this fraction is also 44 percent.

Finally, let us describe in detail the model-implied remote work patterns, summarized in 2. The table reports remote work rates "unconditionally" for all firms and "conditionally" for businesses conducting remote work. In addition, we report work from home rates for various firm groups and for a size- (employment-) and un-weighted sample.[17] While the employment-weighted sample corresponds to the information in the ATUS-ASEC data (which is worker-based), to the best of our knowledge there is no dataset for

[17]In computing these statistics, we exclude "non-employers" which we interpret as firms with employment below or equal to 1.

Table 2: Remote work rates in the model (%)

	Size-weighted		Un-weighted			
	Uncond.	Cond.	Uncond.		Cond.	
	Mean	Mean	Mean	Std	Mean	Std
All	3.8	14.0	4.8	9.5	20.6	8.1
Firms with < 50 workers	3.7	16.0	4.9	9.8	21.4	8.1
Firms younger than 6 years	3.4	16.9	4.9	10.7	24.8	8.9
High-type firms	3.9	13.6	4.5	9.0	19.4	7.7
Low-type firms	3.7	14.8	5.0	10.0	21.7	8.3

Note: The first two columns of the table report size- (employment-) weighted means of remote work rates. The remaining columns compute unweighted means and standard deviations, all reported unconditionally ("Uncond.") and conditionally ("Cond.") on businesses conducting remote work. The rows indicate different firm groups: "all" firms , firms with less than 20 workers, businesses younger than 6 years, "high-type" firms (with $\underline{z}_H$), "low-type" businesses (with $\underline{z}_L$).

the U.S. economy allowing to compute work from home rates at the firm-level. Therefore, one of the contributions of this paper is to use our model to provide such firm-based statistics.

Several patterns stand out. First, there is a large amount of heterogeneity in remote work rates (last and third-last columns). This holds true even within subgroups of firms. Second, conditional remote work rates are considerably higher than unconditional ones reflecting that – on average – only about 23 percent of businesses conduct remote work. Third, conditional and unconditional remote work rates are farther apart among smaller and younger firms. This is because such businesses are less likely to pay the setup costs of remote work. Fourth, conditional on conducting remote work, smaller and younger firms do more of it. Noting that young firms have only about 8 workers on average, this pattern reflects the fact that smaller businesses benefit relatively more from remote work. Finally, since low-type firms are on average smaller, their remote work patterns are similar to those of small businesses. Nevertheless, since high-type firms grow towards their larger size only gradually, their remote work rates are not dramatically different to those of low-type businesses.

5 Macroeconomic Impact of the Remote Work Revolution

In this section, we use our model to quantitatively evaluate how changes in work from home patterns impact business dynamism and, in turn, the macroeconomy. Towards this end, we take our generalized model and compare it to a "remote economy", which is identical to our baseline but features higher remote work rates. The difference in model outcomes between the baseline and the remote economy then offers a quantification of the impact that more prevalent remote work arrangements have on the economy.[18]

5.1 The remote work revolution

As explained in the previous section, in our framework there are three key drivers of remote work decisions: $\widetilde{f}$, $\widetilde{g}$ and $\widetilde{h}$.[19] To discipline changes in these parameters, we adopt the same parameterization strategy as in the previous section and jointly target moments related to remote work which we describe in detail below.

Productivity and price of remote work. Recall that our baseline parameterization uses information on remote work rates overall and by firm size to pin down $\widetilde{f}$ and $\widetilde{g}$. Therefore, we will use exactly the same targets in the *post-pandemic* period to discipline the change in these parameters.

In particular, according to our ATUS-ASEC data, remote work rates increased substantially on average (see Figure 1). Specifically, the average remote work rate shot up from the pre-pandemic 4 percent to a post-COVID average of 24 percent. At the same time, the remote work rate among large firms (with more than 100 workers) relative to small businesses also increased. While before COVID this ratio was 1.12, it increased to 1.23 in the post-pandemic U.S. economy.

Matching these moments results in a parameterization which implies that remote work becomes more productive ($\widetilde{f}$ increases from -0.151 to -0.128) and cheaper ($\widetilde{g}$ increases from 0.325 to 0.488). These changes are consistent with existing evidence that firms and workers are better positioned to work from home more effectively (see e.g., Barrero et al., 2022). That said, the quantitative implications for individual firms remain relatively modest. In particular, an average firm in the baseline economy would see its productivity losses decline from 0.024 to 0.021 percent and its cost savings increase from 1.3 to 1.9 percent.

Preferences for remote work. Recall that our baseline, pre-pandemic, economy assumed that (even if workers preferred remote work) the rare incidence of working from home did not influence wage determination. In contrast, existing evidence suggests that

[18]Note that when comparing the baseline to the remote economy, we consider their respective stationary steady states and ignore transition dynamics. We also note that while existing research points to reasons "Why working from home will stick" Barrero et al. (2021), it remains an open question to what extent the post-pandemic remote work rates will remain elevated. For instance, in September 2024 Amazon famously announced that it will go back to on-site production from 2025. Through the lens of our model, Amazon could simply be viewed as a business with high remote work setup costs. More importantly, however, and as will become clear below, a key force behind our model results is how more favorable or desired remote work increases the incentives of potential startups to enter the economy. At the end of this section, we provide evidence on startups consistent with our model predictions.

[19]We do not consider changes in setup costs κ^{ω}. In our view, the costs of setting up remote work did not change fundamentally. For example, to this date Zoom – the telecommunications platform offering virtual conferencing services – still offers its "Basic" plan free of charge.

the COVID-19 pandemic cast work from home into the mainstream which, in turn, allowed workers to negotiate more freely for this new amenity value of jobs.

To allow for such forces, we release $\widetilde{h}$ in the remote economy and allow firms' wages to respond to remote work decisions. In order to discipline the magnitude of this change, we lean on existing empirical evidence about the value workers place on flexible work arrangements.

For example, Mas and Pallais (2017) provide experimental evidence that workers are on average willing to sacrifice 8% of wages in return for a hybrid work setup. Using survey evidence, Vij et al. (2023) estimate that an average worker in Australia is willing to forgo $4 - 8\%$ of wages for the possibility of remote work, while Barrero et al. (2021) document that U.S. businesses can reduce wage growth pressures by about 1% with a roll-out of remote work. In related studies, Bloom et al. (2015) and Angelici and Profeta (2023) find positive effects of remote work on workers' job satisfaction and Autor et al. (2024) suggest that changes in the amenity-value of jobs played a role in the "unexpected compression" of the age distribution following the pandemic.

To parameterize $\widetilde{h}$ in the remote economy, we use the mid-point of the above values. In particular, we require that in our remote economy workers are willing to sacrifice about 4% of wages in return for a hybrid work arrangement, i.e. $h(0.5) \approx 0.96$.

5.2 Drivers of the Remote Work Revolution

As a first step in our analysis, we use our framework to quantify the underlying drivers of the remote work revolution. To do so, we consider three versions of the remote economy.

In particular, we hold one of the three channels ($\widetilde{f}$, $\widetilde{g}$ or $\widetilde{h}$) unchanged at its baseline value, while letting the other two channels take on values of the remote economy described in Section 5.1. For example, to gauge the impact of changes in the productivity of remote work we compare our remote economy to a counterfactual in which $\widetilde{f}$ is held at it's baseline value, while $\widetilde{g}$ and $\widetilde{h}$ are assumed to take on the remote economy values. Comparing these three versions to the remote economy (in which all three channels change) isolates the importance of the omitted factor. Three key messages stand out.

Preferences for remote work. First, while all three changes (improvements in productivity, declines in costs and stronger preferences for remote work) lead firms to employ a larger share of their workforce remotely, changes in preference are the dominant driver. In particular, had it not been for workers' stronger desire to work from home, the average remote work rate would be "only" 11 percent, instead of the observed 24 percent. In other words, almost 2/3 of the surge in remote work rates is driven by a change in workers' preferences.

This finding is consistent with recent evidence. For instance, Zarate et al. (2024)

find that cultural differences and "individualism" accounts for about 1/3 of the cross-country variation in remote work rates. Similarly, using a calibrated labor market model accommodating amenity-value of jobs, Bagga et al. (2024) find a crucial role of changes in workers' preferences in explaining labor market patterns following the pandemic, including the rise in remote work. Finally, using survey evidence Barrero et al. (2023) find that workers' preferences for a (hybrid) remote work setup are "remarkably prevalent" since the pandemic.

Productivity and cost of remote work. Second, changes in the efficiency of remote work are, intuitively, most important for average firm-level productivity. In particular, had it not been for remote work becoming more efficient, average firm-level productivity would have been almost 1 percent lower compared to the remote economy.

Third, lower costs of remote work are crucial for a shift in the distribution of firms towards smaller businesses. This is intuitive in light of our Proposition 1 which highlights that especially small firms benefit from reductions in (fixed) costs associated with remote work. As will become clear below, this model prediction is also key for understanding the macroeconomic impact of the remote work revolution. We provide detailed empirical evidence consistent with this finding in the following section.

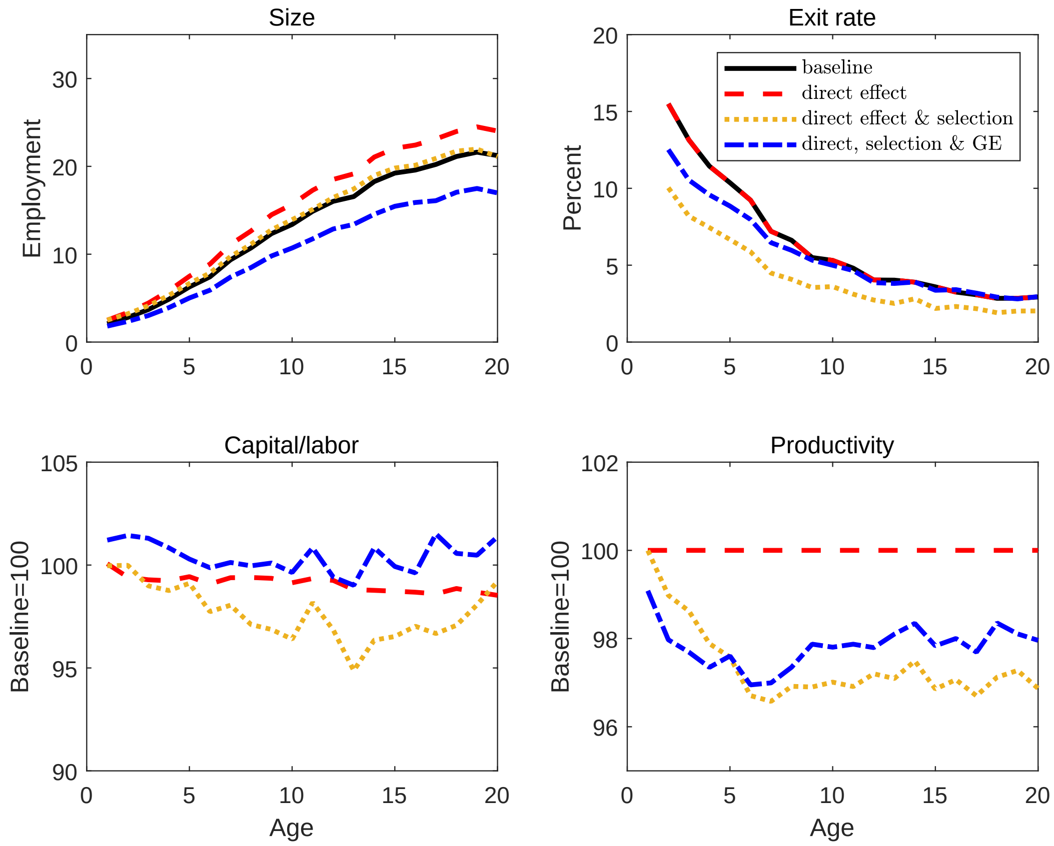
5.3 Remote Work and Business Dynamism

In this subsection, we quantify the connection between work from home decisions and business dynamism. To isolate changes in firms' choices from shifts in the composition of businesses, we first separately discuss firms which "always" and "never" conduct work from home. Thereafter, we turn towards changes in the composition of firms and to the overall impact on business dynamism.

Firm growth and selection: Firms which always conduct remote work. Figure 3 displays how the remote work revolution affects average firm-level employment (top left panel), exit rates (top right panel), capital-labor ratios (bottom left) and productivity (bottom right panel). Each of these are plotted over the life-cycle of firms which always choose to pay the remote work setup cost at entry – both in the baseline and the remote economy.

In addition to our baseline specification (black solid line), we consider 3 different scenarios of the remote economy. First, a partial equilibrium response which ignores both firm selection effects (entry and exit) and changes in equilibrium prices – this is shown by the "direct effects" line. Second, we consider the same partial equilibrium response, but allow for firm selection (changes in entry and exit), while keeping wages fixed – this is shown by the "direct effects & selection" line. Finally, we also plot the

Figure 3: Higher remote work rates: Effects on firms which always conduct remote work



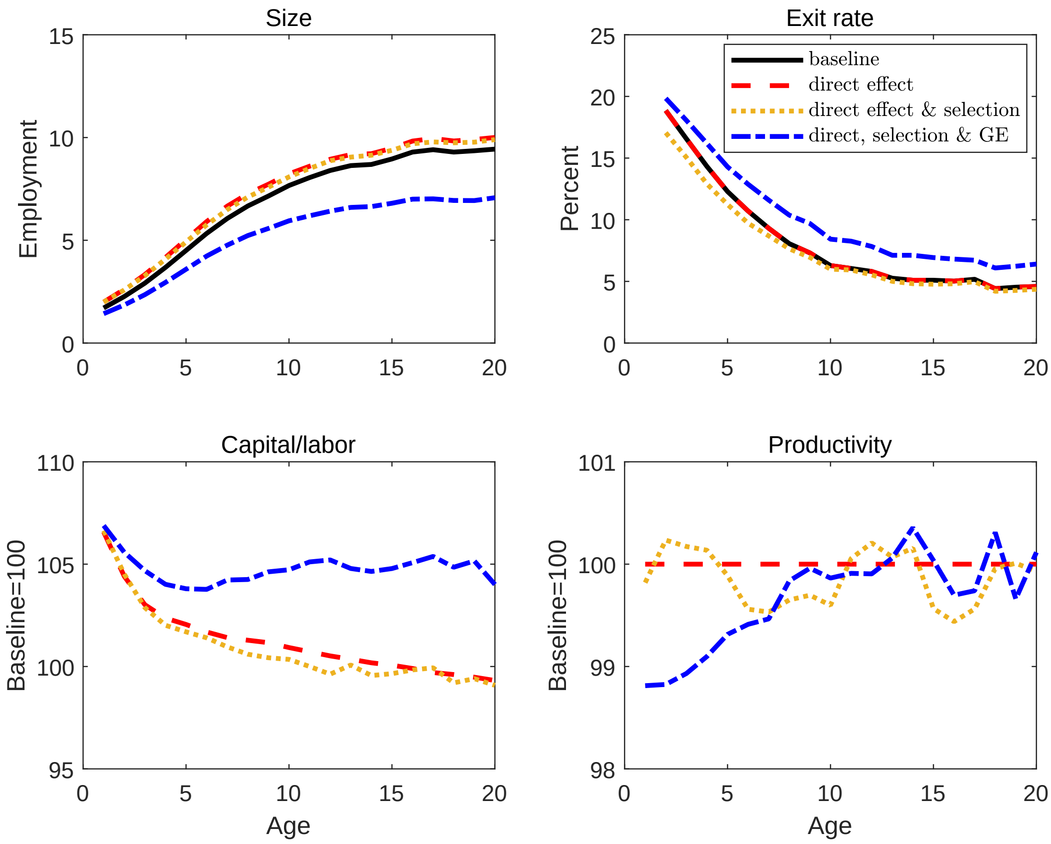
Note: The figure shows average firm-level employment (top left panel), exit rates (top right panel), capital-to-labor ratios (bottom left) and productivity (bottom right panel) as a function of firm age. It does so for the "baseline" model, and for the case when remote work is cheaper and more efficient. The latter is shown in partial equilibrium, ignoring firm selection and GE effects ("direct effect"), in partial equilibrium with firm selection ("direct effect & selection") and in the new general equilibrium ("direct effect, selection & GE"). The bottom two panels are expressed relative to values in the baseline model. All panels are for firms which always conduct remote work from startup, both in the baseline and in the remote economy.

impact in general equilibrium (GE) allowing for a change in wages – this is shown in the "direct effects, selection & GE" line. The latter corresponds to the final stationary steady state of our remote economy.

