Work from Home, Business Dynamism, and the Macroeconomy*

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July 2, 2024

Abstract

The COVID-19 pandemic catalyzed a surge in work from home. We argue that this shift has two opposing macroeconomic effects. On the one hand, cheaper or more efficient remote work increases profitability and encourages firm entry – sparking an economic boom. On the other hand, the distribution of firms tilts towards smaller businesses as they benefit relatively more from (fixed) cost reductions associated with remote work – lowering aggregate productivity. To quantify these opposing effects, we develop a novel quantitative model, discipline it using several U.S. micro-datasets and provide empirical support for its key mechanisms. Our results suggest that if barriers to entry prevent a permanent surge in startups, then the firm-level welfare gains from more favorable remote work can be entirely offset by the fall in aggregate productivity. While recent U.S. data suggests firm entry has indeed persistently increased, evidence from other countries is mixed.

JEL codes: D22, D24, E24, J23, L11, M13.

*We thank Andrea Chiavari, Sergio De Ferra, Wouter den Haan, Martin Ellison, Andrea Ferrero, Michael Haliassos, Marek Ignaszak, Alexandre Kohlhas, Gernot Mueller, Faisal Sohail, Emily Swift, Francesco Zanetti and conference and seminar participants of the T2M conference in Amsterdam, the Goethe University Frankfurt, the Computing in Economics and Finance conference in Singapore, the University of New South Wales and the University of Oxford for useful comments. Sedláček gratefully acknowledges the financial support of the Australian Research Council (grant number FT230100545) and, in early stages of the project, of the European Commission and the European Research Council (grant number 802145).

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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). In this paper, we study the *macroeconomic* impact of this shift.

We argue that more favorable remote work conditions have two opposing macroeconomic effects. On the one hand, they raise overall firm profitability and encourage business entry, rationalizing the recently observed "surprising surge in applications for new businesses" (see Decker and Haltiwanger, 2024). On the other hand, the composition of firms shifts towards smaller businesses because they 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.

To quantify the horse race between entry and aggregate productivity, we develop a novel macroeconomic model in which firms can employ some of their workers remotely. Linking several U.S. micro-datasets, we discipline our model and provide empirical support for its key mechanisms. Our results suggest that if barriers to entry prevent a long-run increase in the number of startups, then weaker aggregate productivity can entirely undo all the firm-level gains brought about by more favorable remote work.

Most recent U.S. data shows that firm entry has in fact remained persistently elevated since the pandemic. Data from other countries, however, sends a more mixed message – similar uptakes of remote work as in the U.S. have not always been accompanied by strong increases in firm entry. Therefore, the welfare impact of more favorable remote work may differ substantially across economies, depending on the country-specific nature of business dynamism.

We begin our analysis by developing a core theoretical framework which allows us to *analytically* show how changes in remote work may 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 optimally by balancing the associated costs and benefits.

On the one hand, remote work reduces costs. This may include lower wage growth pressure, reductions in worker turnover and the associated training and hiring costs, or lower fixed overhead costs because of a reduced need for, or price of, office and 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).

In our model, cheaper or more efficient remote work alone increases overall firm profitability. However, not all firms are affected equally. Small businesses emerge as the "winners" of more favorable remote work. 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. In the aggregate, higher profitability encourages firm entry, but it also raises labor demand and with it the wage rate. The latter makes running a business costlier. Therefore, our core model can rationalize a simultaneous rise in (i) remote work rates, (ii) wages, (iii) business entry *and* exit and (iv) a drop in average firm size.

To test these model predictions empirically, we make use of 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 compute remote work rates at the industry level and 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 use the Quarterly Census of Employment and Wages (QCEW) to obtain industry-level information on wages.

Using the linked data, we leverage variation over time and across industries and estimate a batch of panel regressions connecting changes in remote work rates to changes in business dynamism and wages. We consider the "full" sample period between 2003 (the start of our work from home information from ATUS) and 2022 (the latest available BED data), but also single out the pre-pandemic period between 2003 and 2019. Controlling for time and industry fixed effects and a range of other controls, we document that – in both samples – larger increases in work from home rates are associated with higher business entry and exit, stronger wage increases and larger reductions in average firm size.

To quantify the macroeconomic impact of changes in remote work, we generalize our core framework along several dimensions. First, we introduce 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 conducting production remotely. Note that this operates in the opposite direction to the intensive margin inherited from our core theory – *conditional* on conducting remote work, smaller businesses tend to do more production remotely. Second, we allow firm-level productivity to be affected by persistent idiosyncratic shocks and we *endogenize* the degree of long-run productivity differences. Third, we introduce capital as a production factor and assume that its accumulation is subject to adjustment costs. Finally, we consider flexible labor supply, allowing workers to endogenously respond to remote work changes.

To parameterize the generalized model, we make use of our linked micro-datasets and require the model to match salient (pre-pandemic) features of U.S. data. To discipline the central novel feature of our framework – work from home decisions – we target two key moments in the data: a maximum productivity loss of fully remote work of 14 percent – a midpoint between the estimated values (see Barrero et al., 2023; Gibbs et al., 2023) – and an average pre-pandemic work from home rate of 4 percent which we estimate from ATUS data.[1] The parameterized model does well in matching also a range of other *untargeted* empirical moments related to capital investment rates, firm-level productivity dynamics, the firm size distribution as well as the extent of cost savings of remote work.

To quantitatively isolate the macroeconomic impact of increased work from home arrangements, we compare our baseline economy to a counterfactual which is identical to the baseline but features more efficient and cheaper remote work. We parameterize the counterfactual to mimic the post-pandemic levels of remote work observed in the U.S. economy.[2] The results of the generalized model confirm the qualitative predictions derived from our core theoretical analysis. Quantitatively, our model can account for almost 50 percent of the observed surge in firm entry and much of the decline in firm size and increase in business exit rates.

However, these effects hide large heterogeneity across individual firms. As explained above, the "winners" are smaller businesses conducting remote work which benefit 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 higher wage costs. As a result, entry and exit decisions in the counterfactual 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.[3]

Therefore, the direct welfare gains from cheaper and more efficient remote work are counter-acted 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 increases. To highlight this, we consider a version of the counterfactual economy in which barriers to entry (e.g. financial or regulatory frictions) mute the increase in startups. Our model suggests that, without a permanent rise in firm entry and associated economic boom, the welfare benefits of more favorable remote work can be entirely offset

[1]Note that our parameterization implies only very small efficiency losses on average. In particular, a business with 4% of its employees working remotely faces an efficiency loss of just 0.02%.

[2]We do not consider transition dynamics between the baseline and counterfactual 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.

[3]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.

by a decline in aggregate productivity brought about by the endogenous shift towards smaller firms.[4] While the most recent data from the U.S. suggests that firm entry has in fact increased persistently since the pandemic, the evidence from other countries is mixed. This suggests that the welfare impact of more favorable remote work may differ across economies, depending on the country-specific nature of business dynamism.

As a final step in our analysis, we provide two pieces of evidence in support of our key model mechanism and its quantitative importance. First, the data shows that while the fraction of firms conducting remote work is higher among larger businesses, it is smaller firms which – conditional on having some employees off-site – tend to do more work remotely. Second, the most recent data reveals that – along with the strong rise in remote work and the surge in business entry – the composition of startups has shifted towards smaller entrants. Importantly, our model is consistent with both of these facts not only qualitatively but also *quantitatively*.

Our paper is related to two 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 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; Monte et al., 2023; Richard, 2024). In contrast, we study the implications of remote work for business dynamism with a primary goal of quantifying its *macroeconomic* impact. Second, we connect to the literature on the macroeconomic impact of business dynamism – especially the influence of entry and exit (see e.g. Hopenhayn and Rogerson, 1993; Clementi and Palazzo, 2016; Sedláček and Sterk, 2017; Sedláček, 2020). To the best of our knowledge, we are the first to use these frameworks for analyzing the macroeconomic impact of optimal remote work arrangements.

The rest of the paper is structured as follows. The next section lays out our core model and presents key theoretical results. Section 3 tests these theoretical predictions in the data. Sections 4 and 5 describe the generalized model, parameterize it, lay out our main quantitative results and provide empirical evidence in support of our key findings and model mechanism. 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.

[4] Note that we do not explicitly model additional benefits of remote work such as a decline in commuting time (i.e. increased leisure), gains in flexibility or benefits of home-production (see e.g. Barrero et al., 2023, for a discussion).

Making use of several firm- and individual-level datasets, the next section tests our theoretical predictions empirically. Section 4 then generalizes our baseline theory into a fully fledged structural macroeconomic model of firm dynamics which we use the quantitatively evaluate the impact work from home patterns have on the macroeconomy.

2.1 Model

Consider a framework in which there is a continuum of firms, each producing a final good sold to the household for consumption. 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. We defer a formal definition of the equilibrium to the Appendix.

Production and costs. In our economy, output is produced by individual firms which pay a per-period operational cost, κ_o, to remain in operation. To produce output, businesses use a common production function and combine labor, n, with firm-specific productivity, $z > 0$:

$$y(z) = zn^{\alpha}, \tag{1}$$

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

Labor is supplied by the household for a take-home wage, W, which firms take as given. Moreover, firms must pay a per-worker resource cost, κ_n, representing additional (non-wage) labor costs such as office equipment and supplies, worker training and hiring costs or various employee benefits.