First, ignoring firm selection and general equilibrium effects, firms decide to expand production (top left panel) when remote work becomes cheaper and more efficient. In doing so, firms slightly reduce their capital-labor ratios as they take advantage of the relatively cheaper production factor (bottom left panel). By construction, average TFP (which excludes efficiency losses of remote work, $f(\omega)$) and exit rates are unchanged when ignoring selection and GE effects (right panels).

Next, as predicted by our theoretical analysis in Section 2, more favorable remote work conditions raise profits and firm values which induce greater entry and reduce firm exit (top right panel). Note that firm exit declines more for younger firms. This happens because younger firms are on average smaller and for such businesses the reduction in

Figure 4: Higher remote work rates: Effects on firms which never conduct remote work



Note: The figure shows average firm-level employment (top left panel), exit rates (top right panel), capital-to-labor ratios (bottom left) and productivity (bottom right panel) as a function of firm age. It does so for the "baseline" model, and for the case when remote work is cheaper and more efficient. The latter is shown in partial equilibrium, ignoring firm selection and GE effects ("direct effect"), in partial equilibrium with firm selection ("direct effect & selection") and in the new general equilibrium ("direct effect, selection & GE"). The bottom two panels are expressed relative to values in the baseline model. All panels are for firms which never conduct remote work from startup, both in the baseline and in the remote economy.

(fixed) costs related to work from home is relatively more beneficial. Therefore, some firms which could not afford to stay in business when remote work was costlier can now remain in operation. This selection effect pulls down average firm productivity (bottom right panel) and with it also average firm size (top left panel). We will return to this effect when evaluating the macroeconomic impact of more prevalent remote work.

Finally, with increased entry and lower exit, the number of firms expands. This raises labor demand and with it the equilibrium wage. Such higher labor costs induce firms to scale down production (top left panel) and shift towards capital as a production factor, increasing capital-to-labor ratios above those in the baseline economy (bottom left panel). In addition, higher production costs make it harder for all businesses to survive and exit rates increase across the board – though less so for small firms (top right panel). Because of such weaker firm selection among young firms, average firm-level productivity remains below the baseline. While higher exit rates among older firms lead to a partial productivity catch up, there remains a persistent productivity gap between the remote and baseline economy (bottom right panel).

Firm growth and selection: Firms which never conduct remote work. Figure 4 turns towards firms which never conduct remote work – neither in the baseline, nor in the remote economy. Ignoring selection and general equilibrium effects, cheaper and more efficient work from home leads to an expansion of production even among businesses which operate on-site only (top left panel). The reason for this is that as remote work becomes more favorable, a larger fraction of businesses *expect* they may choose to pay the setup cost at some point in the future. This, in turn, makes businesses front load the costs of building up capital in expectation of being able to take advantage of cheaper labor in the case of going remote (bottom left panel).

The more favorable continuation values, as well as a larger capital stock, reduce firm exit rates slightly (top right panel). Quantitatively, however, this impact is very small and the effect on average TFP is negligible (bottom right panel). However, higher equilibrium wages result in a strong decline in firm size and a rise in exit rates (top panels). Therefore, while fully on-site firms benefit from cheaper and more efficient remote work only indirectly (in expectation), they are directly negatively affected by the general equilibrium increase in wages for which they are not "responsible".

Composition of firms. Let us now turn to investigating how the composition of firms differs between the baseline and the remote economy. First, the share of firms deciding to conduct remote work is higher in the remote economy, at about 40%. More importantly, however, the composition of firm types is different since low-productivity firms (which are on average smaller) benefit relatively more from cheaper work from home. In particular, the share of high-type firms entering the economy drops by more than 13 percent. Moreover, there is also a shift in exit rates with high-type firms seeing their survival rates increase *relatively* more compared to those of low-type firms.[20]

Overall, there is a clear pattern of "winners" and "losers" from the remote work revolution. The winners are small (on average low-productivity) businesses conducting remote work. The losers are larger (typically high-productivity) businesses with high remote work setup costs. While these businesses cannot take advantage of the more favorable work from home conditions, they do feel the pain of the higher equilibrium wage. Quantitatively, compared to the baseline, low-productivity and low-setup cost firm types are almost 50% more common in the remote economy (a firm share of 18.5% vs 12.9%). In contrast, high-productivity and high-setup cost firm types are almost 20% less common in the counterfactual (a firm share of 27.9% vs 33.8%).

[20] Note that the *level* of exit rates among high-productivity firms remains considerably lower compared to those of low-productivity businesses. This is true both in the baseline and remote equilibrium.

5.4 Remote Work and the Macroeconomy

Intuitively, cheaper, more efficient and more desirable remote work frees up existing resources (and creates new ones) and leads to an economic expansion. However, the changes in business dynamism described above, and in particular the changes in the (productivity) composition of firms, serve to offset some of the positive impacts of the remote work revolution. In this section, we quantify these counteracting forces at the macroeconomic level.

Aggregate output and TFP. Let us begin with defining "aggregate TFP" which in our framework is given by:

$$Z = \frac{Y}{(N^{\alpha}K^{1-\alpha})^{\theta}} = \sum_i \sum_l \int \int z f(\omega) \left(\left(\frac{n}{\overline{n}}\right)^{\alpha} \left(\frac{k}{\overline{k}}\right)^{1-\alpha} \right)^{\theta} \Omega^{1-\theta} \widetilde{\mu}_{i,l}(z,k) dz dk, \tag{25}$$

where we will refer to the term $(N^{\alpha}K^{1-\alpha})^{\theta}$ as the "scale" of the economy and where bars indicate averages, such that $N = \overline{n}\Omega$ and $K = \overline{k}\Omega$, and where $\widetilde{\mu} = \mu/\Omega$ is the probability distribution function.

The expression above highlights four drivers of aggregate TFP. First, the distribution of firms across (long-run) productivity levels, $\widetilde{\mu}$. Recall that this is a combination of startup composition and survival rates – both of which are endogenous in our framework. Second, endogenous remote work choices which impact firm-level efficiency, $f(\omega)$. Third, the allocation of inputs across heterogeneous firms, $\left((n/\overline{n})^{\alpha}(k/\overline{k})^{1-\alpha}\right)^{\theta}$. Fourth, the mass of firms, $\Omega^{1-\theta}$, since a greater mass of smaller businesses improves efficiency in the presence of decreasing returns to scale.

Starting with Panel A of Table 3, the first row shows that aggregate output is about 2.9 percent higher in the remote economy. This is the result of both a slightly higher aggregate productivity (second row, first column) and an increased scale of the economy (second row, second column). However, the single most important contributor to both of these is the higher mass of firms, Ω, in the remote economy. In fact, as we have highlighted before, the distribution of firms, $\widetilde{\mu}$, shifts towards low-productivity firm types, dragging down aggregate TFP. We will return to this point below.

Consumption and welfare. The next three columns of Table 3 show how consumption differs between the remote and baseline economies and splits this gap into the contributions of output, investment and costs ($C = Y - I - Costs$). The latter encompass capital adjustment costs, fixed operation costs, non-wage on-site costs, remote work setup costs and the costs of entry.

Overall, Panel A shows that consumption is considerably higher in the counterfactual

Table 3: Impact of increased remote work: Changes in aggregates (in %)

Panel A: Full adjustment							
	Output (Y)		Consumption (C)			Welfare ($\mathcal{W}$)	
Overall	2.9		4.3			0.2	
Components	Z	$(N^{\alpha}K^{1-\alpha})^{\theta}$	Y	I	Costs	C	N
	1.1	1.7	4.3	−0.8	1.0	0.3	−0.1
Panel B: No change in the mass of firms							
	Output (Y)		Consumption (C)			Welfare ($\mathcal{W}$)	
Overall	−1.5		−0.1			0.0	
Components	Z	$(N^{\alpha}K^{1-\alpha})^{\theta}$	Y	I	Costs	C	N
	−0.6	−1.0	−2.3	0.2	2.0	−0.0	0.0

Note: The first row in each panel of the table shows log-changes in aggregate Output (Y), Consumption (C) and Welfare ($\mathcal{W}$). The second row then split the overall changes into the contributions of the various components. All values are reported in percent differences from the baseline economy. Panel A shows the "full adjustment", Panel B considers a scenario with "no change in the mass of firms".

economy, predominantly driven by a rise in aggregate output.[21] In contrast, higher investment (consistent with the increased aggregate capital stock) dampens consumption. This effect is roughly offset by a decline in paid costs, as spending on overhead costs and non-wage labor costs falls due to less costly and more prevalent remote work.

Finally, the last two columns of Table 3 report differences in household welfare ($\mathcal{W} = \log(C) - \sum_j v_j n_j$). Our model predicts that welfare is slightly higher in the remote economy. This is entirely driven by the strong consumption increase. In contrast, households' optimal labor supply is somewhat higher in the remote economy (though accompanied with a lower disutility due to increased remote work rates). Quantitatively, however, this latter effect does not overturn the welfare benefits of higher consumption.

5.5 More firms vs their composition

The remote economy enjoys higher productivity, more output, consumption and increased welfare. In this subsection, we highlight the crucial role of firm entry for these aggregate gains of the remote work revolution.

Remote economy with barriers to firm entry. To make our point, we consider a variant of the remote economy in which firm entry is subdued. We do this as a reduced

[21]The reason why the percentage contribution of output towards consumption is higher than what is reported in the first two columns is that it takes into account the output share in consumption which – given that investment and costs enter negatively – is higher than one. A similar effect holds for the contribution of consumption to welfare.

form way of modeling frictions (e.g., financial or regulatory) impeding a flexible entry response. Practically, we control the extent of firm entry by replacing the entry function (16) with an exogenous rule such that the remote economy features exactly the same mass of firms as the baseline model. In doing so, however, we keep the rest of the model exactly the same, still match all the same moments as before and solve for the general equilibrium wage. The results are in Panel B of Table 3 and the details of our computational strategy are in the Appendix.

Remote work revolution without a surge in startups. Panel B of Table 3 shows the aggregate impact of the remote work revolution in the case where firm entry is held constant. In this case, aggregate TFP is *lower* in the remote economy compared to the baseline. This happens despite the fact that remote work is *more* efficient (i.e., $f(\omega)$ improves) in the remote economy.

The reason lies in the different business dynamism patterns in the remote economy, discussed in Section 5.3. In particular, the remote economy shifts towards smaller, less productive, businesses – the "winners" of more favorable remote work. The losers, typically high-productivity businesses with high remote work setup costs, are effectively crowded out through the general equilibrium forces.

As a result, aggregate output is about 1.5 percent lower in the counterfactual economy. While lower investment and paid costs help offset some of this drop, aggregate consumption still declines slightly. In equilibrium, households choose to reduce their labor supply and, as a result, welfare is effectively the same in both economies.

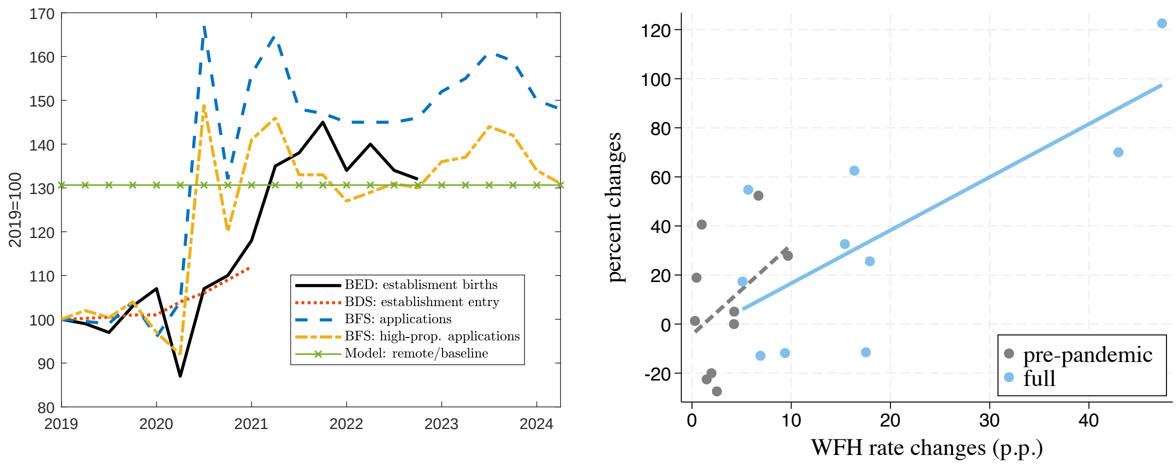
Therefore, while cheaper, more efficient and more desirable remote work arrangements are, all else equal, unambiguously positive for individual workers and firms, they also induce changes in business dynamism. In the absence of increased firm entry and the associated economic boom, the shift towards less productive firms lowers aggregate productivity and leaves welfare effectively unchanged. Therefore, a key insight from our framework is that the overall aggregate effects of the remote work revolution crucially rest on the ease with which startups can enter the economy. We return to this point at the end of the paper when discussing cross-country evidence.

6 Model Validation and Discussion

In this section, we offer empirical support for key model predictions and underlying channels. First, we show that the model is consistent – qualitatively and quantitatively – with the post-pandemic evolution of the U.S. macroeconomy. Next, using micro-data and a novel identification strategy, we provide empirical evidence in support of the key model trade-off between an entry boom and shifts in the composition of firms. These two sets of exercises, therefore, further help validate our theoretical framework.

Figure 5: Model validation: Entry

(a) Aggregate level (b) Industry level



Note: The left panel of the figure shows recent measures of business entry: establishment births from the BED, establishment entry from the BDS, overall applications from the BFS and "high-propensity" applications from the BFS. BFS data are quarterly averages of monthly series, while the BDS data is annual but interpolated to a quarterly frequency. In addition, the left panel also shows the model-implied mass of entrants in the remote economy relative to that in the baseline ("Model: remote/baseline"). The right panel shows changes in remote work rates and entry at the industry-level. Work from home rates are estimated from ATUS as described in the main text. Business entry is taken from the BED. The right panel shows data for the pre-pandemic sample (2003-2019) and the full sample (2003-2022).

6.1 Model Predictions in the Data

As a first step, we confront key model predictions about changes in business dynamism with those observed in U.S. data. In doing so, we focus on the fundamental trade-off between firm entry and changes in the composition of businesses.

Firm entry. As explained in the previous section, a crucial force behind the positive aggregate effects of the remote work revolution is firm entry. We now show that the extent of the model-implied increase in entry is in fact quantitatively reasonable.

Specifically, the U.S. currently finds itself in a "surprising surge in applications for new businesses" (see Decker and Haltiwanger, 2024, p.1). The left panel of Figure 5 shows various recent measures of (planned) business entry in the U.S. economy. These include actual establishment entry taken from the BED and BDS datasets, as well as business applications from the Business Formation Statistics (BFS) of the Census Bureau. The figure displays both overall applications as well as "high-propensity" applications which are deemed as likely converting into actual entry and employment. The latter two are the most timely as the BFS statistics are published monthly. In contrast, the BDS are annual and published with the longest lag.

The figure shows that all measures picked up strongly in 2020, with the BED and BFS measures reaching a new, higher plateau since about 2022. The latest evidence seems to point towards a sustained entry rise. Through the lens of our model, this is consistent with persistently more favorable remote work conditions. Importantly, the figure also shows that the extent of the model-implied rise in firm entry in the remote economy relative to the baseline ("Model: remote/baseline") is quantitatively reasonable, lying on the conservative end of the empirical measures.

While the left panel of Figure 5 focuses on the mass of entrants, the first column of Table 4 reports the change in the entry rate (startups as a share of all businesses). Also in this dimension, our model performs well, accounting for about 46 percent of post-pandemic the entry rate increase observed in the data.[22]

The right panel of Figure 5 further documents that the positive relationship between increases in remote work and firm entry is not limited to the pandemic period or the aggregate economy. In particular, the horizontal axis shows percentage point changes in industry-level work from home rates, while the vertical axis depicts the corresponding percent changes in the numbers of entrants. In all these cases, we consider separately the full sample (2003-2022) and the pre-pandemic period (2003-2019).[23] The figure shows that – consistent with our theoretical model – increases in work from home rates are clearly associated with strong increases in firm entry.

Composition of firms. While a boom in firm entry drives the aggregate benefits of the remote work revolution, in our model these effects are dampened by a shift towards smaller (less productive) firms. Figure 6 and Table 4 show that this prediction is also qualitatively and quantitatively consistent with the data.

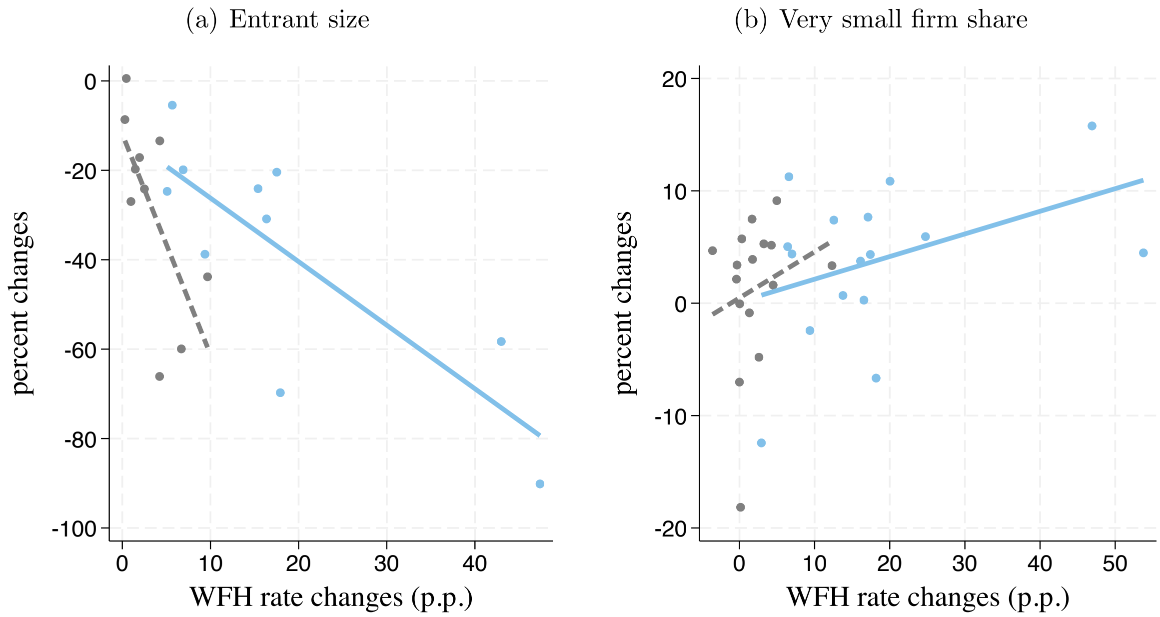
Specifically, the left panel of Figure 6 shows that increases in remote work rates are on average associated with declines in firm size. This holds both before and after the pandemic. This prediction is also confirmed for the aggregate economy in Table 4. In particular, the last four columns of the table show the percent changes in firm sizes of various groups of businesses in the data and the model. Aside from an overall decline in firm size, our framework also aligns well with the observed heterogeneity in firm size declines between firms of different ages and between entering and exiting businesses.

Next, the right panel of Figure 6 documents that increases in remote work are associated with shifts in the entire firm size distribution towards (very) small businesses. Moreover, in the aggregate, the share of very small establishments (1-4 workers) increased by about 4 (5) percentage points among entrants (all businesses). In comparison, our model predicts these shifts to be 5 (7) percentage points, respectively. Therefore, the

[22]The difference between the mass of startups and the entry rate is driven by a stronger model-implied increase in the total number of firms relative to the data. This is to be expected since the model compares long-run equilibria, while in the data the mass of firms is likely still in transition.

[23]We compute changes as the difference in the respective values at the end of the pre-pandemic period (average of 2018Q1-2019Q4) or the full sample (average of 2021Q1-2022Q4) relative to the start of our sample (average of 2003Q1-2004Q4). More details are in the Appendix, including panel regressions with additional controls which confirm our results in Figure 5.

Figure 6: Model validation: Entrant size



Note: The figure depicts super-sector changes in work from home (WFH) rates on the horizontal axis (in percentage points) and (percent) changes in average entrant size (Panel a) and the fraction of very small (1-4 worker) firms (Panel b). Work from home rates are estimated from ATUS as described in the main text. Business sizes are taken from the BED. All panels show data for the pre-pandemic sample (2003-2019) and the full sample (2003-2022).

key trade-off between increased entry and a shift towards small firms highlighted by our framework is also present in the data.

Firm exit. Before moving on, let us highlight that our model is also consistent with the observed increase in firm exit rates. Moreover, it correctly predicts that this increase is mainly concentrated in older businesses. Through the lens of our model, this is because younger businesses tend to be smaller and, therefore, benefit relatively more from the remote work revolution.

Overall, the above evidence suggests that the key model predictions are observed in the data. Moreover, the strength with which business dynamism changes – both in terms of the firm size distribution and aggregate business entry and exit – is also in line with the empirical evidence.

6.2 Model Mechanism in the Data

As a final step in our analysis, we use firm-level data to provide further evidence in support of the underlying mechanisms operating in our model. In particular, based on existing research (see Section 4), our framework assumes that at the firm-level remote work reduces (i) productivity, (ii) wage costs and (iii) non-wage costs (both fixed and variable).

Table 4: Changes in business dynamism (in %)

	Entry rate	Exit rate			Size			
		All	Young	Old	Entrants	Young	Old	Exiters
Data	+28	+15	+1	+22	−24	−18	−15	−22
Model	+13	+13	+5	+19	−16	−18	−15	−21

Note: The table shows changes in the "entry rate", "exit rate" (of young, old and all firms), and firm "size" (of entrants, young, old and exiting firms). Young is defined as less than 6 years, "old" refers to 16-20 year old firms. The top row shows the BED data, while the bottom row shows model-predicted differences based on a comparison of the remote and baseline economies.

A key empirical challenge for an independent validation of these mechanisms is that, to the best of our knowledge, there is no comprehensive *firm-level* information on remote work rates in the U.S. economy. Therefore, to identify the impact of changes in remote work on firms' costs and productivity, we propose a novel identification strategy.

Impact of remote work on firm-level outcomes: Identification. To gauge the impact of changes in remote work conditions on firm-level outcomes, we propose a novel identification strategy. In particular, we will exploit information on firms' "rental commitments" as reported in Compustat. Concretely, rental commitments represent the minimum rental expense due in the next five years reported in firms' balance sheets under all existing non-cancelable leases.

Importantly, rental commitments are reported separately for up to five years ahead. Therefore, to the extent that firms in 2019 did not predict the need for flexibility in their rental contracts (to help them deal with the pandemic-induced forced work from home), the information on rental commitments constitutes exogenous variation in the *exposure* of firms to the remote work revolution.

Intuitively, businesses with no future rental commitments were "exposed" to the remote work revolution because they were free to adjust their rental expenses. In contrast, businesses with rental commitments up to five years in advance were not exposed. Even if their employees started to work remotely during the pandemic, their rental costs were pre-committed. Moreover, because exposed firms can reap the cost-saving benefits of remote work, they will be relatively more incentivized to choose higher remote work rates. Therefore, while our rental commitment exposure measure is most closely related to rental costs, we will also use it in the context of other firm-level variables. Most notably, firm-level productivity, wage costs and fixed costs – the channels present in our model.

In the data, about 40 percent of all firms report both rental expenditures and commitments. Among these, firms are roughly equally split between no commitments and rental commitments five years into the future. Moreover, looking into the history of these firms, there is little evidence of "commitment types." For instance, out of the firms reporting commitments in 2019, more than 2/3 reported having no commitments at some point in the previous 15 years. Therefore, these statistics suggest that rental commitments in 2019 represent exogenous variation across firms.

Impact of remote work on firm-level outcomes: Estimation. To gauge the impact of the work from home revolution on firm-level outcomes, we use Compustat data between 2016 and 2023 to estimate the following set of regressions:

$$\ln y_{j,t} = \alpha + \beta_E \mathbb{1}(E)_j + \beta_T \mathbb{1}(T)_{j,t} + \beta_{E,T} \mathbb{1}(T)_{j,t} \mathbb{1}(E)_j + \mathbf{X}'\theta + \epsilon_{j,t}, \tag{26}$$

where $y_{j,t}$ are the outcome variables of interest described below, $\mathbb{1}(E)_j$ is an indicator function equal to one if firm j in 2019 had no rental commitments in future years (and were therefore "exposed" to the remote work revolution) and zero otherwise. The term $\mathbb{1}(T)_{j,t}$ is an indicator equal to one in periods 2020-2023 and zero otherwise and the term $\mathbf{X}_{j,t}$ represents control variables which include sector, city and year fixed effects (see the Appendix for further details).[24]

As noted above, we will consider several outcome variables of interest. First and foremost, we consider rental expenditures per worker, $rent_{j,t}/n_{j,t}$, as a key measure of non-wage variable costs. In our model, this maps directly into $g(\omega)\kappa_n$. Second, following Gorodnichenko and Weber (2016), we use firms selling, general, and administrative expenses, $SGA_{j,t}$, as a measure of their fixed costs, $g(\omega)\kappa_o$. Third, while the wage bill is not separately reported in Compustat, it is a major part of the costs of goods sold, $COGS_{j,t}$. Therefore, we use information on these variable costs to proxy firms' wage bills, $h(\omega)Wn$. Finally, we consider firms labor productivity, $sales_{j,t}/n_{j,t}$, as a final variable of interest which in our model maps to $f(\omega)y/n$.

Note that while rental commitments directly affect firms' ability to change $rent/n$, they impact the remaining variables indirectly. This is because exposed firms are more likely to adopt remote work, that is, increase ω, because they can more easily reap its cost-saving benefits.

Impact of remote work on firm-level outcomes: Results. Table 5 provides the results. The coefficients, $\beta_{E,T}$, measure how costs and productivity of exposed firms changed between 2016-2019 and 2020-2023, i.e., during the onset of the remote work revolution, relative to changes observed in non-exposed firms. To the extent that our exposure measure captures differences in the uptake of remote work across firms, our theoretical results predict that $\beta_{E,T} < 0$.[25]

[24] Controlling for city and year fixed effects accounts for potential geographical heterogeneity and trends in rental prices, κ_n.

[25] In our model, the remote work revolution was associated with changes in structural parameters making work from home more efficient (an increase in $f(\omega)$). Despite this effect, the model would still predict $\beta_{E,T} < 0$ in the case of labor productivity, simply because of the strength of the rise in remote

Table 5: Estimation results

	rental costs		fixed costs		variable costs		productivity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure, $\beta_{E,T}$	-0.46^{***}	-0.55^{***}	-0.19^{**}	-0.10^{**}	-0.10	-0.09^{**}	-0.07^{*}	-0.06^{**}
	(0.05)	(0.07)	(0.08)	(0.04)	(0.08)	(0.04)	(0.04)	(0.03)
Fixed effects		✓		✓		✓		✓
R-squared	0.02	0.43	0.06	0.55	0.0002	0.50	0.01	0.41
Observations	23,006	23,006	23,018	23,018	25,666	25,666	25,139	25,139

Note: The table presents the coefficients of interest on exposed firms in periods 2020-2023 from regressions (26), $\beta_{E,T}$. Fixed effects include sector, city and year fixed effects. Standard errors (reported in brackets) are clustered at the firm level.

Indeed, the table shows that all coefficients are negative. Understandably, the coefficients on rental costs are strongest as our exposure measure is based on rental commitments. Nevertheless, the results suggests that exposed firms also experienced stronger declines in fixed and variable costs as well as a stronger drop in labor productivity compared to non-exposed firms. Moreover, with the exception of one specification all these effects are also statistically significant. These results, therefore, provide an independent empirical validation of our model mechanisms.

The Appendix C.8 provides further details and robustness checks. These include specifications with firm fixed effects, an event study design as well as specifications considering the feasibility of remote work across industries based on Dingel and Neiman (2020). All these provide additional confirmation of our results. Moreover, we also consider a placebo test, estimating regressions (26) in the period 2010-2017 during which remote work did not experience such a strong increase. In this case, the coefficients $\beta_{E,T}$ are not statistically different from zero, validating our novel identification strategy.

6.3 Discussion

Our quantitative analysis is based on a new model in which heterogeneous businesses optimally choose the extent of remote work. In this subsection, we discuss some features of the current model and sketch potential extensions which may be fruitful avenues for future research.

Aggregate growth. In our framework, firms differ in the *level* of their long-run productivity. While these long-run differences are endogenous and indeed respond to changes in remote work conditions, for tractability we have abstracted from innovation and aggregate growth.

Some recent evidence (see Lin et al., 2023) suggests that remote collaboration may be linked to lower chances of breakthrough innovations. Therefore, in future research,

work rates.

it would be interesting to investigate how remote work interacts with innovation across heterogeneous firms – both at the intensive margin for a given set of incumbent businesses, and at the extensive margin, i.e., how remote work changes affect the incentives for the entry of innovative businesses. If the shift towards less productive firms identified in this paper would also lead to a decline in the innovative capacity of the economy, the welfare conclusions may be even less favorable.

Labor adjustment costs. While our model considers capital adjustment costs, future research may focus also on the costs of hiring and firing workers. More detailed data could inform researchers about how remote work affects the costs of attracting and retaining workers and how important these costs are for different types of firms.

On the one hand, the possibility of hiring workers remotely could loosen potential frictions in attracting (high-skilled) labor which may be locally scarce. On the other hand, while the costs of running a hiring process remotely may be lower, the efficiency of screening and information extraction could be reduced.

Agglomeration effects. While not considered in this paper, an additional channel through which remote work may impact *aggregate* outcomes is through agglomeration effects. For instance, using job posting wage data, Liu and Su (2024) show that remote work lead to a decrease in the urban productivity premium. They attribute this to "weakened agglomeration economies due to decreased interpersonal interactions." Within our framework, weakened agglomeration economies would further drag down aggregate productivity – over and above the impact of changes in business dynamism discussed in this paper.

Other factors and transition dynamics. Our model predicts that almost half of the entry rate spike during and in the aftermath of the COVID pandemic can be explained by increased remote work arrangements. Of course, other factors may have also contributed to the entry rate increase – e.g., the Payment Protection Program, or geographic restructuring of production in urban areas (see e.g., Decker and Haltiwanger, 2024).

Finally, let us note that the patterns of remote work are still evolving. While beyond the scope of this paper, it would be interesting to analyze the transition dynamics from the pre- to the post-pandemic worlds to gauge the timing of firm selection and the implications for aggregate outcomes in the medium run.