Work from home. We assume that all firms have the possibility of letting a fraction, $\omega \in [0, 1]$, of their employees work from home. Note that we abstract from fixed costs of *setting up* remote work. We do so for tractability, but relax this assumption in the generalized model of Section 4. 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.

There are both costs and benefits of remote work. On the one hand, work from home helps reduce firms' costs. This may occur because remote work reduces the need for some of the non-wage labor costs, κ_n, discussed above (see e.g. Barrero et al., 2022), but also because it can reduce quit rates and the associated turnover and training (Bloom et al., 2024).[5] In addition, remote work also lowers overhead costs, κ_o, e.g. because firms

[5] In this section, we assume households take ω as given and we abstract from direct impacts of work from home on wages – e.g. because businesses can recruit from low-wage areas. However, wages can change in general equilibrium.

require less production or office space (see e.g. Barrero et al., 2023, for a discussion). We model these effects by allowing (non-wage) labor and overhead costs to fall as remote work rates rise according to $g(\omega) \in [0, 1]$, with $g'(\omega) < 0$.

On the other hand, 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).[6] Therefore, we assume that firm productivity decreases as remote work rates increase according to $f(\omega) \in [0, 1]$, with $f'(\omega) < 0$.

Therefore, in our setting we can write firm profits as:

$$\pi(z) = f(\omega)y(z) - Wn - g(\omega)(\kappa_n n + \kappa_o). \tag{2}$$

The mass of firms, entry and exit. All businesses are subject to an exogenous risk of shutting down, $\delta \in [0, 1)$. In addition, businesses may choose to shut down endogenously. This happens if firm value, $v(z)$, falls below zero:

$$v(z) = \max\left\{0, \max_{n,\omega} \sum_{t=0}^{\infty} [\beta(1-\delta)]^t \pi(z)\right\} = \max\left\{0, \max_{n,\omega} \frac{\pi(z)}{1-\beta(1-\delta)}\right\}, \tag{3}$$

where $\beta \in (0, 1)$ is a discount factor. The above gives rise to a survival threshold, $\widetilde{z}$, below which firms choose to shut down. This cutoff productivity – which endogenizes the distribution of firms in the economy – is implicitly defined by:

$$\pi(\widetilde{z}) = f(\omega(\widetilde{z}))y(\widetilde{z}) - Wn(\widetilde{z}) - g(\omega(\widetilde{z}))(\kappa_n n(\widetilde{z}) + \kappa_o) = 0, \tag{4}$$

where we have made clear that employment, as well as remote work rates, are endogenous choices which depend on firms' productivity levels.

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

[6] 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.

condition:

$$\kappa_e = \int v(z)h(z)dz, \tag{5}$$

which implicitly defines the mass of startup attempts, M_e. The mass of entrants is given by $(1-H(\widetilde{z}))M_e$, since not all startup attempts are viable. In equilibrium, entry is equal to exit and the total mass of firms, M, is stationary:

$$(1-H(\widetilde{z}))M_e = \delta M. \tag{6}$$

Aggregates. Assuming fixed labor supply, N, and denoting the mass of firms with productivity z by $\mu(z)$ – where $\mu(z) = 0$ for $z < \widetilde{z}$ and $\mu(z) = h(z)/(1-H(\widetilde{z}))$ otherwise – the labor market clearing condition is given by:

$$N = \int n\mu(z)dz = M\overline{n}, \tag{7}$$

where $\overline{n}$ is average firm size. Finally, the aggregate resource constraint is given by:

$$Y = C + \kappa_e M_e + \int g(\omega)(n\kappa_n + \kappa_o)\mu(z)dz, \tag{8}$$

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.

2.2 Theoretical Results

In what follows, we study analytically optimal work from home choices, ω^*. In doing so, we pay special attention to their interaction with firm entry, exit and employment decisions which shape the distribution of firms and, in turn, macroeconomic outcomes. 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.

PROPOSITION **1** (Optimal work from home rates)
In the framework described above and for interior solutions, optimal work from home rates, ω^*, satisfy the following

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

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

b) if $\kappa_o > 0$, then

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

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). This mimics the tradeoff of optimal labor demand which is governed by the returns to scale parameter, α. Therefore, in the absence of fixed overhead costs, optimal remote work rates are also determined by α, adjusted for by a factor representing the share of costs which can be reduced by remote work.

The second part of Proposition 1 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.

However, as explained above, our results in this section pertain to the intensive margin of remote work. In our generalized model, we allow also 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 costs of setting up remote work.

Changes in work from home arrangements. We now analyze the impact of changes in work from home conditions. 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. Without loss of generality, we define these parameters such that their increase leads to a rise in work from home rates:

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

The parameters $\widetilde{f}$ and $\widetilde{g}$ can be thought of as summarizing the efficiency of remote work technologies and their relative price.[7] The following proposition describes how exogenous changes to $\widetilde{f}$ and $\widetilde{g}$ impact optimal work from home rates, firm profits and the exit threshold in partial equilibrium, i.e. assuming a fixed mass of firms and a fixed wage rate.

Proposition **2** (Changes in remote work conditions)
All else equal and assuming internal optimal work from home rates, ω^*, exogenous changes

[7] Note that what is important for firms' decisions is the efficiency and costs of remote work *perceived* by individual businesses. This allows $\widetilde{f}$ and $\widetilde{g}$ to also capture, in a reduced for way, changes in productivity perceptions or the stigma associated with remote work (see e.g. Barrero et al., 2021, 2023).

in $\widetilde{f}$ and $\widetilde{g}$ have the following impact:

a) Work from home rates:

$$\frac{\partial \omega^*}{\partial \widetilde{g}} > 0, \frac{\partial \omega^*}{\partial \widetilde{f}} > 0,$$

b) Firm profits:

$$\frac{\partial \pi}{\partial \widetilde{g}} > 0, \frac{\partial \pi}{\partial \widetilde{f}} > 0,$$

c) Survival threshold:

$$\frac{\partial \widetilde{z}}{\partial \widetilde{g}} < 0, \frac{\partial \widetilde{z}}{\partial \widetilde{f}} < 0,$$

Part a) of Proposition 2 shows that, intuitively, cheaper or more efficient work from home leads to a greater uptake of remote work arrangements. Such productivity boosts or cost reductions are then also associated with higher profits, since businesses can effectively produce more or at lower costs – see Part b).

Finally, Part c) of Proposition 2 shows how the distribution of firms shifts in response to changes in remote work arrangements. In particular, as firms become more profitable, even relatively less productive businesses can afford to remain in operation, reducing the threshold $\widetilde{z}$. This, in turn, shifts the distribution of surviving businesses towards less productive (smaller) firms.

As will become clear, remote-work-induced changes in the distribution of firms will be a quantitatively important mechanism in our generalized model of Section 4. We will show that our framework is consistent with data in this regard not only qualitatively, but also quantitatively.

General equilibrium. In general equilibrium, however, the wage and the mass of firms adjust. The overall effect of these changes is a-priori unclear and depends on the particular size of the fixed cost and the distribution of firms. However, in the empirically relevant case, higher profits associated with cheaper and more efficient remote work encourage firm entry which increases labor demand and with it the wage, see (5). More startups lead to an increase in the number of firms as well as a rise in business exit, see (6). Finally, together with heightened wages, these forces lead to a decline in average firm size, see (7).

To summarize, our framework shows how individual firms optimally balance the costs and benefits of remote work. With positive fixed costs, this balance is asymmetric across firms with less productive businesses choosing higher remote work rates. When remote work becomes more favorable, our framework can rationalize the simultaneous increase in work from home rates, business entry and exit and a decline in average size.

3 Empirical Evidence

Having established a theoretical link between remote work and business dynamism, we now turn to empirical evidence on these patterns. We first describe work from home rates in the cross-section and how they have evolved over time. Next, we estimate the relationship between changes in work from home rates and changes in measures of business dynamism.

3.1 Data and Definitions

Our analysis combines information on individuals and businesses from five different datasets. In what follows, we describe the main data sources as well as the methodology of constructing our key variable of interest: working from home rates.

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. As mentioned, while our core theoretical results pertain to firms conducting remote work, the generalized model in the next section also allows for an extensive margin of work from home.

To measure the extensive margin, we rely on the Business Response Survey (BRS) of the Bureau of Laobr Statistics (BLS) which started only 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.[8] In addition, utilizing the Annual Social and Economic Supplement (ASEC) of the CPS allows us to infer the size of establishments for which individuals in the ATUS report working remotely.

While the fraction of establishments conducting remote work is directly reported in the BRS, we measure the intensive margin following Barrero et al. (2023). In particular, we focus on individuals' time allocated to working and its location as reported in the ATUS. We count working days of individual j, d_j, as those in which individuals devote at least 6 hours to work in their main job.[9] Analogously, we define days worked from

[8]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).

[9]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

home, d_j^{home}, as those in which individuals spend at least 6 hours working from home in their main job. A key object of interest is then the *work from home rate* in period t, ω_t, which we define as the number of days spent working at home, d_t^{home} as a fraction of all work days, d_t.

We compute work from home rates at the industry level by complementing information from ATUS with industry classification data from the CPS. Anticipating the quarterly frequency of our business dynamism information (described below), we define work from home rates in industry i and quarter t as the sum of all days worked from home by individuals working in industry i relative to the total number of work days in that industry:

$$\omega_{i,t} = \frac{\sum_{j=1}^{J_{i,t}} d_{j,\tau}^{home}}{\sum_{j=1}^{J_{i,t}} d_{j,\tau}}, \tag{9}$$

where $J_{i,t}$ is the number of individuals reporting in industry i in quarter t.