Cross-country comparison. A key result of our framework is that the strength of an increase in firm entry is indicative of the aggregate gains from the remote work revolution. In the Appendix, we show that while work from home rates spiked in a relatively similar fashion across many developed economies, changes in firm entry vary quite substantially. For instance, while Sweden has experienced a strong increase in firm entry – almost double that of the U.S. – Germany saw a *decline* in the number of startups. This suggests that institutional or other barriers to firm entry may play a key role in the ability of different countries to reap the benefits of remote work becoming cheaper, more efficient and more desirable.

7 Conclusion

In this paper, we study the macroeconomic impact of the large increase in work from home arrangements observed since the COVID-19 pandemic. We do so by proposing a new macroeconomic model of business dynamism in which firms can optimally choose to conduct part of their production remotely. We show analytically how such a framework generates a link between observed work from home rates, firm entry, and the composition of firms. Extending our baseline framework along several dimensions, we then quantify the macroeconomic impact of the remote work revolution and validate our model's mechanisms using a novel identification strategy.

We find that the observed rise in remote work rates can account for almost half of the firm entry rate increase since the COVID-19 pandemic. It also leads to an increase in output, consumption and welfare. However, these effects crucially depend on the strength and persistence with which firm entry increases. Indeed, if other frictions prevent business entry to rise sustainably, the shift towards smaller and less productive firms will dominate and eliminate all direct benefits of more favorable remote work.

Our paper also opens the door to several additional aspects which would be interesting to study. For example, how does remote work interact with other (e.g., financial or labor market) frictions? How may remote work arrangements affect firm-level and aggregate outcomes in the presence of two-sided heterogeneity and bargaining between workers and firms? We leave these and other questions for future research.

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References

Aksoy, Cevat, Jose Barrero, Nicholas Bloom, Steven Davis, Mathias Dolls, and Pablo Zarate (2022) "Working From Home Around the World," Brookings Papers on Economic Activity.

Angelici, Marta and Paola Profeta (2023) "Smart Working: Flexibility without Constraints," *Management Science*, 70 (3).

Autor, David, Arindrajit Dube, and Annie McGrew (2024) "The Unexpected Compression: Competition at Work in the Low Wage Labor Market," NBER Working Paper 31010.

Bagga, Sadhika, Lukas Mann, Ayşegül Şahin, and Giovanni L. Violante (2024) "Job Amenity Shocks and Labor Reallocation," working paper.

Barrero, Jose, Nicholas Bloom, and Steven Davis (2021) "Why Working From Home Will Stick," NBER Working Paper 28731.

Barrero, José M., Nick Bloom, and Steven J. Davis (2023) "The Evolution of Work from Home," *Journal of Economic Perspectives*, 37 (4), 1–28.

Barrero, José M., Nick Bloom, Steven J. Davis, Brent Meyer, and Emil Mihaylov (2022) "The Shift to Remote Work Lessens Wage-Growth Pressures," NBER Working Paper 30197.

Basu, Susanto and John G. Fernald (1997) "Returns to Scale in U.S. Production: Estimates and Implications," *Journal of Political Economy*, 105 (2), 249–283.

Battiston, Diego, Jordi Blanes i Vidal, and Tom Kirchmaier (2021) "Face-to-Face Communication in Organizations," *Review of Economic Studies*, 88 (2), 574–609.

Bloom, Nicholas, James Liang, John Roberts, and Zhichun Jenny Ying (2015) "Does Working from Home Work? Evidence from a Chinese Experiment," *Quarterly Journal of Economics*, 130 (1), 165–218.

Bloom, Nick, Ruobing Han, and James Liang (2024) "Hybrid working from home improves retention without damaging performance," *Nature*, 630 (8018), 920–925.

Boedo, Hernan and Toshihiko Mukoyama (2012) “Evaluating the Effects of Entry Regulations and Firing Costs on International Income Differences,” *Journal of Economic Growth*, 17, 143–170.

Choudhury, Prithwiraj, Cirrus Foroughi, and Barbara Zepp Larson (2021) “Work-from-Anywhere: The Productivity Effects of Geographic Flexibility,” *Startegic Management Journal*, 42 (4), 655–683.

Clementi, Gian Luca and Berardino Palazzo (2016) “Entry, Exit, Firm Dynamics, and Aggregate Fluctuations,” *American Economic Journal: Macroeconomics*, 8 (3), 1–41.

Cooper, Russell W. and John C. Haltiwanger (2006) “On the Nature of Capital Adjustment Costs,” *The Review of Economic Studies*, 73 (3), 611–633.

Davis, Morris, Andra Ghent, and Jesse Gregory (2024) “The Work-From-Home Technology Boom and its Consequences,” *The Review of Economic Studies*, rdad114.

Decker, Ryan A. and John Haltiwanger (2024) “Surging business formation in the pandemic: Causes and consequences?” *Brookings Papers on Economic Activity.*

Dingel, Jonathan and Brent Neiman (2020) “How Many Jobs Can Be Done from Home?” *Journal of Public Economics*, 189.

Emanuel, Natalia and Emma Harrington (2023) “Working Remotely? Selection, Treatment, and the Market for Remote Work,” Federal Reserve Bank of New York Staff Report 1061.

Foster, Lucia, John Haltiwanger, and Chad Syverson (2008) “Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?” *American Economic Review*, 98 (1), 394–425.

Gibbs, Michael, Friederike Mengel, and Christoph Siemroth (2023) “Work from Home and Productivity: Evidence from Personnel and Analytics Data on Information Technology Professionals,” *Journal of Political Economy Microeconomics*, 1 (1).

Gorodnichenko, Yuriy and Michael Weber (2016) “Are Sticky Prices Costly? Evidence from the Stock Market,” *American Economic Review*, 106 (1).

Haltiwanger, John, Ron Jarmin, Robert Kulick, and Javier Miranda (2016) “High Growth Young Firms: Contribution to Job, Output and Productivity Growth,” mimeo.

Hamermesh, Daniel S., Harley Frazis, and Jay Stewart (2005) “Data Watch: The American Time Use Survey,” *Journal of Economic Perspectives*, 19 (1), 221–232.

Hansen, Stephen, Peter Lamber, Nicholas Bloom, Steven Davis, Raffaella Sadun, and Bledi Taska (2023) "Remote Work Across Jobs, Companies, and Space," NBER Working Paper 31007.

He, Haoran, David Neumark, and Qian Weng (2021) "Do Workers Value Flexible Jobs? A Field Experiment," *Journal of Labor Economics*, 39 (3).

Hopenhayn, Hugo and Richard Rogerson (1993) "Job Turnover and Policy Evaluation: A General Equilibrium Analysis," *Journal of Political Economy*, 101 (5), 915–938.

Ignaszak, Marek and Petr Sedláček (2023) "Customer Acquisition, Business Dynamism and Aggregate Growth," mimeo.

Krause, Simon, Andreas Trumpp, Tobias Dichtl, Susanne Kiese, and Alexander Rutsch (2024) "The Impact of Working from Home on the German Office Real Estate Market," EconPol Forum, vol. 25, CES-Ifo.

León-Ledesma, Miguel and Mathan Satchi (2019) "Appropriate Technology and Balanced Growth," *Review of Economic Studies*, 86, 807–835.

Lin, Yiling, Carl Benedikt Frey, and Lingfei Wu (2023) "Remote Collaboration Fuses Fewer Breakthrough Ideas," *Nature*, 623, 987–991.

Liu, Sitian and Yichen Su (2024) "The Effect of Working from Home on the Agglomeration Economies of Cities: Evidence from Advertised Wages," mimeo.

Mas, Alexandre and Amanda Pallais (2017) "Valuing Alternative Work Arrangements," *American Economic Review*, 107 (12), 3722–59.

Monte, Ferdinando, Charly Porcher, and Esteban Rossi-Hansberg (2023) "Remote Work and City Structure," Working Paper 31494, National Bureau of Economic Research.

Natalia, Monteiro, Straume Odd Rune, and Valente Marieta (2019) "Does Remote Work Improve or Impair Firm Labour Productivity? Longitudinal Evidence from Portugal," CESifo Working Paper 7991.

Peters, Michael (2020) "Heterogeneous Markups, Growth, and Endogenous Misallocation," *Econometrica*, 88, 2037–2073.

Poschke, Markus (2010) "The Regulation of Entry and Aggregate Productivity," *The Economic Journal*, 120, 1175–1200.

Richard, Morgane (2024) "The Spatial and Distributive Implications of Working-from-Home: A General Equilibrium Model," mimeo.

Sedláček, Petr (2020) "Lost Generations of Firms and Aggregate Labor Market Dynamics," *Journal of Monetary Economics*, 111, 16–31.

Sedláček, Petr and Vincent Sterk (2017) "The Growth Potential of Startups over the Business Cycle," *American Economic Review*, 107 (10), 3182–3210.

Vij, Akshay, Flavio Souza, Helen Barrie, V Anilan, Sergio Sarmiento, and Lynette Washington (2023) "Employee Preferences for Working From Home in Australia," *Journal of Economic Behavior and Organization*, 214.

Yang, Longqi, David Holtz, Sonia Jaffee, Siddharth Suri, Shilpi Sinha, Jeffrey Weston, and Connor Joyce et al. (2022) "The Effects of Remote Work on Collaboration among Information Workers," *Nature Human Behavior*, 6, 43–54.

Zarate, Pablo, Mathias Dolls, Steven Davis, Nicholas Bloom, Jose Maria Barrero, and Cevat Giray Aksoy (2024) "Why Does Working From Home Vary Across Countries and People?," NBER Working Paper 32374.

Online Appendix

Table of Contents

A Core Model: Additional Details and Proofs

This Appendix provides additional details on the stylized model of Section 2, as well as all the theoretical proofs.

A.1 Model Details

In this Appendix, we provide the remaining details to our stylized model. In particular, we describe the household problem and formally define the equilibrium.

Household Problem. A representative household owns all businesses in the economy and optimally chooses aggregate consumption, C, such that:

$$C = \sum_j (W_j n_j + \pi_j).$$

where the aggregate price is normalized. $W_j = h(\omega_j)W$ is the firm-specific wage. n_j and π_j are firm j's employment and profit, respectively.

Equilibrium. A stationary equilibrium consists of (i) a value function $v(z)$ and policy functions $n(z)$ and $\omega(z)$, and (ii) a fully on-site wage rate $W \geq 0$, mass of startup attempts $M_e \geq 0$, and a measure of incumbents $\mu(z)$, such that:

- $v(z)$, $n(z)$ and $\omega(z)$ solve the incumbent's problem (3),
- the free entry condition (4) is satisfied with equality if $M_e > 0$,
- the labor and goods markets clear:

$$\begin{aligned} N &= \int n\mu(z)dz \\ Y &= C + \kappa_e M_e + \int g(\omega)(\kappa_n n + \kappa_o)\mu(z)dz, \end{aligned}$$

  where total output, $Y = \int f(\omega)y\mu(z)dz$, is used for household consumption, C, and for entry, non-wage labor and overhead costs.

- and the distribution of firms satisfies: $\mu(z) = h(z)$.

A.2 Proofs

In what follows, we provide all the proofs to our propositions in the main text, assuming that $h(\omega) = g(\omega)$. For simplicity, we first denote $\kappa_n + W = \kappa$.

Proof of Proposition 1. Differentiating $\pi(z)$ w.r.t. ω and n gives the FOCs:

$$\begin{aligned} f'(\omega)zn^{\alpha} - g'(\omega)(\kappa n + \kappa_o) &= 0 \\ f(\omega)z\alpha n^{\alpha-1} - g(\omega)\kappa &= 0 \end{aligned}$$

a) if $\kappa_o = 0$, then combining the two FOCs and rearranging gives ω^* such that:

$$\frac{f'(\omega^*)}{f(\omega^*)}\frac{g(\omega^*)}{g'(\omega^*)} = \alpha,$$

b) if $\kappa_o > 0$, differentiating equations (A6) and (A7) w.r.t. z and rearranging, we obtain:

$$\{(\frac{f''g' - g''f'}{g'^3})f\alpha(\alpha-1) - [\frac{f'}{g'}(\alpha-1) + \frac{\kappa_o}{zn^{*\alpha}}]^2\}\frac{\partial\omega^*}{\partial z} = \frac{f\alpha\kappa_o}{g'z^2n^{*\alpha}}$$

Since $\kappa_o > 0$ and $g' < 0$, the RHS is negative. Hence $\frac{\partial\omega^*}{\partial z} < 0$ if and only if:

$$(\frac{f''g' - g''f'}{g'^3})f\alpha(\alpha-1) > [\frac{f'}{g'}(\alpha-1) + \frac{\kappa_o}{zn^{*\alpha}}]^2 \tag{A1}$$

We can further derive the necessary condition from (A1):

$$\frac{f''}{f'} > \frac{g''}{g'}$$

Proof of Proposition 2. Assume two coefficients $\widetilde{f}$ and $\widetilde{g}$ that govern the velocity of productivity loss and cost savings. Specifically, we have: $\frac{\partial f(\omega;\widetilde{f})}{\partial\widetilde{f}} > 0$, $\frac{\partial g(\omega;\widetilde{g})}{\partial\widetilde{g}} < 0$, $\frac{\partial^2 f(\omega;\widetilde{f})}{\partial\omega\partial\widetilde{f}} > 0$ and $\frac{\partial^2 g(\omega;\widetilde{g})}{\partial\omega\partial\widetilde{g}} < 0$ when $\omega \in (0, 1]$.

For simplicity, we denote $\frac{\partial f(\omega;\widetilde{f})}{\partial\widetilde{f}}$ as f_2, $\frac{\partial f(\omega;\widetilde{f})}{\partial\omega}$ as f_1, $\frac{\partial^2 f(\omega;\widetilde{f})}{\partial\omega\partial\widetilde{f}}$ as f_{12}, and $\frac{\partial^2 f(\omega;\widetilde{f})}{\partial\omega^2}$ as f_{11}. Similar for $g(\widetilde{g}, \omega)$. We can rewrite Equation (A6) and (A7) as:

$$f_1(\omega^*;\widetilde{f})zn^{*\alpha} - g_1(\omega^*;\widetilde{g})(\kappa n^* + \kappa_o) = 0 \tag{A2}$$

$$f(\omega^*;\widetilde{f})z\alpha n^{*\alpha-1} - g(\omega^*;\widetilde{g})\kappa = 0 \tag{A3}$$

Proof of $\frac{\partial v_e}{\partial\widetilde{f}} > 0$. By the envelope theorem, we have:

$$\frac{\partial\pi^*}{\partial\widetilde{f}} = f_2(\omega^*;\widetilde{f})zn^{*\alpha} > 0 \tag{A4}$$

Note that:

$$\begin{aligned} v_e &= \int v(z)h(z)dz \\ &= \int \frac{\pi^*(z)}{1-\beta(1-\delta)}h(z)dz \end{aligned}$$

Since $\frac{\partial h(z)}{\partial \widetilde{f}} = 0$ and $h(z) \geq 0$, we have:

$$\frac{\partial v_e}{\partial \widetilde{f}} = \int \frac{\partial \pi^*(z)}{\partial \widetilde{f}} \frac{h(z)}{1-\beta(1-\delta)}dz > 0$$

Proof of $\frac{\partial v_e}{\partial \widetilde{g}} > 0$. By the envelope theorem, we have:

$$\frac{\partial \pi^*}{\partial \widetilde{g}} = -g_2(\omega^*;\widetilde{g})(\kappa n^* + \kappa_o) > 0 \tag{A5}$$

Similarly, we have:

$$\frac{\partial v_e}{\partial \widetilde{g}} = \int \frac{\partial \pi^*(z)}{\partial \widetilde{g}} \frac{h(z)}{1-\beta(1-\delta)}dz > 0$$

Interior Solutions. Start with the FOCs:

$$f'(\omega)zn^\alpha - g'(\omega)(\kappa n + \kappa_o) = 0 \tag{A6}$$

$$f(\omega)z\alpha n^{\alpha-1} - g(\omega)\kappa = 0 \tag{A7}$$

Solve the optimal employment, n^*, from equation (A7):

$$n^* = (\frac{fz\alpha}{g\kappa})^{\frac{1}{1-\alpha}}$$

Substituting n^* into equation (A6), we have

$$\frac{zf'(\omega^*)}{g'(\omega^*)} - \kappa n^{*1-\alpha} - \kappa_0 n^{*-\alpha} = 0 \tag{A8}$$

Define the followings for simplicity:

$$\begin{aligned} F(\omega) &= \alpha z f(\omega) \\ G(\omega) &= \kappa g(\omega) \end{aligned}$$

Then we can rewrite equation (A8) as:

$$\frac{1}{\alpha}\frac{F'/F}{G'/G} - 1 - \frac{\kappa_0}{\kappa}(\frac{F}{G})^{-\frac{1}{1-\alpha}} = 0$$

Denote $H(\omega) = \frac{1}{\alpha}\frac{F'/F}{G'/G} - 1 - \frac{\kappa_0}{\kappa}(\frac{F}{G})^{-\frac{1}{1-\alpha}}$. By the intermediate value theorem, the sufficient condition for interior solutions is thus:

$$H(0)H(1) < 0$$

B Generalized Model: Additional Details and Results

This Appendix provides a formal definition of equilibrium in the generalized model.

B.1 Equilibrium Definition in Generalized Model

A stationary equilibrium consists of (i) value functions $v(z,k)$, $v^{\omega}(z,k)$, $v^{x}(z,k)$ and policy functions $n(z,k)$, $\omega(z,k)$, $\widetilde{r}(z,k)$, $\widetilde{z}(k)$, $x(z,k)$ and (ii) a fully on-site wage rate $W \geq 0$, a mass of entrants $M \geq 0$ and a measure of incumbents $\overline{\mu}(z,k)$ (with $\mu(z,k)$ denoting the probability distribution), such that:

- $v(z,k)$, $v^{\omega}(z,k)$, $v^{x}(z,k)$, $n(z,k)$, $\omega(z,k)$, $\widetilde{r}(z,k)$, $\widetilde{z}(k)$, $x(z,k)$ solve the incumbent's problem (11);
- the free entry condition (17) is satisfied;
- the goods and labor markets clear (18), (19);
- the distribution of firms satisfies

  $$\overline{\mu}(z',k') = \int\int \Phi(z',k'|z,k)d\overline{\mu}(z,k) + M\mathbb{1}[k' = x(z',0)]H(z'),$$

  where

  $$\Phi(z',k'|z,k) = F(z'|z)\mathbb{1}[k' = x(z,k) + (1-\delta)k(z,k)]\mathbb{1}[\widetilde{z}(k)],$$

  and where $\mathbb{1}[\widetilde{z}(k)]$ is an indicator function equal to 1 when firms decide to remain in operation, $F(z'|z)$ is the transition function for productivity shocks described in (8) and, therefore, where $\Phi(z',k'|z,k)$ denotes the transition from (z,k) to (z',k'). $\widetilde{r}(z,k)$ denotes the decision of first-time work from home.

B.2 Computational Strategy

- Given $\widetilde{f}$, $\widetilde{g}$ and $\widetilde{h}$, guess the equilibrium fully on-site wage W.
- For all pairs (z,k) on the grid, such that $\mu(z,k) > 0$, the optimal choices of $(n_{j,t}, x_{j,t})$ (for onsite firms) and $(n_{j,t}, \omega_{j,t}, x_{j,t})$ (for work-from-home firms) are the solutions to the following problem:

$$
\begin{aligned}
v_j(z_{j,t},k_{j,t}) &= \max_{n_{j,t},x_{j,t}} \{\pi_{j,t} + \beta(1-\delta)u_j(z_{j,t},k_{j,t})\} \\
\pi_{j,t} &= f(\omega_{j,t})y_{j,t} - W(\omega_{j,t})n_{j,t} - g(\omega_{j,t})(\kappa_n n_{j,t} + \mu_\kappa) - x_{j,t} - \zeta(x_{j,t},k_{j,t}) \\
u_j(z_{j,t},k_{j,t}) &= \int \max \begin{bmatrix} v_j^x(k_{t+1}), \mathbb{E}_t v_j(z_{j,t+1},k_{t+1}) - \widetilde{\kappa}_o, \\ \mathbb{E}_t v_j^\omega(z_{j,t+1},k_{j,t+1}) - \widetilde{\kappa}_o - \kappa_j^\omega \end{bmatrix} dH_\kappa(\widetilde{\kappa}_o) \\
v_j^x(z_{j,t},k_{j,t}) &= k_{j,t}(1-\delta_k) - \zeta(-k_{j,t}(1-\delta_k),k_{j,t}) \\
v_j^\omega(z_{j,t},k_{j,t}) &= \max_{n_{j,t},\omega_{j,t},x_{j,t}} \left\{\pi_{j,t} + \beta(1-\delta)u_j^\omega(z_{j,t},k_{j,t})\right\} \\
u_j^\omega(z_{j,t},k_{j,t}) &= \int \max\left[v_j^x(k_{t+1}), \mathbb{E}_t v_j^\omega(z_{j,t+1},k_{t+1}) - \widetilde{\kappa}_o\right] dH_\kappa(\widetilde{\kappa}_o)
\end{aligned}
$$

- Using the free entry condition and the entry function, compute the mass of startup attempts, s_i, and the mass of successful startups, m_i:

$$
\begin{aligned}
\kappa_e &= \frac{m_i}{s_i}\sum_l p_l \int_z \max\left[v(z,0;\underline{z}_i,\kappa_l^\omega), v^\omega(z,0;\underline{z}_i,\kappa_l^\omega) - \kappa_l^\omega\right] dH_z(z) \\
m_i &= \Psi_i^\phi s_i^{1-\phi}
\end{aligned}
$$

- Using s_i, m_i, the aggregate resource constraint and consumption FOC to pin down the implied mass M:

$$
\begin{aligned}
Y &= C + S\kappa_e + \sum_i\sum_l \int\int \left[\zeta(x,k) + g(\omega)(\kappa_n n + \mu_\kappa) + \hat{\kappa}_o + \kappa_l^\omega \mathbb{1}_{i,l}(z,k)\right]\mu_{i,l}(z,k)dzdk \\
W &= \upsilon C
\end{aligned}
$$

- Iterate on finding a equilibrium wage such that the following is satisfied:

$$
M = \sum_i m_i
$$

B.3 Solution to the Counterfactual Economy with "Fixed Mass of Firms"

The solution to the counterfactual economy with "no change in the mass of firms" is generated by the following steps:

- The first two steps are the same as in the last subsection.
- Using the free entry condition and the entry function, compute the probability of successful startups.

- Compute the “hypothetical” mass of startups such that the total mass of firms is the same as in the benchmark economy. Use the probability of successful startups obtained from the last step to back out the “hypothetical” mass of startup attempts.

- Using the “hypothetical” mass of startups attempts and successful startups, and the resource constraint to compute the aggregate consumption.

- Iterate on finding an equilibrium fully on-site wage such that the consumption FOC is satisfied.

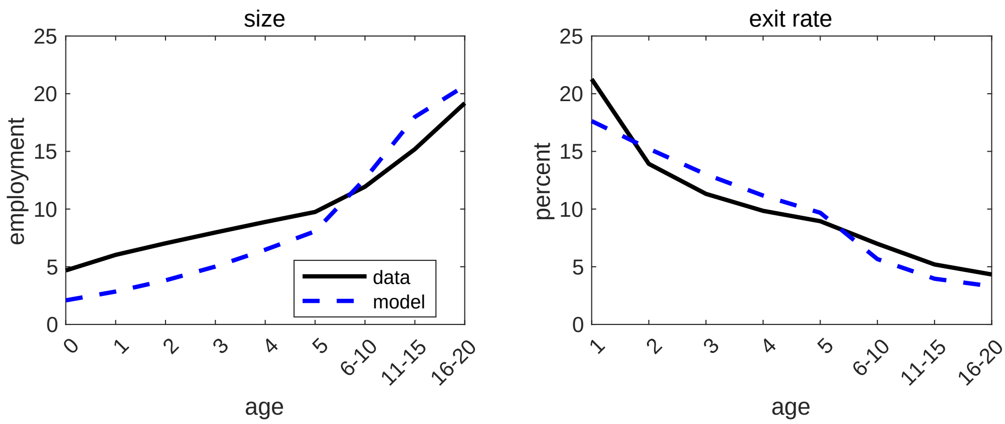
B.4 Robustness: Elasticity of Entry Function

As discussed in the calibration section, the elasticity of the entry function, ϕ, is important for the response of startups to changes in remote work conditions. In this Appendix, we provide a sensitivity analysis with respect to ϕ.

In particular, we consider higher (0.2) and lower (0.1) values of ϕ and re-calibrate both cases to match the same targets as our baseline economy. Table A1 and A4 show the calibrated parameters, respectively. Table A2 to A6 show the results.

While the elasticity of entry matters for the strength of the entry response, it matters less for changes in firm sizes and aggregates. The reason is that a shallower (stronger) entry response is compensated for by a stronger (weaker) change in firm selection. Therefore, aggregate outcomes are effectively identical across the 3 sets of ϕ values.

Figure A1: Life-cycle profiles of size and exit rates: Data and model



Note: The left panel shows average establishment size (employment) by age, while the right panel shows average exit rates by age for the model and the data. The latter is taken from the BED, averaged over the years 2003-2019.

Table A1: Parameter values and targeted moments

	Parameter	Value	Target/Source	Data	Model
β	Discount factor	0.96	Interest rate of approx. 4%		
α	Labor elasticity of output	0.65	Labor share in income of approx. 65%		
θ	Returns to scale	0.90	Basu, Fernald (1997) estimate		
δ_k	Capital depreciation	0.08	Cooper, Haltiwanger (2006)		
υ	Disutility of labor	0.018	Normalization, $W = 1$		
κ_e	Entry cost	0.72	Normalization, $s_H + s_L = 1$		
ϕ	Elasticity of entry function	0.10	Sedláček and Sterk (2017)		
κ_L^ω	"Low" remote work setup costs	0	Normalization, minimum remote work setup cost of 0		
$\widetilde{f}$	Speed of remote work productivity losses	-0.151	Average work from home rate, ATUS	4.1%	3.9%
$\widetilde{g}$	Speed of remote work cost savings	0.325	Work from home rates in 100+ over 100- firms, ATUS & ASEC	1.12	1.12
$\widetilde{h}$	Household preferences for remote work	0	Wages unresponsive to remote work	0	0
κ_n	Non-wage labor costs	0.255	Rental expenses - size coefficient, Compustat (see (24)	0.86	0.91
κ_H^ω	"High" remote work setup costs	5.3	Share of large firms conducting remote work, BRS	30%	29%
Ψ_ω	Share of "low" remote work setup costs	0.195	Share of firms conducting remote work, BRS	23%	23%
Ψ_L	Mass of "low" business opportunities	$8.0e-7$	Share of small (< 50) businesses, BED	95%	94%
Ψ_H	Mass of "high" business opportunities	$2.4e-8$	Startup success rate, BED	21%	23%
$\underline{z}_H$	Mean "high" productivity	0.131	Average establishment size, BED	15.4	15.0
$\underline{z}_L$	Mean "low" productivity	0.104	Average establishment size of small (< 50) businesses, BED	6.8	7.6
ρ	Productivity persistence	0.723	Establishment size life-cycle profile, BED	see Figure 2	
σ_z	Productivity shock dispersion	0.208	Establishment size life-cycle profile, BED	see Figure 2	
ζ_0	Capital adjustment costs, fixed	0.001	Establishment size life-cycle profile, BED	see Figure 2	
ζ_1	Capital adjustment costs, variable	0.61	Establishment size life-cycle profile, BED	see Figure 2	
δ	Exogenous exit rate	0	Establishment exit life-cycle profile, BED	see Figure 2	
μ_κ	Overhead costs, mean	0.795	Establishment exit life-cycle profile, BED	see Figure 2	
σ_κ	Overhead costs, dispersion	2.49	Establishment exit life-cycle profile, BED	see Figure 2	

Note: The table presents values for all model parameters. The first three columns describe each parameter and its parameterized value, while the last two columns indicate the most relevant target or data source.

Table A2: Model Results: Remote work and business entry and exit ($\phi = 0.1$)

	Rate		Size	
	Entry	Exit	Entrants	Exiters
Data	+28%	+15%	−24%	−22%
Model	+19%	+19%	−19%	−25%

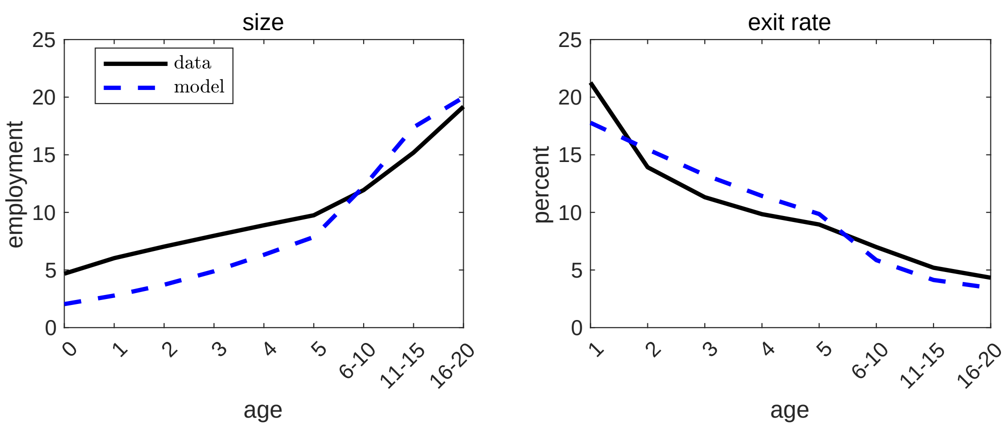
Note: The table shows changes in entry and exit rates (first two columns) and changes in average of entrants and of exiting businesses (last two columns). The top row shows changes in the BED data, while the bottom row shows the model-predicted changes.

Table A3: Impact of increased remote work: Changes in aggregates ($\phi = 0.1$)

	Output (Y)		Consumption (C)			Welfare ($\mathcal{W}$)	
Overall	3.2		4.7			0.2	
Components	Ω	$\overline{y}$	Y	I	Costs	C	N
	28.9	−25.6	4.8	−1.0	0.9	0.3	−0.1

Note: The first row of the table shows log-changes in aggregate Output (Y), Consumption (C) and Welfare ($\mathcal{W}$). The second row then split the overall changes into the contributions of the various components. All values are reported in percent changes from the pre-pandemic baseline.

Figure A2: Life-cycle profiles of size and exit rates: Data and model



Note: The left panel shows average establishment size (employment) by age, while the right panel shows average exit rates by age for the model and the data. The latter is taken from the BED, averaged over the years 2003-2019.