Business entry, exit and size. 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.[10] 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. This data, therefore, allows 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.[11]

Finally, the BED does not report overall establishment size at a quarterly frequency.

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.

[10]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.

[11]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.

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.[12]

Wage and industry information. Information on wages is taken from the QCEW. In particular, we use weekly wage information, averaged to the quarterly frequency. Finally, as with working from home, we are interested in the industry-level patterns of business entry, exit, size and wages. For our purposes, the BED and QCEW have information at the super-sector level. Due to low within-industry sample sizes we exclude "natural resources and mining" and "financial activities", which leaves us with quarterly information between 2003Q1-2022Q4 for 10 industries.[13]

3.2 Empirical Analysis

In what follows, we first provide descriptive statistics on how work from home has evolved over time and in the cross-section. We then move on to estimating the relationship between work from home rates and business dynamism.

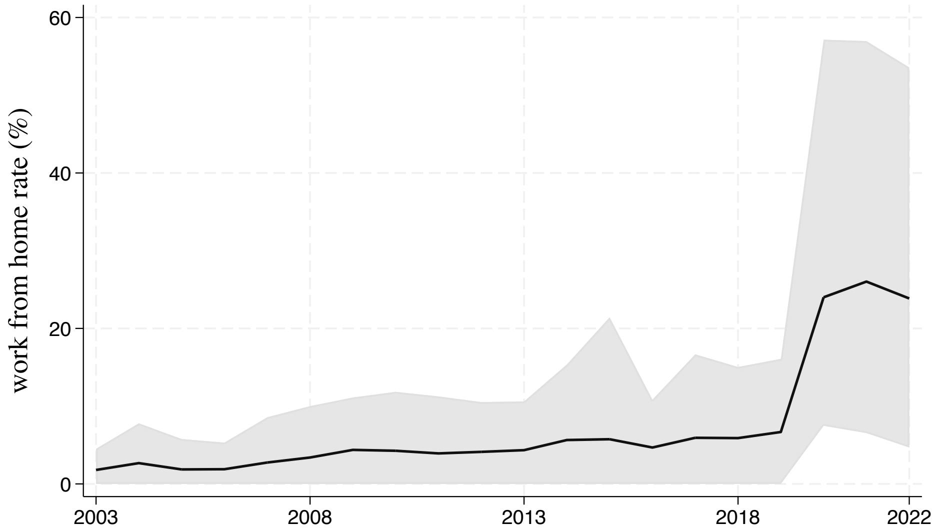
Work from home: Heterogeneity across sectors. According to the Business Response Survey, the fraction of establishments with some employees working remotely was 23.3% in February 2020, i.e. just before the onset of the pandemic. Turning to the intensive margin of remote work, the American Time Use Survey 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.

[12]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.

[13]Note that data on deaths runs only to 2022Q3. The Appendix shows that we obtain similar results when using a more disaggregated 2-digit NAICS classification. However, at this level of disaggregation, the BED has quarterly information only on openings (births and seasonal re-openings) and closings (deaths and temporary closures).

Figure 1: Work from home rate: Changes over time



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).

Work from home: Changes over time. 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. As is clear from the figure, work from home has been on a gradually increasing trend from the start of our sample. In particular, average remote work rates increased from about 1.8% in 2003 to 6.7% in 2019.

Across all sectors, however, the COVID-19 pandemic had a profound impact on remote work, inducing a dramatic increase. In 2020 (Q2-Q4), the first year of the pandemic, work from home rates jumped to 31%. While the most recent time periods have seen a slight reversal, work from home rates remain substantially elevated compared to the pre-pandemic period. Specifically, the average remote work rate in 2022 was 24%. All these patterns are consistent with evidence from other sources for the U.S. economy, as well as with international data (see e.g. Barrero et al., 2023; Bloom et al., 2023; Decker and Haltiwanger, 2024).

Business dynamism: Changes over time. It is well documented that business dynamism has been on a secular decline for several decades. This is true not only for the U.S. economy (see e.g. Decker et al., 2016b) but also for other developed countries across the globe (see e.g. Calvino et al., 2020). Broadly speaking, these patterns are characterized by declining entry rates and a shift of the firm size and age distributions towards larger and older businesses. With these changes comes a drop in job creation and destruction rates and an overall slowdown of productivity-enhancing worker and firm churn (see e.g. Decker et al., 2016a).

Since the middle of the COVID-19 pandemic, however, the U.S. economy has experienced a "surprising surge in applications for new businesses" (see Decker and Haltiwanger, 2024, p.1). This rise has spilled over into higher rates of establishment entry apparent in the BED data. In particular, compared to the pre-pandemic average of 9%, the entry rate in 2022 was almost a third higher at 12%. Moreover, while job creation from establishment births increased, it did so less than proportionally to the number of new establishments. Therefore, the average size of new establishments has declined from about 4 in the pre-pandemic sample to just under 3 workers in 2022. Business exit patterns have experienced similar dynamics. In particular, the exit rate in 2022 was almost a fifth higher than the pre-pandemic average while the size of exiting establishments dropped by a quarter.

Work from home and business dynamism: Raw data. We now turn to the link between work from home rates and business entry and exit. First, Figure 2 shows how changes in remote work rates relate to business entry, exit, wage rate and the average size of entering 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, wage rate and entrant size. In all these cases, we consider separately the full sample (2003-2022) and the pre-pandemic period (2003-2019).[14]

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, exit as well as with rises in wages. In addition, in our sample, increases in remote work rates are associated with declines in average entrant size.[15] 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.

Work from home and business dynamism: Estimation. To test the above relationships more formally, we estimate the following panel regressions:

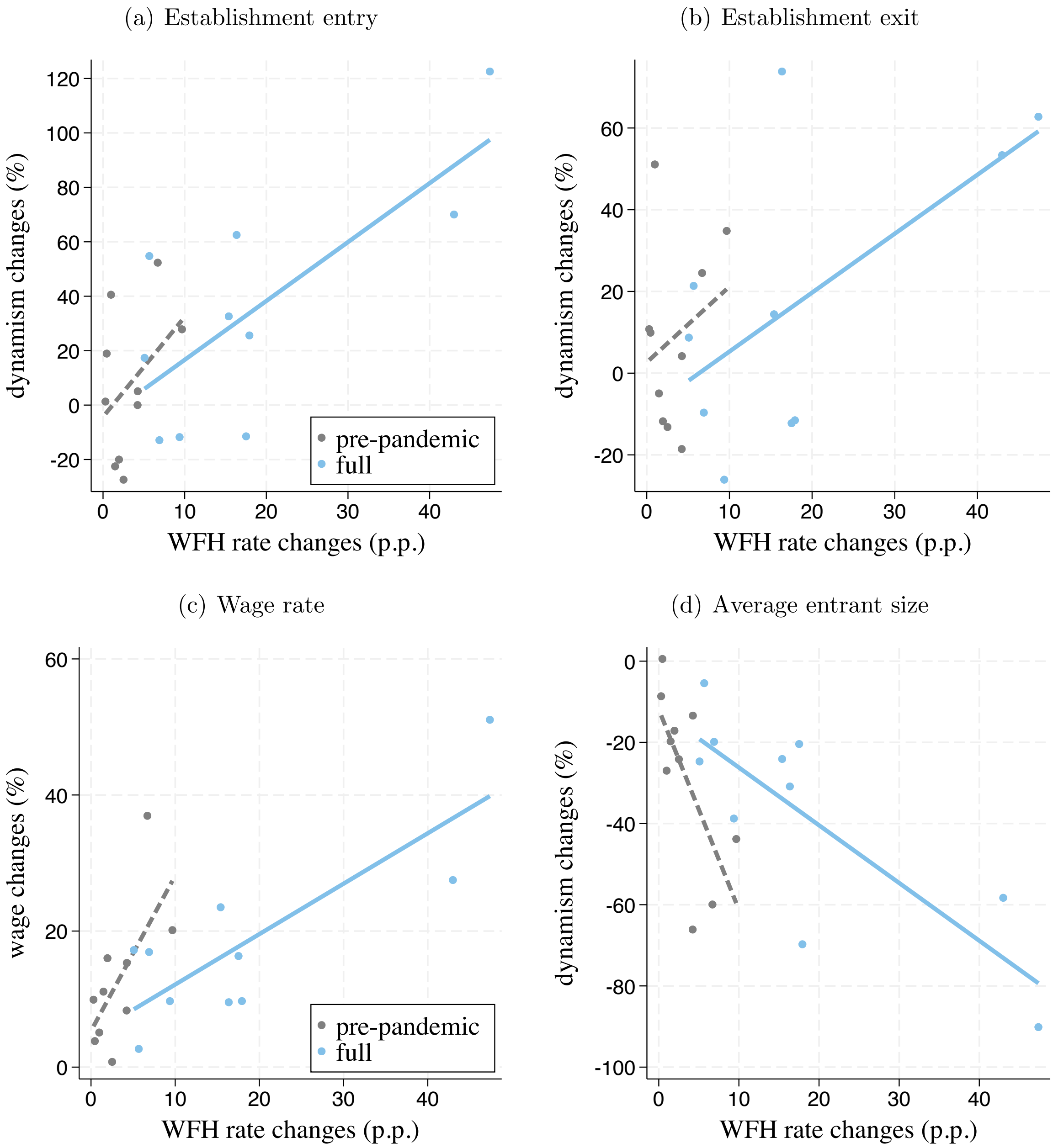
$$y_{i,t} = \delta_i + \delta_t + \beta \overline{\omega}_{i,t} + \Gamma X_{i,t} + \epsilon_{i,t}, \tag{10}$$

where $y_{i,t}$ represents, respectively, (the logs of) business entry, exit, size or wages in industry i and period t, δ_i are industry fixed effects, δ_t are time fixed effects, $X_{i,t}$ is a

[14]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).