Table A4: Parameter values and targeted moments

	Parameter	Value	Target/Source	Data	Model
β	Discount factor	0.96	Interest rate of approx. 4%		
α	Labor elasticity of output	0.65	Labor share in income of approx. 65%		
θ	Returns to scale	0.90	Basu, Fernald (1997) estimate		
δ_k	Capital depreciation	0.08	Cooper, Haltiwanger (2006)		
υ	Disutility of labor	0.022	Normalization, $W = 1$		
κ_e	Entry cost	0.63	Normalization, $s_H + s_L = 1$		
ϕ	Elasticity of entry function	0.20	Sedláček and Sterk (2017)		
κ_L^ω	"Low" remote work setup costs	0	Normalization, minimum remote work setup cost of 0		
$\widetilde{f}$	Speed of remote work productivity losses	-0.151	Average work from home rate, ATUS	4.1%	3.9%
$\widetilde{g}$	Speed of remote work cost savings	0.325	Work from home rates in 100+ over 100- firms, ATUS & ASEC	1.12	1.12
$\widetilde{h}$	Household preferences for remote work	0	Wages unresponsive to remote work	0	0
κ_n	Non-wage labor costs	0.255	Rental expenses - size coefficient, Compustat (see (24)	0.86	0.91
κ_H^ω	"High" remote work setup costs	5.3	Share of large firms conducting remote work, BRS	30%	29%
Ψ_ω	Share of "low" remote work setup costs	0.195	Share of firms conducting remote work, BRS	23%	23%
Ψ_L	Mass of "low" business opportunities	$3.8e-4$	Share of small (< 50) businesses, BED	95%	94%
Ψ_H	Mass of "high" business opportunities	$3.8e-5$	Startup success rate, BED	21%	21%
$\underline{z}_H$	Mean "high" productivity	0.131	Average establishment size, BED	15.4	14.3
$\underline{z}_L$	Mean "low" productivity	0.104	Average establishment size of small (< 50) businesses, BED	6.8	7.4
ρ	Productivity persistence	0.723	Establishment size life-cycle profile, BED	see Figure 2	
σ_z	Productivity shock dispersion	0.208	Establishment size life-cycle profile, BED	see Figure 2	
ζ_0	Capital adjustment costs, fixed	0.001	Establishment size life-cycle profile, BED	see Figure 2	
ζ_1	Capital adjustment costs, variable	0.61	Establishment size life-cycle profile, BED	see Figure 2	
δ	Exogenous exit rate	0	Establishment exit life-cycle profile, BED	see Figure 2	
μ_κ	Overhead costs, mean	0.795	Establishment exit life-cycle profile, BED	see Figure 2	
σ_κ	Overhead costs, dispersion	2.49	Establishment exit life-cycle profile, BED	see Figure 2	

Note: The table presents values for all model parameters. The first three columns describe each parameter and its parameterized value, while the last two columns indicate the most relevant target or data source.

Table A5: Model Results: Remote work and business entry and exit ($\phi = 0.2$)

	Rate		Size	
	Entry	Exit	Entrants	Exiters
Data	+28%	+15%	−24%	−22%
Model	+11%	+11%	−13%	−19%

Note: The table shows changes in entry and exit rates (first two columns) and changes in average of entrants and of exiting businesses (last two columns). The top row shows changes in the BED data, while the bottom row shows the model-predicted changes.

Table A6: Impact of increased remote work: Changes in aggregates ($\phi = 0.2$)

	Output (Y)		Consumption (C)			Welfare ($\mathcal{W}$)	
Overall	2.6		4.1			0.2	
Components	Ω	$\overline{y}$	Y	I	Costs	C	N
	20.7	−18.1	3.9	−0.8	1.1	0.3	−0.1

Note: The first row of the table shows log-changes in aggregate Output (Y), Consumption (C) and Welfare ($\mathcal{W}$). The second row then split the overall changes into the contributions of the various components. All values are reported in percent changes from the pre-pandemic baseline.

C Empirical Analysis: Additional Exercises and Robustness

In this Appendix, we consider various robustness checks to some of our empirical results as well as a set of additional estimates.

C.1 Heterogeneity of Remote Work Across Sectors

According to the Business Response Survey, the fraction of establishments with some employees working remotely was 23.3% in February 2020. Turning to the intensive margin of remote work, the American Time Use Survey suggests that the fraction of hours worked remotely in 2019 was "only" about 6.7%.

Both these averages, however, hide large amounts of heterogeneity across sectors. Intuitively, remote work – both at the extensive and intensive margins – is most common in the service sectors. For instance, the information sector is characterized by almost 59% of establishments reporting some employees working remotely with an average 8.8% of hours worked from home. Professional and business services, as well as financial services have similarly high rates of remote work. In contrast, accommodation and food services have the lowest remote work rates with only 2.1% of establishments reporting some employees working remotely and an average 1.3% of hours worked from home. Construction and retail trade have similarly low levels of remote work.

C.2 Work from Home and Business Dynamism

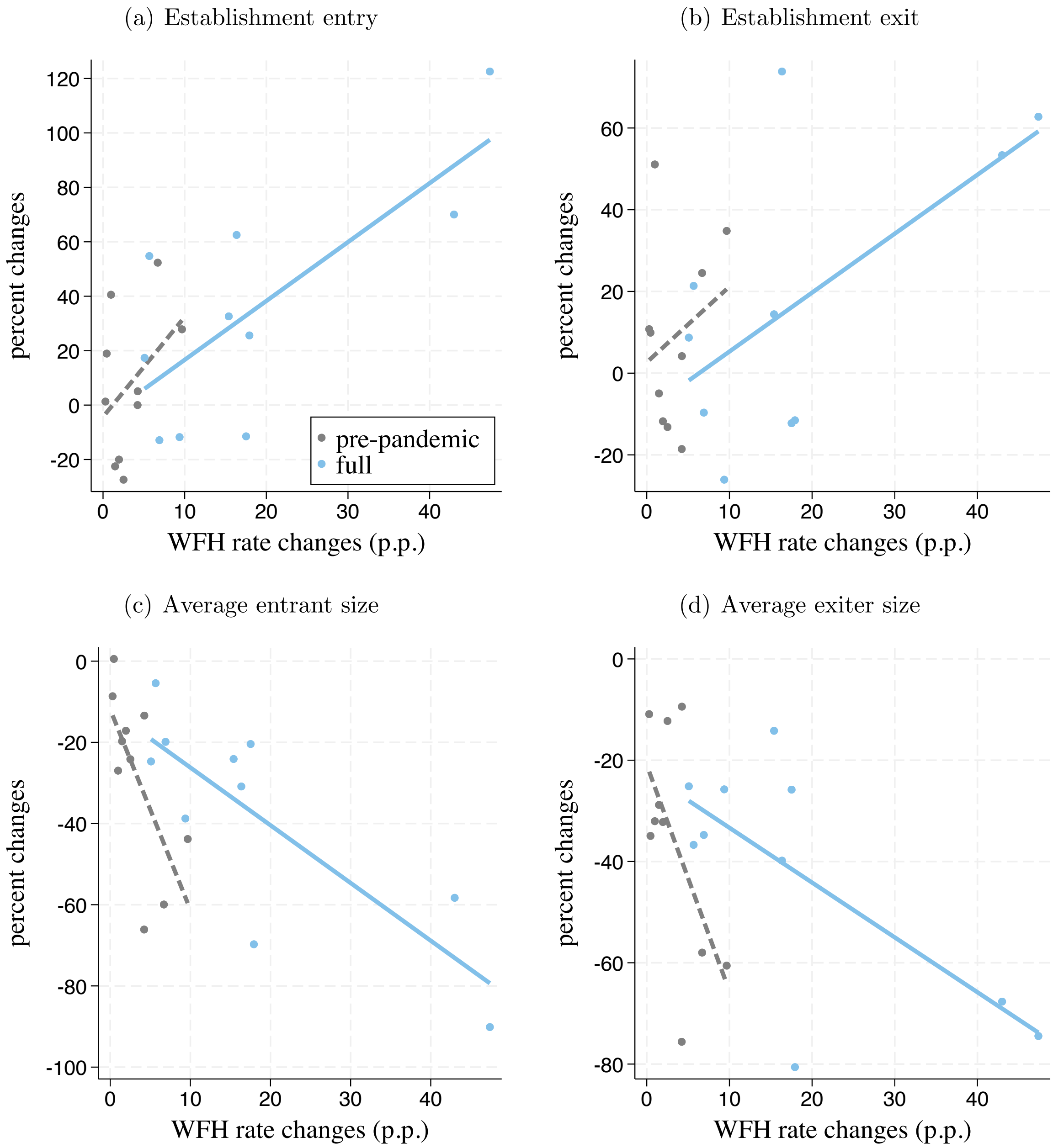
We now turn to the link between work from home rates and business entry and exit.

Raw data. Figure A3 shows how changes in remote work rates relate to business entry, exit, the average size of entering and exiting establishments. Specifically, the horizontal axis shows percentage point changes in industry-level work from home rates, while the vertical axis depicts the corresponding percent changes in the numbers of entrants and exiters, and their respective sizes. In all these cases, we consider separately the full sample (2003-2022) and the pre-pandemic period (2003-2019).[1]

The figure shows that – consistent with our core theoretical model – increases in work from home rates are clearly associated with strong increases in firm entry and exit, coupled with declines in the size of entering and exiting businesses. Note that these patterns are not a pandemic-only phenomenon. In fact, the relationship is somewhat weaker during the pandemic which saw unprecedented increases in work from home rates.

[1] We compute changes as the difference in the respective values at the end of the pre-pandemic period (average of 2018Q1-2019Q4) or the full sample (average of 2021Q1-2022Q4) relative to the start of our sample (average of 2003Q1-2004Q4).

Figure A3: Work from home and business dynamism: Changes across industries



Note: The figure depicts super-sector changes in work from home (WFH) rates on the horizontal axis (in percentage points) and (percent) changes in the number of entrants (Panel a), exiters (Panel b), average entrant size (Panel c) and average exiter size (Panel d). Work from home rates are estimated from ATUS as described in the main text. Business entry, exit and sizes are taken from the BED. All panels show data for the pre-pandemic sample (2003-2019) and the full sample (2003-2022).

Estimation. To test the above relationships more formally, we estimate the following panel regressions:

$$y_{i,t} = \delta_i + \delta_t + \beta \overline{\omega}_{i,t} + \Gamma X_{i,t} + \epsilon_{i,t}, \tag{A9}$$

Table A7: Working from home and business dynamism: Regression results

	Entry	Exit	Entrant Size	Exiter Size
A: Pre-pandemic sample (2003Q1-2019Q4)				
Work from home rate, β	1.414^{***}	1.214^{***}	-1.315^{***}	-1.235^{***}
	(0.218)	(0.240)	(0.191)	(0.180)
R-squared	0.502	0.405	0.420	0.566
# observations	590	590	590	590
B: Full sample (2003Q1-2022Q4)				
Work from home rate, β	1.400^{***}	0.905^{***}	-0.712^{***}	-0.408^{***}
	(0.117)	(0.120)	(0.106)	(0.085)
R-squared	0.705	0.547	0.486	0.581
# observations	710	700	710	700

Note: The table reports results from estimating (A9). Panel A reports estimates using the pre-pandemic period (2003Q1-2019Q4) only, while Panel B report results for our entire sample period (2003Q1-2022Q4). All specifications include industry and time fixed effects as well as lagged values of the dependent variable and industry-level real output growth rates. Standard errors are reported in brackets – all estimates are significant at the 1 percent level.

where $y_{i,t}$ represents, respectively, (the logs of) business entry, exit, average entrant's or exiter's size in industry i and period t, δ_i are industry fixed effects, δ_t are time fixed effects, $X_{i,t}$ is a set of control variables and $\overline{\omega}^L_{i,t} = 1/(L+1)\sum_{l=0}^{L} \omega_{i,t-l}$ are time-varying moving averages of work from home rates. Coefficient β is the primary object of interest as it provides a concise summary of the potentially dynamic (lagged) effects of working from home rates on business dynamism.[2]

In estimating β, we control for a range of variables. First, $X_{i,t}$ includes lags of our (average) work from home measure, $\overline{\omega}$. Second, in addition to controlling for industry differences through fixed effects, δ_i, and aggregate trends through time fixed effects, δ_t, we also include industry-specific real output growth rates, $g_{i,t}$, taken from the Bureau of Economic Analysis. Finally, as before, we consider two sample periods for our specifications: "pre-pandemic" sample and "full" sample.

Table A7 shows that even after controlling for a range of other factors, changes in remote work rates are strongly related to changes in business dynamism. Moreover, the direction of these relationships remains the same as in the raw data. In particular, higher remote work rates are related to more business entry and exit, but smaller sizes of entrants and exiting businesses.

[2] In our baseline specification we use $L = 4$. The Appendix provides robustness exercises with respect to L.

C.3 Robustness: Working Outside the Workplace

In this Appendix, we use work-outside-workplace rate to replace work from home rate in the empirical analysis. The construction of work-outside-workplace is similar to that of work from home rate, defined in equation (23), in that we count a day as work outside workplace if the individual spent in total at least 6 hours working at home or other places except their workplace.

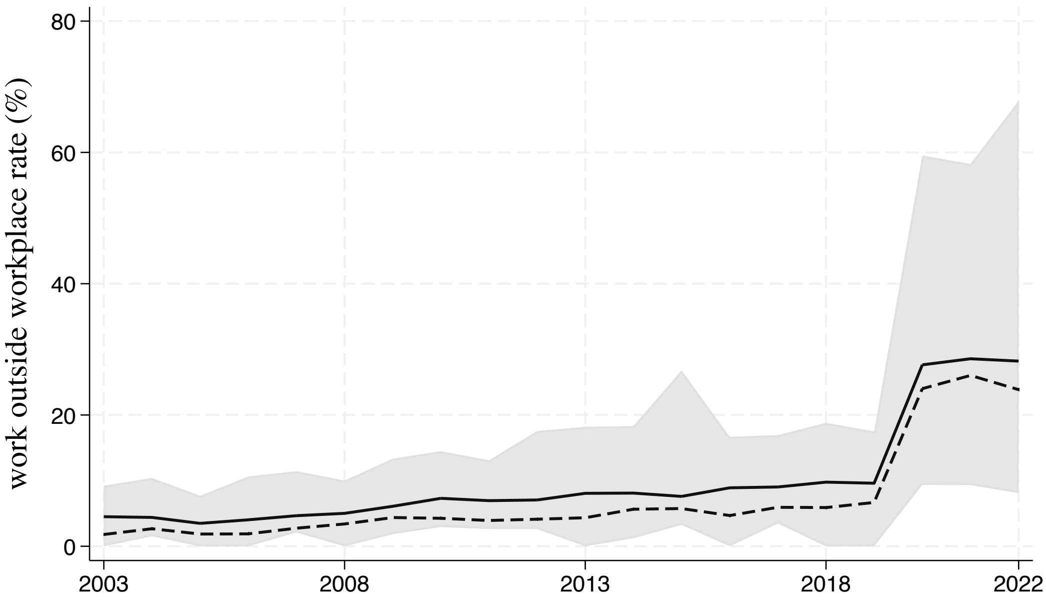
Figure A4 shows the evolution of working-outside-workplace rate from 2003 to 2022. In addition, Figure A5 plots how changes in remote work rates are connected to changes in establishment entry and exit across industries. Finally, Table A8 shows the associated panel regression results. All these are very similar to the outcomes presented in the main text which are based on work from home definitions.

Table A8: Working outside workplace and business dynamism: Regression results

	Entry	Exit	Entrant Size	Exiter Size
A: Pre-pandemic sample (2003Q1-2019Q4)				
Work from home rate, β	0.832^{***}	0.875^{***}	-0.519^{***}	-0.674^{***}
	(0.187)	(0.202)	(0.167)	(0.156)
R-squared	0.465	0.384	0.351	0.526
# observations	590	590	590	590
B: Full sample (2003Q1-2022Q4)				
Work from home rate, β	1.299^{***}	0.924^{***}	-0.723^{***}	-0.393^{***}
	(0.116)	(0.115)	(0.104)	(0.082)
R-squared	0.685	0.538	0.463	0.569
# observations	710	700	710	700

Note: The table reports results from estimating (A9). Panel A reports estimates using the pre-pandemic period (2003Q1-2019Q4) only, while Panel B report results for our entire sample period (2003Q1-2022Q4). All specifications include industry and time fixed effects as well as lagged values of the dependent variable and industry-level real output growth rates. Standard errors are reported in brackets – all estimates are significant at the 1 percent level.

Figure A4: Work outside workplace rate: Changes over time



Note: The figure shows work outside workplace rates over time for the aggregate economy (solid black line) and the range of values across industries (shaded area). The work from home rates over time for the aggregate economy (dashed black line) is added for comparison.

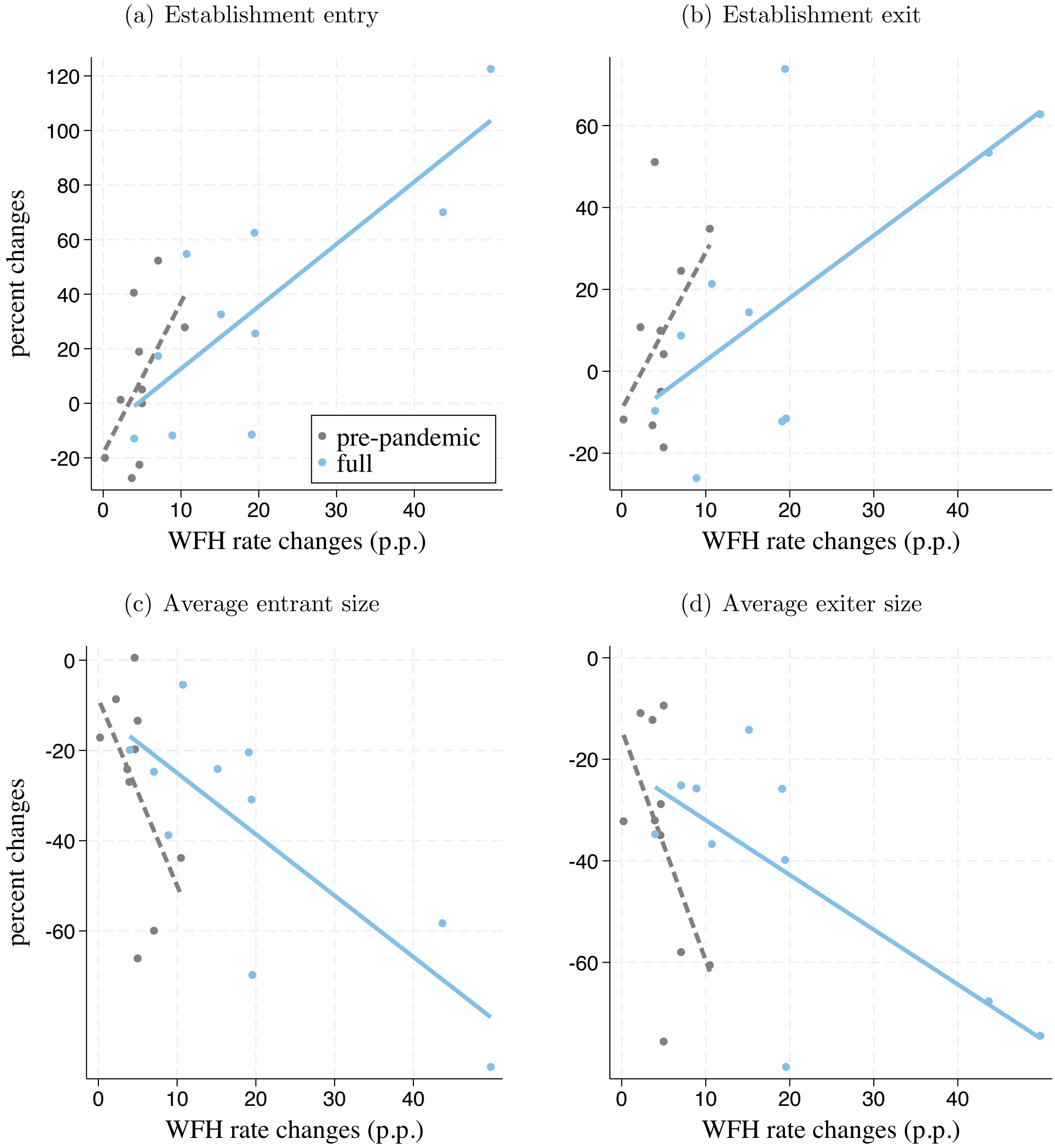
C.4 Robustness: Using Average Size

In the main text, we use average entrant size as a measurement of employment. Here we provide the results using average size computed from QCEW. Figure A6 shows how the change in remote work is associated with changes in average establishment size. Table A9 shows the results of panel regression.

Table A9: Working from home and establishment size

	Average Size
A: Pre-pandemic sample (2003Q1-2019Q4)	
Work from home rate, β	-0.604^{***}
	(0.236)
R-squared	0.115
# observations	590
B: Full sample (2003Q1-2022Q4)	
Work from home rate, β	-0.605^{***}
	(0.110)
R-squared	0.256
# observations	710

Figure A5: Work outside workplace and business dynamism: Changes across industries

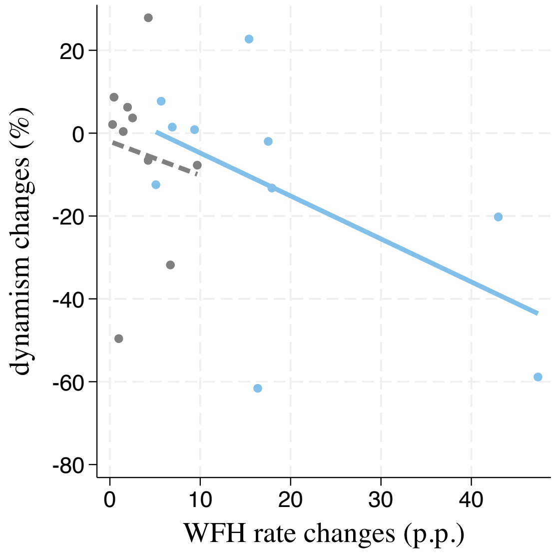


Note: The figure depicts super-sector changes in work outside workplace rates on the horizontal axis (in p.p.) and (percent) changes in the number of entrants (Panel a), exiters (Panel b), average entrant size (Panel c) and average exiter size (Panel d). All panels show data for the pre-pandemic sample (2003-2019) and the full sample (2003-2022).

C.5 Robustness: 2-digit Sectors

We use annual establishment age data at 2-digit level from BED, where establishment entry is reflected in the number of establishments of age less than one year. The average entrants size can be computed using the corresponding employment. The information on establishment exit cannot be deduced from the age data as it would be mixed with

Figure A6: Work from home and establishment size: Changes across industries



Note: The figure depicts super-sector changes in work from home rates on the horizontal axis (in p.p.) and (percent) changes in the average establishment size. Data is for the pre-pandemic sample (2003-2019) and the full sample (2003-2022).

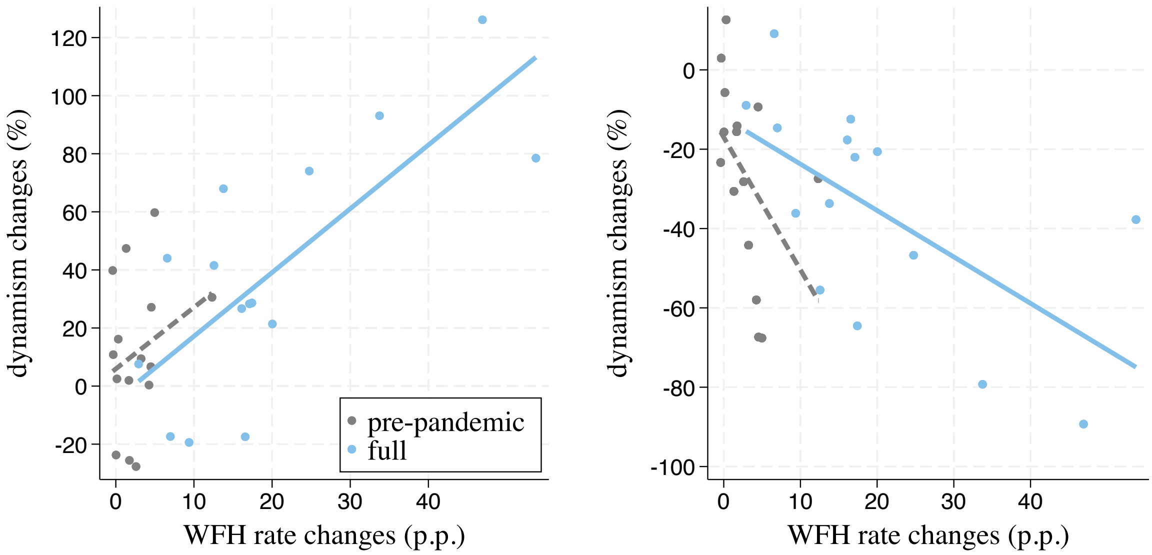
temporary closings and reopening. We dropped "Agriculture, forestry, fishing, and hunting", "Mining, quarrying, and oil and gas extraction" and "Management of companies and enterprises", due to limited observations in ATUS. Besides, "Finance and insurance" sector is excluded, consistent with the previous analysis at the super sector level. Figure A7 shows the linkage between work from home rates and business entry. Table A10 shows the results of fixed effect regression, where the average WFH rate is constructed with two lags, i.e., average of the current and the previous two years' WFH rate.

Table A10: Working from home and business entry: 2-digit sectors

	Entry	Entrant Size
A: Pre-pandemic sample (2003Q1-2019Q4)		
Work from home rate, β	1.118***	−1.169***
	(0.415)	(0.328)
R-squared	0.524	0.361
# observations	225	225
B: Full sample (2003Q1-2022Q4)		
Work from home rate, β	2.079***	−1.147***
	(0.199)	(0.156)
R-squared	0.718	0.521
# observations	270	270

Figure A7: Work from home and business entry: Changes across 2-digit sectors

(a) Establishment entry (b) Average entrant size



Note: The figure depicts 2-digit-sector changes in work from home rates on the horizontal axis (in p.p.) and (percent) changes in the number of entrants (Panel a) and average entrant size (Panel b). All panels show data for the pre-pandemic sample (2003-2019) and the full sample (2003-2022).

C.6 Robustness: Openings and Closings

As discussed in the main text, BED establishment openings include both births and re-openings, while establishment closings include both deaths and temporary closings. Here we use quarterly establishment openings and closings at the super sector level, consistent with the analysis in the main text. Table A11 reports the results. In Table A12, we further investigate the 2-digit scenario.

C.7 Robustness: Different Lag Lengths

In the main text, we use the current quarter and the last year's WFH rates to construct the regressor. To further validate the lagged impacts of working from home on business entry and exit, we consider $L = 2$ and $L = 6$ in constructing the average WFH rate. Table A13 and A14 report the results.

Table A11: Working from home, establishment openings and closings (super sectors)

	Openings	Closings
A: Pre-pandemic sample (2003Q1-2019Q4)		
Work from home rate, β	0.997***	0.854***
	(0.176)	(0.177)
R-squared	0.440	0.466
# observations	590	590
B: Full sample (2003Q1-2022Q4)		
Work from home rate, β	0.951***	0.682***
	(0.099)	(0.098)
R-squared	0.701	0.651
# observations	710	710

Note: The table reports results from estimating (A9). Panel A reports estimates using the pre-pandemic period (2003Q1-2019Q4) only, while Panel B report results for our entire sample period (2003Q1-2022Q4). All specifications include industry and time fixed effects as well as lagged values of the dependent variable and industry-level real output growth rates. Standard errors are reported in brackets – all estimates are significant at the 1 percent level.

Table A12: Working from home, establishment openings and closings (2-digit sectors)

	Openings	Closings
A: Pre-pandemic sample (2003Q1-2019Q4)		
Work from home rate, β	0.428***	0.333***
	(0.149)	(0.153)
R-squared	0.348	0.350
# observations	756	756
B: Full sample (2003Q1-2022Q4)		
Work from home rate, β	1.093***	0.809***
	(0.072)	(0.074)
R-squared	0.689	0.621
# observations	923	923

Note: The table reports results from estimating (A9). Panel A reports estimates using the pre-pandemic period (2003Q1-2019Q4) only, while Panel B report results for our entire sample period (2003Q1-2022Q4). All specifications include industry and time fixed effects as well as lagged values of the dependent variable and industry-level real output growth rates. Standard errors are reported in brackets – all estimates are significant at the 1 percent level.

Table A13: Working from home and business dynamism ($L = 2$)

	Entry	Exit	Wages	Entrant Size
A: Pre-pandemic sample (2003Q1-2019Q4)				
Work from home rate, β	0.756^{***}	0.772^{***}	0.410^{***}	-0.820^{***}
	(0.165)	(0.181)	(0.069)	(0.141)
R-squared	0.473	0.381	0.680	0.418
# observations	590	590	590	590
B: Full sample (2003Q1-2022Q4)				
Work from home rate, β	0.991^{***}	0.591^{***}	0.311^{***}	-0.579^{***}
	(0.105)	(0.108)	(0.044)	(0.094)
R-squared	0.692	0.532	0.719	0.479
# observations	710	700	710	710

Note: The table reports results from estimating (A9). Panel A reports estimates using the pre-pandemic period (2003Q1-2019Q4) only, while Panel B report results for our entire sample period (2003Q1-2022Q4). All specifications include industry and time fixed effects as well as lagged values of the dependent variable and industry-level real output growth rates. Standard errors are reported in brackets – all estimates are significant at the 1 percent level.

Table A14: Working from home and business dynamism ($L = 6$)

	Entry	Exit	Wages	Entrant Size
A: Pre-pandemic sample (2003Q1-2019Q4)				
Work from home rate, β	1.606^{***}	1.425^{***}	0.795^{***}	-1.695^{***}
	(0.257)	(0.289)	(0.108)	(0.233)
R-squared	0.522	0.446	0.724	0.403
# observations	550	550	550	550
B: Full sample (2003Q1-2022Q4)				
Work from home rate, β	1.532^{***}	1.163^{***}	0.394^{***}	-0.766^{***}
	(0.128)	(0.133)	(0.055)	(0.119)
R-squared	0.722	0.561	0.725	0.473
# observations	670	660	670	670

Note: The table reports results from estimating (A9). Panel A reports estimates using the pre-pandemic period (2003Q1-2019Q4) only, while Panel B report results for our entire sample period (2003Q1-2022Q4). All specifications include industry and time fixed effects as well as lagged values of the dependent variable and industry-level real output growth rates. Standard errors are reported in brackets – all estimates are significant at the 1 percent level.

C.8 Robustness: Remote work exposure

In this Appendix, we provide additional robustness with regard to our novel identification strategy in Section 6.

Sectors where remote work is more feasible. First, we test whether the exposed firms experienced an even stronger decline in rental costs if they operated in industries where remote work is particularly feasible. Towards this end, we make use of a classification of occupations (and in turn industries) in terms of their remote work feasibility from Dingel and Neiman (2020):

$$\begin{aligned} \ln\left(\frac{rent_{j,t}}{n_{j,t}}\right) =& \alpha + \beta_E \mathbb{1}(E)_j + \beta_T \mathbb{1}(T)_{j,t} + \beta_H \mathbb{1}_j(H) \\ &+ \mathbb{1}(T)_{j,t} \left(\beta_{E,T} \mathbb{1}(E)_j + \beta_{E,H,T} \mathbb{1}(H)_j \mathbb{1}(E)_j\right) + \mathbf{X}'\theta + \epsilon_{j,t}, \end{aligned} \tag{A10}$$

where $\mathbb{1}(H)_j$ is an indicator function equal to one if firm j operates in one of the 5 industries with the highest feasibility of remote work. Our model predicts that $\beta_{0,H} < 0$ as exposed firms in "high-feasibility" industries are particularly positioned to take advantage of the cost-saving nature of remote work.

Table A15 shows the results. Indeed, exposed firms operating in sectors where remote work is particularly feasible experienced stronger declines in rental costs. That said, direct exposure itself remains to lead to rental cost declines in a statistically significant manner.

Table A15: Estimation results: Rental costs, $rent/n$

	(1)	(2)
Exposed firms, $\beta_{E,T}$	-0.38^{***}	-0.47^{***}
	(0.05)	(0.07)
Exposed firms in high-industries, $\beta_{E,H,T}$	-0.80^{***}	-0.50^{**}
	(0.09)	(0.21)
Fixed effects		✓
R-squared	0.02	0.43
Observations	22,903	22,903

Note: The table presents the key coefficients of interest from regression (A10). Fixed effects include sector, city and year fixed effects. Standard errors are clustered at the firm level and reported in brackets.