[15]The Appendix shows that this holds true also when focusing on the size of exiting establishments, as well as an alternative measure of overall establishment size.

Figure 2: 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), wages (Panel c) and average entrant size (Panel d). Work from home rates are estimated from ATUS as described in the main text. Business entry and exit are taken from the BED, average size and wages are from the QCEW. All panels show data for the pre-pandemic sample (2003-2019) and the full sample (2003-2022).

set of control variables and $\overline{\omega}_{i,t}^{L} = 1/(L+1)\sum_{l=0}^{L} \omega_{i,t-l}$ 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

Table 1: Working from home and business dynamism: Regression results

	Entry	Exit	Wages	Entrant Size
A: Pre-pandemic sample (2003Q1-2019Q4)				
Work from home rate, β	1.414***	1.214***	0.623***	-1.315***
	(0.218)	(0.240)	(0.090)	(0.191)
R-squared	0.502	0.405	0.707	0.420
# observations	590	590	590	590
B: Full sample (2003Q1-2022Q4)				
Work from home rate, β	1.400***	0.905***	0.427***	-0.712***
	(0.117)	(0.120)	(0.049)	(0.106)
R-squared	0.705	0.547	0.721	0.486
# observations	710	700	710	710

Note: The table reports results from estimating (10). 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.

on business dynamism.[16]

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 1 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, exit, higher wages and smaller size of entrants. In the Appendix, we show that the latter holds also when considering overall establishment size or the size of exiting businesses.

4 Generalized Model

In this section we generalize our theoretical model along several dimension and parameterize it to match important features of U.S. data. Then, we use this generalized model as a laboratory to *quantitatively* evaluate how increases in work from home rates impacts on the macroeconomy.

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

4.1 Environment

The generalized model retains the structure of our core framework, but extends it along several important dimensions. First, we introduce fixed costs (heterogeneous across firms) of setting up remote work. Second, 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. Third, we introduce physical capital as a production factor, the accumulation of which is subject to adjustment costs. All these extensions have an impact on the model-implied distribution of firms conducting remote work and, therefore, the responsiveness of the economy to structural changes – including those driving work from home decisions. Finally, we allow for flexible labor supply and solve the model in general equilibrium. These latter two extensions are important as they endogenize the household's response to work from home decisions of firms and the resulting equilibrium wage.

As before, we will use upper-case letters to denote aggregates and lower-case letters to denote firm-level variables. 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 extent of remote work arrangements. Note that 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 and individual firms with the subscript j.

Work from home. As in our stylized model, work from home has two effects at the firm level. First, remote work is associated with efficiency losses in production, summarized by $f(\omega_{j,t})$. Second, employing a fraction of workers off-site reduces firms' 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 (but does not have to) employ workers remotely in all future periods, i.e. $\omega_{j,t} \in [0, 1]$. Below, we provide details about the decisions of paying the fixed setup cost and employing workers remotely, conditional on having paid the fixed setup cost in the past.

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

$$\ln z_{j,t} = \underline{z}_j(1-\rho) + \rho \ln z_{j,t-1} + \epsilon_t, \tag{11}$$

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.

With the exception of $\underline{z}_j$, all the above productivity parameters are assumed to be common across businesses. In contrast, the unconditional, long-run, mean of firm-level productivity $\underline{z}_j$ is assumed to be heterogeneous across firms.

Permanent firm 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:

$$y_{j,t} = f(\omega_{j,t}) z_{j,t} \left(n_{j,t}^{\alpha} k_{j,t}^{1-\alpha}\right)^{\theta}, \tag{12}$$

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

Capital adjustment and fixed operational costs. While labor is hired on the spot market from the household, firms accumulate capital subject to adjustment costs. In particular, we assume that 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:

$$k_{j,t+1} = x_{j,t} + (1-\delta_k) k_{j,t}, \tag{13}$$

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

In order to produce, firms must pay a per-period fixed overhead cost, κ_o. 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.

Firm values and optimal decisions. Every period, 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 doing so, however, they must first pay the fixed cost of setting up remote work.

Formally, businesses make their decisions in order 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 is given by

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

where $\pi_{j,t} = y_{j,t} - W n_{j,t} - g(\omega_{j,t})(\kappa_n n_{j,t} + \mu_\kappa) - x_{j,t} - \zeta(x_{j,t}, k_{j,t})$ are per-period profits. 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 conduct remote work. Formally, the continuation value is given by

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

where $\mathbb{E}$ is an expectation operator with respect to the evolution of firm-level productivity. The exit value, v^x, is given by

$$v_j^x(z_{j,t}, k_{j,t}) = k_{j,t}(1-\delta_k) - \zeta(-k_{j,t}(1-\delta_k), k_{j,t}), \tag{16}$$

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

$$v_j^{\omega}(z_{j,t}, k_{j,t}) = \max_{n_{j,t},\omega_{j,t},x_{j,t}} \left\{\pi_{j,t} + \beta(1-\delta)u_j^{\omega}(z_{j,t}, k_{j,t})\right\}, \tag{17}$$

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

$$u_j^{\omega}(z_{j,t}, k_{j,t}) = \int \max\left[v_j^{x}(k_{t+1}), \mathbb{E}_t v_j^{\omega}(z_{j,t+1}, k_{t+1}) - \widetilde{\kappa}_o\right] dH_{\kappa}(\widetilde{\kappa}_o). \tag{18}$$

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, i.e. when $\omega_{j,t} = 0$ but $\omega_{j,t+s} > 0$ for $s > 0$.

Firm entry. Having described incumbent businesses, we now turn to entry decisions. 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, modelled along the lines of Sedláček and Sterk (2017).

In particular, potential startups are free to choose which type of long-run productivity business 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"

$$m_i = \Psi_i^{\phi} s_i^{1-\phi}, \tag{19}$$

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

$$\kappa_e = \frac{m_i}{s_i} \sum_l p_l \int_z \max \left[v(z, 0; \underline{z}_i, \kappa_l^\omega), v^\omega(z, 0; \underline{z}_i, \kappa_l^\omega) - \kappa_l^\omega \right] dH_z(z), \tag{20}$$

where we assume that firms enter with zero capital and an initial productivity draw from the distribution $H_z(z)$. The overall 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. This, however, 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 the distribution of startup types.

Representative household. We assume a representative household which owns all businesses in the economy and optimally chooses aggregate consumption, C, and labor, N. Formally, per-period utility is given by

$$\ln C - \upsilon N, \tag{21}$$

where $\upsilon > 0$ is the disutility of labor and where we have assumed labor to be indivisible following the tradition of Hansen (1985) and Rogerson (1988). The representative household maximizes the expected present value of life-time utility subject to its budget constraint:

$$C = WN + \Pi, \tag{22}$$

where, normalizing the aggregate price level $P = 1$, real aggregate profits are given by Π. The resulting optimal labor supply condition takes on the familiar form:

$$W = \upsilon C. \tag{23}$$

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 conditions describe goods and labor market clearing:

$$Y = \sum_i \sum_l \int \int y \, \mu_{i,l}(z,k) dz dk, \tag{24}$$

$$N = \sum_i \sum_l \int \int n \, \mu_{i,l}(z,k) dz dk. \tag{25}$$

Finally, the aggregate resource constraint is given by

$$Y = C + S\kappa_e + \sum_i \sum_l \int \int \left[\zeta(x,k) + g(\omega)(\kappa_n n + \mu_\kappa) + \widehat{\kappa}_o + \kappa_l^\omega \mathbb{1}_{i,l}(z,k) \right] \mu_{i,l}(z,k) dz dk, \tag{26}$$

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 entry costs, 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.

4.2 Parametrization and Model Performance

To parameterize our model, we consider a period length of one year. Our starting point will be a model which targets moments of the U.S. economy in the pre-pandemic period of 2003 to 2019. All model parameters are summarized in Table 2. The next section describes in detail how we quantitatively isolate the macroeconomic impact of changes in work from home arrangements.

Data. To parameterize our model, we use information from four data sets already described in Section 3: (i) the Business Employment Dynamics, (ii) the American Time Use Survey, (iii) the Annual Social and Economic Supplement of the Current Population Survey and (iv) the Business Response Survey. As we describe below, these allow us to target moments related to business dynamism, remote work rates, their distribution over firm sizes and the share of establishments conducting remote work.

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 and cost saving functions, $f(\omega)$ and $g(\omega)$. Towards this end, we follow León-Ledesma and Satchi (2019) in their analysis of technology adjustment and specify both f and g as versions of exponential functions:

$$f = \exp\left(-\widetilde{f}\omega^2\right), \tag{27}$$

$$g = \exp\left(-\widetilde{g}\omega\right). \tag{28}$$

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

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

$$\zeta(x,k) = \zeta_0(x)k + \frac{\zeta_1}{2}\left(\frac{x}{k}\right)^2 k, \tag{29}$$

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

Finally, we parameterize the distribution of long-run productivity types and setup costs of remote work. 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^ω_L and κ^ω_H), two parameters controlling the masses of low and high productivity types ($\Psi_L > 0$ 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 to 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 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. Finally, we assume that the low remote work setup cost is $\kappa^\omega_L = 0$. 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.