Event study design. We use an event-study design to estimate the impact of the remote work revolution on firms' rental costs:

$$\ln(rent_{j,t}/n_{j,t}) = \alpha + \beta_{0Y} \mathbb{1}_{0Y} + \beta_{5Y} \mathbb{1}_{5Y} + \sum_{k=-3}^{3} \mathbb{1}_{t=2019+k} \left(\mathbb{1}_{0Y} \beta_{0,k} + \mathbb{1}_{5Y} \beta_{5,k}\right) + \mathbf{X}'\theta + \epsilon_{j,t}, \tag{A11}$$

where $rent_{j,t}$ again represent rental expenses of firm j in year t, $\mathbb{1}_{0Y}$ ($\mathbb{1}_{5Y}$) is an indicator function equal to one if firm j in 2019 had no rental commitments in future years (had rental commitments five years into the future) and zero otherwise and where $\mathbf{X}_{j,t}$ include sector, city and year fixed effects.

The key coefficients of interest are $\beta_{0,k}$ and $\beta_{5,k}$. These highlight the difference in per-worker rental costs between "exposed" firms which can flexibly adjust their rental costs in face of the remote work revolution ($\beta_{0,k}$) and "non-exposed" firms, i.e. those which cannot flexibly adjust their rental commitments ($\beta_{5,k}$). In addition, we also consider a specification in which the above indicator functions are interacted with sectors in which remote work is particularly feasible based on the occupations which dominate them (see Dingel and Neiman, 2020):

$$\ln(rent_{j,t}/n_{j,t}) = \alpha + \beta_L \mathbb{1}_L + \beta_H \mathbb{1}_H + \beta_{1Y}\mathbb{1}_{1Y} + \beta_{5Y}\mathbb{1}_{5Y} \tag{A12}$$

$$+ \sum_{k=-3}^{3} \mathbb{1}_{t=2019+k}\mathbb{1}_L \left(\mathbb{1}_{0Y}\beta^L_{0,k} + \mathbb{1}_{5Y}\beta^L_{5,k}\right) \tag{A13}$$

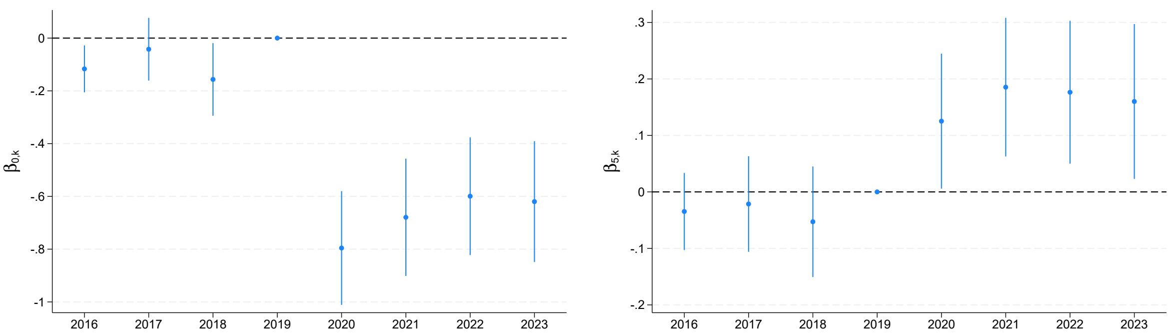
$$+ \sum_{k=-3}^{3} \mathbb{1}_{t=2019+k}\mathbb{1}_H \left(\mathbb{1}_{0Y}\beta^H_{0,k} + \mathbb{1}_{5Y}\beta^H_{5,k}\right) + \mathbf{X}'\theta + \epsilon_{j,t}, \tag{A14}$$

where $\mathbb{1}_L$ ($\mathbb{1}_H$) is an indicator which is equal to one for the 5 industries with the lowest (highest) feasibility of remote work.

Figure XYZ presents the results showing that exposed firms experienced a strong drop in rental costs during the pandemic. Moreover, this was further exacerbated for firms in sectors with high feasibility of remote work.

Figure A8: Event study: Rental costs, $rent/n$

(a) Without rental commitments, $\beta_{0,k}$ (b) With 5-year rental commitments, $\beta_{5,k}$

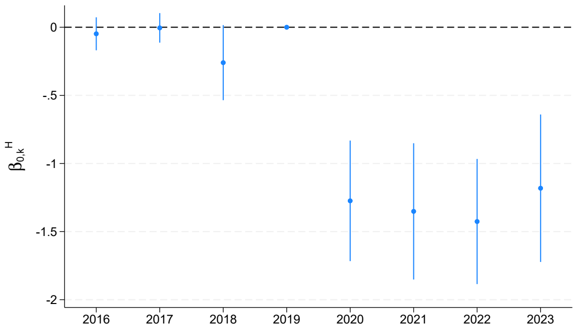


Note: This figure shows the regression results for equation (A11).

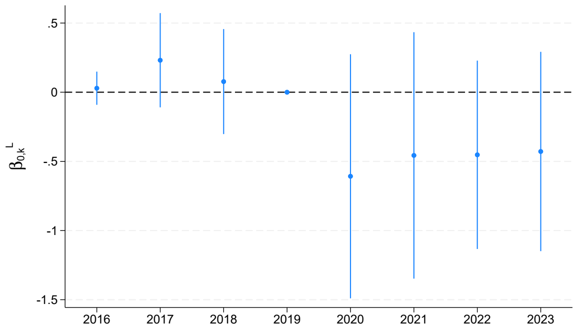
Firm fixed effects. Next, we consider a specification of our main regression with the addition of firm fixed effects. Table A16 shows that are main results are largely robust to this alternative specification.

Figure A9: Event study: Rental costs, $rent/n$, in sectors with high and low wfh-feasibility

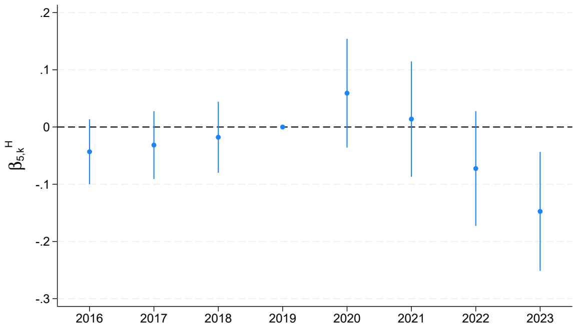
(a) High wfh without rental commitments, $\beta^H_{0,k}$



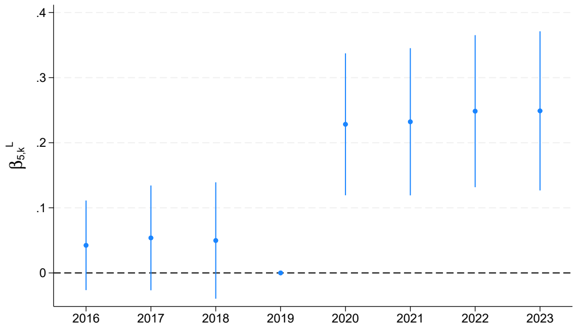
(b) Low wfh without rental commitments, $\beta^L_{0,k}$



(c) High wfh with rental commitments, $\beta^H_{5,k}$



(d) Low wfh with rental commitments, $\beta^L_{5,k}$



Note: This figure shows the regression results for equation (A12).

Table A16: Estimation results: Firm fixed effects

	rental costs		fixed costs		variable costs		productivity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure, $\beta_{E,T}$	-0.47^{***}	-0.66^{***}	-0.19^{**}	-0.03	-0.10	-0.05	-0.07^{*}	-0.06^{**}
	(0.05)	(0.06)	(0.08)	(0.03)	(0.08)	(0.03)	(0.04)	(0.03)
Fixed effects		✓		✓		✓		✓
R-squared	0.02	0.05	0.06	0.05	0.0002	0.02	0.01	0.01
Observations	23,003	23,003	23,016	23,016	25,679	25,679	25,139	25,139

Note: The table presents the coefficients of interest on exposed firms in periods 2020-2023 from regressions (26), $\beta_{E,T}$. Fixed effects include sector, city and year fixed effects. Standard errors (reported in brackets) are clustered at the firm level.

Placebo estimation. Table A17 shows results using our estimation in the main text, but estimating it on firms in the period between 2010-2017 (with exposure defined as no commitments in 2014). In contrast to our results in the main text, the placebo treatment does not uncover any significantly negative coefficients.

Descriptive statistics. Table A18 divides the firms in the sample into four categories: firms reporting rental expenses only, rental commitments only, both rental expenses and commitments, and neither of them. We further shows in each category, the fraction of firms in the entire sample, their average age, median size, median total assets, and average

Table A17: Estimation results: 2010-2017 Placebo

	rental costs		fixed costs		variable costs		productivity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure, $\beta_{E,T}$	0.05	0.05	-0.06	-0.11	0.17^{*}	-0.01	0.02	-0.002
	(0.06)	(0.07)	(0.10)	(0.07)	(0.10)	(0.05)	(0.05)	(0.04)
Fixed effects		✓		✓		✓		✓
R-squared	0.0001	0.44	0.14	0.58	0.01	0.52	0.03	0.43
Observations	22,932	22,932	22,952	22,952	25,882	25,882	25,302	25,302

Note: The table presents the coefficients of interest on exposed firms in periods 2020-2023 from regressions (26), $\beta_{E,T}$. Fixed effects include sector, city and year fixed effects. Standard errors (reported in brackets) are clustered at the firm level.

buildings over assets ratio.

Table A18: Descriptive Statistics: Raw Data (2016-2023)

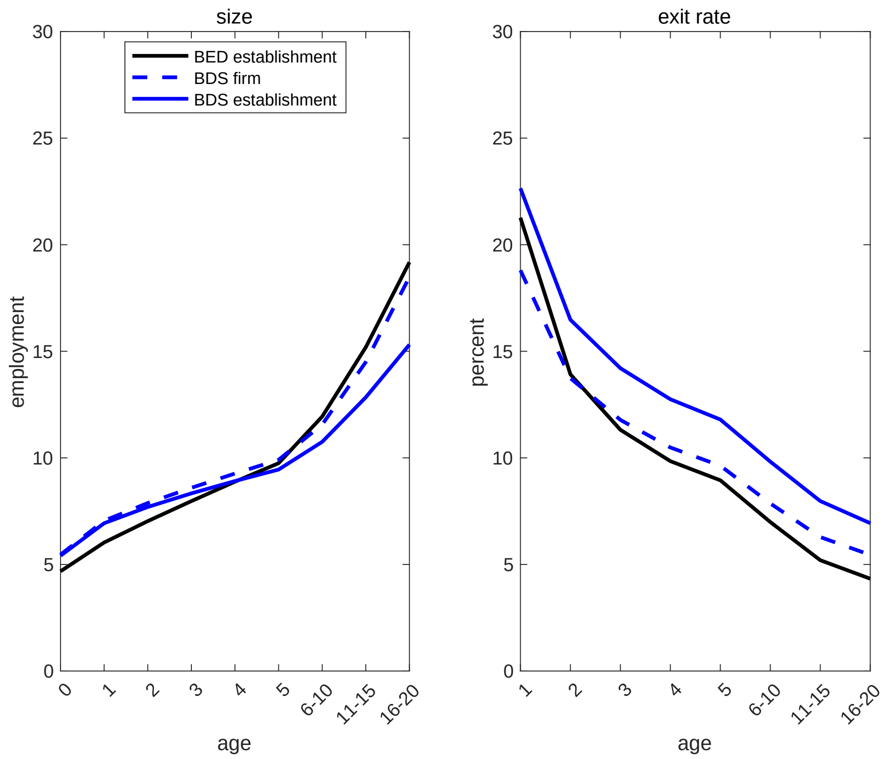
Firms reporting	fraction	age	size	total assets	buildings/assets
Rental expenses	0.52	18.1	1.02	945.6	0.050
Rental commitments	0.40	18.3	0.99	716.4	0.052
Both	0.37	18.5	1.14	771.1	0.052
Neither	0.46	10.9	0.21	1131.9	0.047

Note: Size (Compustat item emp) is in thousands. Total assets (Compustat item at) is in millions. Buildings represent Compustat item fatb, i.e., Property, Plant and Equipment - Buildings at Cost. Employment and total assets are reported in median values. Age and buildings over assets ratio are reported in mean values.

C.9 Comparison between BED and BDS Data

Although we use BED data at the establishment level for calibration, we provide a comparison between BED and BDS data here. From Figure A10, life-cycle profiles of size and exit rates of BED establishments are close to those of BDS firms.

Figure A10: Life-cycle profiles of size and exit rates: BED and BDS



Note: The left panel shows average establishment size from BED and firm/establishment size from BDS by age, while the right panel shows average exit rates by age.

C.10 Aligning Compustat with the BED

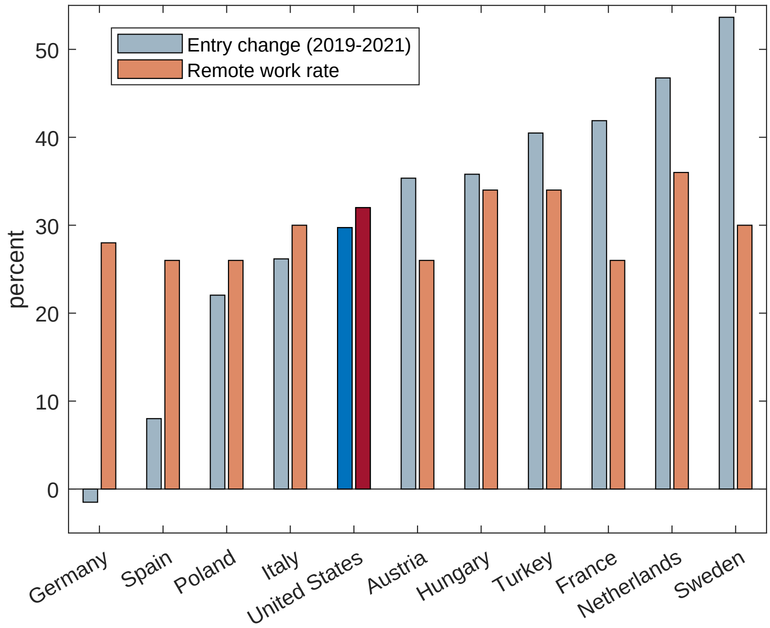
Compustat sample consists only of publicly listed companies that differ significantly from the universe of firms in the U.S. (i.e. the BED data and our model, which targets exit and size profiles in the latter). To address this issue, we follow Ignaszak and Sedláček (2023) and construct a set of firm-specific weights based on the firm size (employment) distribution in Compustat.

Aligning model-simulated data with Compustat information. Formally, we pool all observations across all years and calculate the empirical distribution of firm size in Compustat. Let f_e denote the frequency of firm size e in Compustat. Given that our model is parameterized to business dynamics from the BED, we need to realign the model distribution to that of Compustat whenever comparing model moments to those which have counterparts in Compustat. Towards this end, in any "Compustat-related" regression in the model we weigh the model-simulated data with the respective empirical weights from Compustat, f_e.

C.11 Cross-country comparison

Figure A11 shows a comparison between remote work rates and firm entry across countries. The figure shows that while the increase in remote work rates was similar across countries, entry changes were not. Our model suggests that this is indicative of cross-country differences in the welfare effects of the remote work revolution.

Figure A11: Business entry and remote work across countries



Note: The figure shows changes in firm entry between 2019 and 2021 and remote work rates in 2021 across countries. While the entry data is taken from Eurostat, remote work rates are taken from Aksoy et al. (2022).