Indirect inference. The remainder of the parameters are set to match a range of business dynamism and work from home moments in the data. As explained above, we make use of BED data on establishment size and exit rates and the information from

Table 2: 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	0.0173	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	0.00	Normalization, minimum remote work setup cost of 0		
$\widetilde{f}$	Speed of remote work productivity losses	-0.151	Productivity loss of fully remote work, Battiston et al. (2021)	14%	14%
$\widetilde{g}$	Speed of remote work cost savings	0.325	Average work from home rate, ATUS	4.1%	3.9%
κ_n	Non-wage labor costs	0.255	Avg wfh rate of 100+ over 100− firms, ATUS & ASEC	1.12	1.12
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 3	
σ_z	Productivity shock dispersion	0.208	Establishment size life-cycle profile, BED	see Figure 3	
ζ_0	Capital adjustment costs, fixed	0.001	Establishment size life-cycle profile, BED	see Figure 3	
ζ_1	Capital adjustment costs, variable	0.61	Establishment size life-cycle profile, BED	see Figure 3	
μ_κ	Overhead costs, mean	0.795	Establishment exit life-cycle profile, BED	see Figure 3	
σ_κ	Overhead costs, dispersion	2.49	Establishment exit life-cycle profile, BED	see Figure 3	

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.

ATUS and the BRS on remote work rates and the share of establishments conducting remote work.

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 15 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 speed of productivity declines and cost savings of remote work ($\widetilde{f}$, $\widetilde{g}$), the level of non-wage labor costs (κ_n), the level of high setup costs (κ_H^ω) and the respective fraction of startups with such setup costs, $1-\Psi_\omega$.

The long-run productivity means and the mass of low- and high-productivity business opportunities determine the shape of the firm size distribution and the overall probability of starting up a business. We interpret the startup probability ($M/(s_H+s_L)$) as the within first year survival rate which we measure in the data using the quarterly information in the BED. Next, we let our model target three moments of the firm size distribution: average size overall and the share and average size of small firms (those with fewer than 50 employees).

The persistence and dispersion of firm-level productivity as well as parameters related to capital adjustment costs are closely linked to business growth rates. Therefore, we target the entire life-cycle profile of establishment size from startups (age 0) to age 20 taken from the BED and averaged over the years 2003 and 2019.[17]

Next, overhead cost parameters are tied to patterns of firm exit. Therefore, using the same data source as for establishment size, we target the entire life-cycle profile of exit rates between the ages 1 and 20.

Finally, we need to set the work from home parameters in our model. To determine the speed of productivity declines induced by remote work, $\widetilde{f}$, we target the productivity loss of fully remote production estimated in the data. While detailed research in this area is still relatively rare, the few existing studies put this value in the range of about $8-19\%$ (see Battiston et al., 2021; Yang et al., 2022; Emanuel and Harrington, 2023; Gibbs et al., 2023). Therefore, in our baseline specification we target the midpoint of these estimates, 14%. The parameter $\widetilde{g}$ controls the speed of cost savings from remote work. For a given value of $\widetilde{f}$, the parameter $\widetilde{g}$ disciplines the cost-benefit trade-off inherent to optimal work from home rates. Hence, we target average work from home rates estimated from ATUS data between the years 2003 and 2019.

To pin down non-wage labor costs, κ_n, we use the link between ATUS and ASEC

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

and target average work from home rates in large firms (with more than 100 employees) relative to those in all remaining businesses. Recall from Section 2, fixed costs are key for generating heterogeneity in remote work rates across the firm size distribution. Therefore, given all other parameters, κ_n controls the strength of this size dependence.

Finally, the level and share of high setup costs (κ_H^{ω} and $1 - \Psi_{\omega}$) are disciplined by the following two moments from the BRS: the fraction of firms conducting remote work overall (23%) and among large firms with more than 100 employees (30%). Intuitively, since the minimum setup cost is $\kappa_L^{w} = 0$, all firms with such costs will choose to "pay" them. Therefore, the fraction of firms conducting remote work is informative about Ψ_{ω}. In contrast, only relatively productivity (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}.

Practically, we compute the selected model-generated moments and compare them to 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 15 parameters using 25 moments (12 firm size moments, 8 firm exit moments and 5 work from home moments). Details of the computational strategy are provided in the Appendix.

Model performance. Table 2 and Figure 3 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.

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 at 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).

Fifth, 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 less 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.

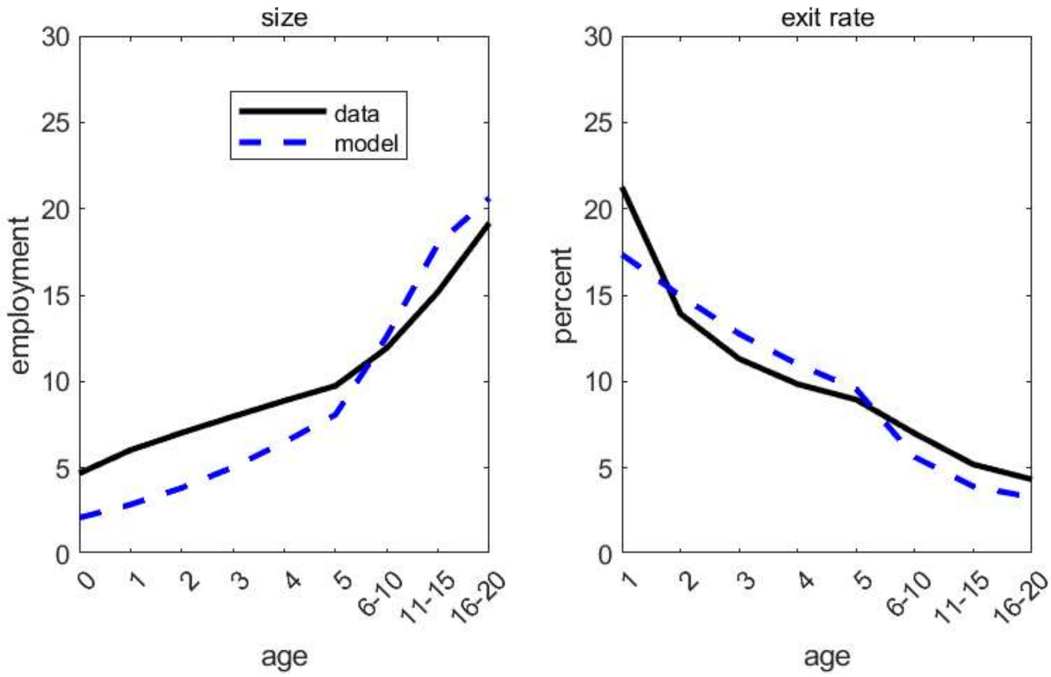
Finally, let us provide a sense of the magnitude of the productivity losses and cost savings implied by our parameterization. In our baseline economy, an average firm which has 4 percent of its employees working remotely faces an efficiency loss of just 0.02 percent. On the other hand, this average firm saves 1.3 percent on its labor (and overhead) costs. These results are broadly consistent with the empirical evidence that partial remote work arrangements come with essentially no productivity loss (see Barrero et al., 2023) and that flexible work arrangements can reduce (wage) costs by about 1 percent (see Barrero et al., 2022).

5 Macroeconomic Impact of Work from Home

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 counterfactual economy which is identical but features higher remote work rates. The difference in model outcomes between these two economies then offers a quantification of the impact of more prevalent remote work arrangements.

Model-implied work from home patterns. Before describing our counterfactual economy and moving on to the main results, let us first describe the heterogeneity in remote work implied by our model. Specifically, Table 3 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-

Figure 3: 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.

(employment-) and un-weighted sample.[18] 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 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.

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

Table 3: 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

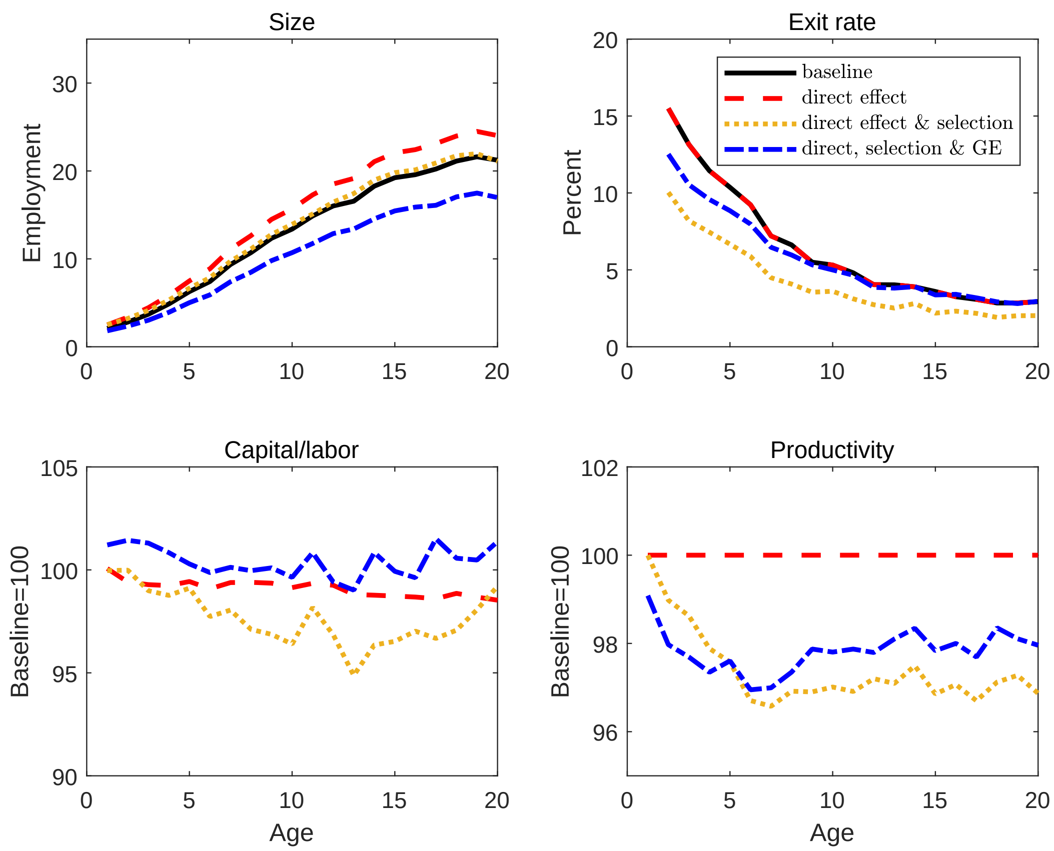
Note: The first two columns of the table report size- (employment-) weighted means of remote work rates. The remaining columns compute unweighted means and standard deviations, all reported unconditionally ("Uncond.") and conditionally ("Cond.") on businesses conducting remote work. The rows indicate 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 counterfactual economy. As explained above, the counterfactual economy is designed to be identical to our generalized model with the only exception being that it features higher remote work rates. We choose the magnitude of the latter to mimic the remote work rates observed in the post-pandemic U.S. economy. To generate higher remote work rates in our model, we adjust the parameters governing the efficiency and cost of remote work ($\widetilde{f}$ and $\widetilde{g}$). To discipline these parameters in the counterfactual economy, we use the post-pandemic values of the same two targets employed in the baseline calibration: the average work from home rate and that of large firms (with more than 100 workers) relative to all remaining businesses. Between the pre- and post-pandemic periods in the U.S., the former grew from 4.1 to 24 percent and the latter increased from 1.12 to 1.23.[19]

Note that when comparing the baseline to the counterfactual economy, we consider their respective stationary steady states and ignore transition dynamics. The reason is that while the COVID-19 pandemic sparked a greater adoption of remote work, it did so to a large extent because of truly extraordinary events such as lockdowns. While this period deserves study in its own right, we focus on the medium- to long-run implications of more prevalent remote work and we believe that a sustained increase in work from home can only be supported by an associated rise in its efficiency or decline in its cost.

[19] We do not consider changes in setup costs κ^{ω}. In our view, the costs of setting up remote work up 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. To put the resulting parameterization into perspective, note that an average firm in the baseline economy would see its productivity losses decline from 0.02 to 0.015 percent and its cost savings increase from 1.3 to 2.2 percent if it were to face the counterfactual values of the remote work parameters $\widetilde{f}$ and $\widetilde{g}$.

Figure 4: 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 counterfactual economy.

5.1 Work from Home 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 4 displays how cheaper and more efficient work from home 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 counterfactual economy.

In addition to our baseline specification (black solid line), we consider 3 different scenarios, all based on our counterfactual 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 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 counterfactual economy.

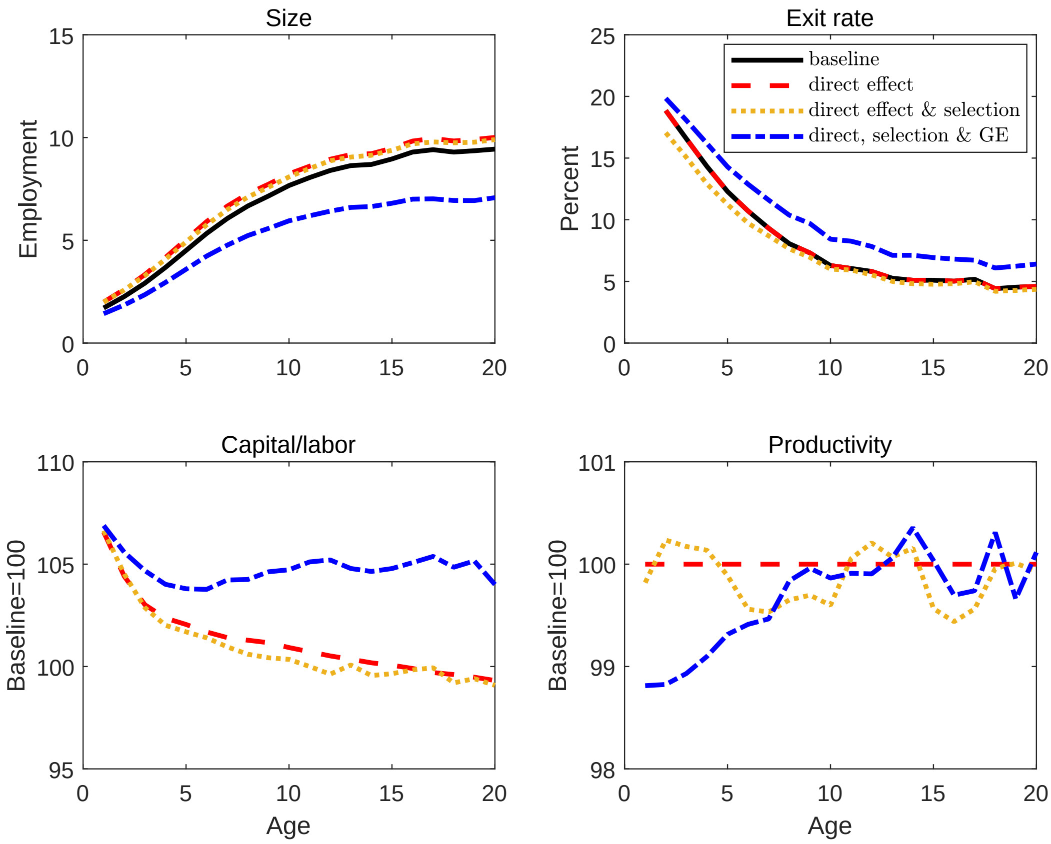
First, ignoring firm selection and general equilibrium effects, firms decide to expand production when remote work (and therefore production) becomes cheaper and more efficient (top left panel). In doing so, firms slightly reduce their capital-labor ratios as they take advantage of the relatively cheaper 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, more favorable remote work conditions raise profits and firm values which induce greater entry and reduce firm exit (top right panel) – as predicted by our theoretical, partial equilibrium analysis, in Section 2. 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 (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 counterfactual and baseline economy (bottom right panel).

Firm growth and selection: Firms which never conduct remote work. Figure 5 turns towards firms which never conduct remote work – neither in the baseline, nor in the counterfactual economy. Note that since firms which have not paid the setup cost

Figure 5: 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 counterfactual economy.

of remote work cannot directly take advantage of cheaper and more efficient work from home, all the patterns shown in Figure 5 occur either because firms expect to do remote work in the future or because of general equilibrium effects.

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 wish 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, reduces 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" for. Indeed, the increase in wages is dominantly driven by firms conducting remote work and by new entrants.

Composition of firms. The paragraphs above described the impact of cheaper and more efficient remote work for a given set of firms – those that always and never conduct remote work. We now turn to investigating how the composition of firms differs between the baseline and the counterfactual economies.

First, the share of firms deciding to conduct remote work is higher in the counterfactual 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 about 13 percent. Moreover, there is also a shift in exit rates with high-type firms seeing their survival rates decrease *relatively* more compared to those of low-type firms.[20]

Overall, there is a clear pattern of "winners" and "losers" from cheaper and more efficient remote work. 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.[21] 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 counterfactual 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%).

To summarize, compared to the baseline, the counterfactual economy is characterized by a higher mass of entrants with a larger fraction of businesses conducting remote work. At the same time, however, the distribution of firms is tilted towards low-productivity businesses as they are the ones which benefit relatively more from cheaper and more efficient remote work. This trade-off between the strength of the entry response and the changes in firm productivity will be important when we turn to the macroeconomic impact of more favorable remote work.

[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 counterfactual, post-pandemic, equilibrium.

[21] Note that our model does not assume that all small firms are unproductive. Indeed, even high-productivity firms enter the economy small and grow only gradually over time. These firm-level dynamics are disciplined by matching the life-cycle patterns of firm growth and exit observed in the data.

5.2 Work from Home and the Macroeconomy

Intuitively, cheaper and more efficient remote work frees up existing resources (and creates new ones) which can be invested elsewhere. As will become clear, the economy uses these resources for investment into aggregate capital and firm entry. However, the changes in business dynamism described above, and in particular the changes in the (productivity) composition of firms, serve to offset the positive impacts of more efficient and cheaper remote work. We now turn to discussing the overall macroeconomic impact of this trade-off, quantified in Table 4.

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

$$Z = \frac{Y}{(N^{\alpha}K^{1-\alpha})^{\theta}} = \sum_i \sum_l \int \int z f(\omega) \left(\left(\frac{n}{\overline{n}}\right)^{\alpha} \left(\frac{k}{\overline{k}}\right)^{1-\alpha} \right)^{\theta} \Omega^{1-\theta} \widetilde{\mu}_{i,l}(z,k) dz dk, \tag{30}$$

where we will refer to the term $(N^{\alpha}K^{1-\alpha})^{\theta}$ as the "scale" of the ecnomy 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 endogenous entry composition and survival rates. 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 4, the first row shows that aggregate output is about 2.9 percent higher in the counterfactual 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 counterfactual 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 4 show how consumption differs between the counterfactual 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 4: 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.[22] 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 4 report differences in household welfare ($\mathcal{W} = \log(C) - \upsilon N$). Our model predicts that welfare is slightly higher in the counterfactual economy. This is entirely driven by the strong consumption increase. In contrast, households' optimal labor supply is somewhat higher in the counterfactual economy. Quantitatively, however, this latter effect does not overturn the welfare benefits of higher consumption.

The role of firm entry. The counterfactual economy with more favorable remote work conditions features a higher aggregate TFP, more output, consumption and welfare. While these results may seem straightforward – given the counterfactual economy features cheaper and more efficient remote work – in what follows we show that in fact the changes in business dynamism in the counterfactual economy effectively undo almost all the direct benefits of more favorable remote work. What ultimately matters for the macroeconomy and improvements in welfare is the response of firm entry.

To make this point, we consider a variant of the counterfactual economy in which firm

[22] 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.

entry is muted. This can be viewed as a reduced form way of modelling frictions (e.g. financial or regulatory) impeding a flexible entry response. Practically, we achieve this by replacing the entry function (19) with an exogenous rule such that the counterfactual 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 4 and the details of our computational strategy are in the Appendix.

In this case, when the mass of firms remains the same as in the baseline economy, aggregate TFP *falls*. Note that this happens despite the fact that remote work is *more* efficient (i.e. $f(\omega)$ improves) in the counterfactual economy. The reason lies in the different business dynamism patterns in the counterfactual economy, discussed in Section 5.1. In particular, the counterfactual 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 increase in wages.

In addition to lower aggregate productivity, the higher equilibrium wage in the counterfactual economy induces firms to scale down production. 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 compensate the decline in consumption with less labor supply. As a result, welfare is effectively the same in both economies.

Therefore, while cheaper and more efficient remote work arrangements are, all else equal, unambiguously positive for individual firms, they also induce changes in business dynamism. The shift towards less productive firms, combined with an increase in equilibrium wages, more than offset these direct positive effects. Ultimately, the overall aggregate effects rest on how strongly firm entry will respond to changes in remote work arrangements. If other frictions (e.g. financial constraints or governmental regulation) prevent businesses from starting up at a sustainably higher rate, then the direct benefits of cheaper and more efficient remote work can be entirely undone by a shift towards smaller and less productive firms.

5.3 Model Mechanism in the Data

Our analysis shows that more attractive remote work particularly favors small businesses. This is a key model mechanism behind our quantitative results. In this subsection, we offer empirical evidence in support of this model mechanism.

Remote work of large vs small firms. Throughout the paper, we have made a distinction between the extensive and intensive margins of remote work. On the one

Table 5: Higher remote work and firm size and exit: Model and data

	Size		Exit rates	
	Young	Old	Young	Old
Data	−18%	−15%	+1%	+22%
Model	−18%	−15%	+5%	+19%

Note: The table shows changes in firm "size" and "exit rates" for "young" (less than 6 years) and "old" (16-20 years) firms. The top row shows the BED data, while the bottom row shows model-predicted differences based on a comparison of the counterfactual and baseline economies.

hand, the presence of positive fixed setup costs in our model makes only relatively larger firms conduct remote work. On the other hand, *conditional* on conducting remote work, the presence of fixed costs which can be mitigated by employing some workers remotely makes smaller firms benefit relatively more.

Both these patterns are essential for our model results and both are consistent with the data. Indeed, we parameterize our model to match the empirically observed size heterogeneity along the extensive margin. Specifically, while the share of firms conducting remote work overall is 23 percent, it is 30 among businesses with more than 100 workers. While to the best of our knowledge there is no firm-level dataset allowing to comprehensively measure the intensive margin, the BRS offers a measure of one of the extremes – the fraction of businesses which are *fully* remote. According to the BRS, it is smaller firms which operate much more often fully remotely. Specifically, over 11% of businesses with less than 500 workers are fully remote, while this fraction is only 1.6% for firms with more than 500 workers.

Changes in the share of small firms. As explained, a key channel through which more favorable remote work affects the macroeconomy is the shift towards (very) smaller businesses. Section 4.2 already reported that our model does a good job at matching the firm size distribution – both along targeted and untargeted moments. We now turn to investigating the *change* in the firm size distribution induced by more favorable remote work conditions.

Recall that our counterfactual economy mimics the increase in remote work rates observed in the post-pandemic U.S. economy. Keeping in mind that we are comparing stationary steady states and ignoring transition dynamics, we can nevertheless gauge how our model predictions compare to the data.

In the data, the share of very small establishments (1-4 workers) increases by about 4 (5) percentage points among entrants (all businesses). Compared with the baseline model, the share of entrants (all businesses) with 1-4 workers is 5 (7) percentage points higher in the counterfactual economy with higher remote work rates. Therefore, the strength with which the firm size distribution shifts towards small firms in the model is *quantitatively* realistic.

Table 6: Higher remote work and business entry and exit: Model and data

	Rate		Size	
	Entry	Exit	Entrants	Exiters
Data	+28%	+15%	−24%	−22%
Model	+13%	+13%	−16%	−21%

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 the BED data, while the bottom row shows model-predicted differences based on a comparison of the counterfactual and baseline economies.

Changes in life-cycle patterns. Using the same logic as above, we can look at differences in firms' life-cycle dynamics, which play an important role as discussed in Section 5.1. Towards this end, Table 5 reports changes in average size and exit rates of young (less than 6 years) and old (16-20 years) businesses. As can be seen, the model aligns with the data well. In particular, while young firms experienced the strongest declines in firm sizes, exit rates increased (relatively) the most among old firms.

Changes in overall business dynamism. As a final validation step, we circle back to our core theoretical predictions and investigate *quantitatively* changes in business entry, exit and size.

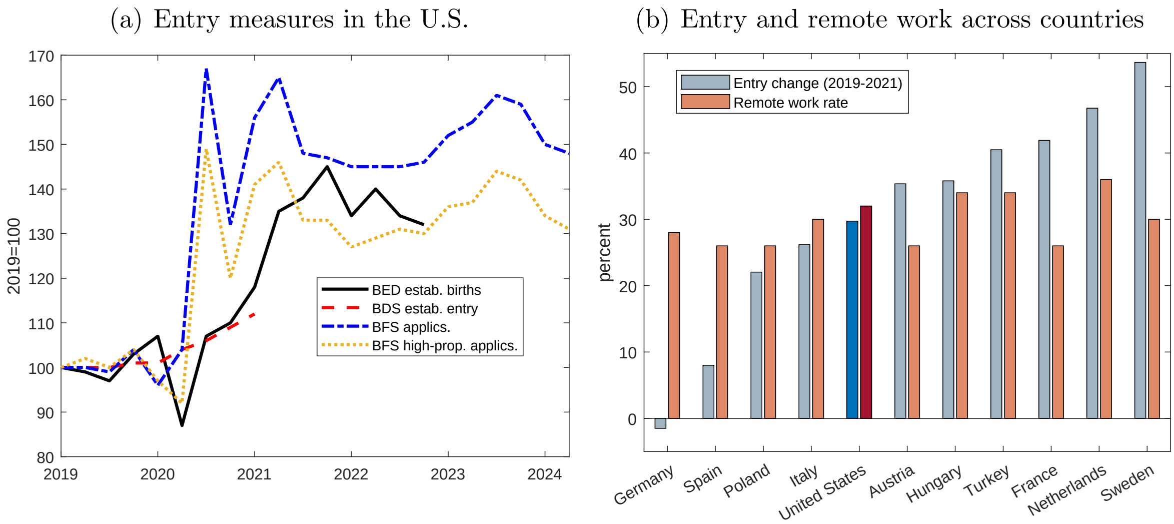
As discussed in Decker and Haltiwanger (2024), the increase in firm entry in the aftermath of the pandemic is surprising in the context of the last several decades of declining business dynamism. Our model, however, provides a rationalization for this sudden development. In fact, Table 6 suggests that more attractive work from home arrangements can go a long way in explaining such patterns. In particular, increased uptake of remote work alone can account for about 46 percent of the entry rate increase. In addition, the remaining columns report that our model also explains a large part of the rise in exit rates and the decline in firm sizes of entering and exiting businesses. This is a combination of lower average firm productivity but also a higher equilibrium wage rate.

Overall, the above evidence suggests that the key model mechanism, whereby smaller businesses benefit relatively more from favorable remote work, is consistent with 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.

5.4 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

Figure 6: Business entry and remote work across countries



Note: Panel a) 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. Panel b) of 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).

of the current model and sketch potential extensions which may be fruitful avenues for future research.

Sustained firm entry across countries. Our framework suggests that firm entry is crucial for understanding the overall impact more favorable remote work conditions may have on the macroeconomy. Currently, the U.S. is experiencing a "surprising surge in applications for new businesses" (see Decker and Haltiwanger, 2024, p.1). Our analysis shows, however, that a key question is whether or not this surge will be sustained in the long-run.

Panel a) of Figure 6 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 so called "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, but more data will be crucial to evaluate the medium- to long-run effect on the number of firms.

Panel b) of Figure 6 then shows changes in firm entry (between 2019 and 2021) and remote work rates (in 2021) across several developed economies. Having in mind that this period was still mired by the COVID-19 pandemic, the data sends a mixed message. On the one hand, work from home rates are relatively similar across economies with about one quarter to one third of work days being done remotely. On the other hand, however, entry changes vary substantially across economies. 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 the welfare impact of more favorable remote work arrangements may vary substantially across countries with differences in business dynamism playing a key role.

Household welfare. Our model predicts that more favorable remote work arrangements can lead to a slight increase in household welfare – at least if entry responds strongly enough. It is worth noting that other considerations – mainly on the household side – may strengthen these welfare conclusions. For instance, it would be interesting to incorporate welfare benefits of reduced commuting time or benefits from home production (see e.g. Barrero et al., 2023, for a discussion).

Aggregate growth. In our framework, firms differ in the *level* of their long-run productivity. And 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, 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.

Other factors and transition dynamics. Our model predicts that almost one 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.

6 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 and firm entry, exit and employment. In addition, we confirm the model's predictions in the data and extend our baseline framework along several dimensions to quantify the macroeconomic impact of work from home.

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 in future research. 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 believe that more work – including the collection of economy-wide information on remote practices *at the firm-level* – is needed to better understand the aggregate impact of the increasing trend of remote work.

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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:

$$C = WN + \Pi,$$

where the aggregate price is normalized, N is the fixed labor supply and Π is the real aggregate profits.

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

- $v(z)$, $n(z)$, $\omega(z)$ and $\widetilde{z}$ solve the incumbent's problem (3) and satisfy the exit threshold (4),
- the free entry condition (5) is satisfied with equality if $M_e > 0$,
- the labor and goods markets clear (7), (8),
- and the distribution of firms satisfies: $\mu(z) = 0$ for $z < \widetilde{z}$ and $\mu(z) = h(z)/(1-H(\widetilde{z}))$ otherwise .

A.2 Proofs

In what follows, we provide all the proofs to our propositions in the main text.

Interior Solutions. Start with the FOCs:

$$f'(\omega)zn^{\alpha} - g'(\omega)(\kappa_n n + \kappa_o) = 0 \quad \text{(A1)}$$

$$f(\omega)z\alpha n^{\alpha-1} - W - g(\omega)\kappa_n = 0 \quad \text{(A2)}$$

Solve optimal employment, n^*, from equation (A2):

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

Substituting n^* into equation (A1), we have

$$\frac{zf'(\omega^*)}{g'(\omega^*)} - \kappa_n n^{*1-\alpha} - \kappa_0 n^{*-\alpha} = 0 \quad \text{(A3)}$$

Define the followings for simplicity:

$$F(\omega) = \alpha z f(\omega)$$

$$G(\omega) = W + \kappa_n g(\omega)$$

Then we can rewrite equation (A3) as:

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

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

$$h(0)h(1) < 0$$

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

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

$$f(\omega)z\alpha n^{\alpha-1} - W - g(\omega)\kappa_n = 0$$

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

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

b) if $\kappa_o > 0$, differentiating equations (A1) and (A2) 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:

$$(\frac{f''g' - g''f'}{g'^3})f\alpha(\alpha-1) > [\frac{f'}{g'}(\alpha-1) + \frac{\kappa_o}{zn^{*\alpha}}]^2 \tag{A4}$$

We can further derive the necessary condition from (A4):

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

Proof of Proposition 3. Assume two coefficients $\widetilde{f}$ and $\widetilde{g}$ that govern the velocity of productivity loss and cost saving. 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 (A1) and (A2) as:

$$f_1(\omega^*;\widetilde{f})zn^{*\alpha} - g_1(\omega^*;\widetilde{g})(\kappa_n n^* + \kappa_o) = 0 \tag{A5}$$
$$f(\omega^*;\widetilde{f})z\alpha n^{*\alpha-1} - W - g(\omega^*;\widetilde{g})\kappa_n = 0 \tag{A6}$$

Proof of $\frac{\partial\omega^*}{\partial \widetilde{f}} > 0$. Differentiating Equations (A5) and (A6) w.r.t. $\widetilde{f}$ and rearranging, we obtain:

$$[\frac{f_{11}g_1 - f_1g_{11}}{g_1^3}f\alpha(\alpha-1) - (\frac{f_1}{g_1}(\alpha-1) + \frac{\kappa_o}{zn^{*\alpha}})^2]\frac{\partial\omega^*}{\partial \widetilde{f}} = \frac{f_2f_1 - f_{12}f}{g_1^2}\alpha(\alpha-1) + \frac{f_2}{g_1}\frac{\alpha\kappa_o}{zn^{*\alpha}}$$

Assuming condition (A4) holds, $\frac{\partial\omega^*}{\partial \widetilde{f}} > 0$ if and only if the RHS is positive:

$$\frac{f_1f_2 - f_{12}f}{g_1^2}\alpha(\alpha-1) + \frac{f_2}{g_1}\frac{\alpha\kappa_o}{zn^{*\alpha}} > 0 \tag{A7}$$

We can further obtain the necessary condition for $\frac{\partial\omega^*}{\partial \widetilde{f}} > 0$ from (A7):

$$\frac{f_1f_2 - f_{12}f}{g_1^2}\alpha(\alpha-1) > 0 \iff f_1f_2 < f_{12}f$$

where we use the assumption that $\alpha < 1$.

Proof of $\frac{\partial \omega^*}{\partial \widetilde{g}} > 0$. Differentiating Equations (A5) and (A6) w.r.t. $\widetilde{g}$ and rearranging, we obtain:

$$[\frac{f_{11}g_1 - f_1 g_{11}}{g_1^3} f\alpha(\alpha-1) - (\frac{f_1}{g_1}(\alpha-1) + \frac{\kappa_o}{zn^{*\alpha}})^2]\frac{\partial \omega^*}{\partial \widetilde{g}} = \frac{g_{12}f_1 f}{g_1^3}\alpha(\alpha-1) - \frac{g_2\kappa_n}{g_1 zn^{*\alpha-1}}(\frac{\alpha f_1}{g_1} - \frac{\kappa_n}{zn^{*\alpha-1}})$$

Assuming condition (A4) holds, $\frac{\partial \omega^*}{\partial \widetilde{g}} > 0$ if and only if the RHS is positive:

$$\frac{g_{12}f_1 f}{g_1^3}\alpha(\alpha-1) - \frac{g_2\kappa_n}{g_1 zn^{*\alpha-1}}(\frac{\alpha f_1}{g_1} - \frac{\kappa_n}{zn^{*\alpha-1}}) > 0 \tag{A8}$$

Proof of $\frac{\partial \pi^*}{\partial \widetilde{f}} > 0$ and $\frac{d\widetilde{z}}{d\widetilde{f}} < 0$. By the envelope theorem, we have:

$$\frac{\partial \pi^*}{\partial \widetilde{f}} = f_2(\omega^*; \widetilde{f})zn^{*\alpha} > 0 \tag{A9}$$

Since $\pi^*(\widetilde{z}) \equiv 0$, fixing $\widetilde{g}$ and using the envelope theorem, we have:

$$0 \equiv \frac{d\pi^*(\widetilde{z}(\widetilde{f}))}{d\widetilde{f}} = \frac{\partial \pi^*}{\partial \widetilde{f}}|_{z=\widetilde{z}} + \frac{\partial \pi^*}{\partial \widetilde{z}}\frac{d\widetilde{z}}{d\widetilde{f}} \tag{A10}$$

As $\frac{\partial \pi^*}{\partial \widetilde{f}} > 0$ from (A9) and by the envelope theorem $\frac{\partial \pi^*}{\partial z} = f(\omega^*; \widetilde{f})n^{*\alpha} > 0$, we have:

$$\frac{d\widetilde{z}}{d\widetilde{f}} < 0$$

Proof of $\frac{\partial \pi^*}{\partial \widetilde{g}} > 0$ and $\frac{d\widetilde{z}}{d\widetilde{g}} < 0$. By the envelope theorem, we have:

$$\frac{\partial \pi^*}{\partial \widetilde{g}} = -g_2(\omega^*; \widetilde{g})(\kappa_n n^* + \kappa_o) > 0 \tag{A11}$$

Since $\pi^*(\widetilde{z}) \equiv 0$, fixing $\widetilde{f}$ and using the envelope theorem, we have:

$$0 \equiv \frac{d\pi^*(\widetilde{z}(\widetilde{g}))}{d\widetilde{g}} = \frac{\partial \pi^*}{\partial \widetilde{g}}|_{z=\widetilde{z}} + \frac{\partial \pi^*}{\partial \widetilde{z}}\frac{d\widetilde{z}}{d\widetilde{g}} \tag{A12}$$

As $\frac{\partial \pi^*}{\partial \widetilde{g}} > 0$ from (A11) and $\frac{\partial \pi^*}{\partial z} > 0$, we have

$$\frac{d\widetilde{z}}{d\widetilde{g}} < 0$$

A.3 Additional theoretical results.

While not the focus of our analysis in the main text, we can also describe the relative strength of cost- vs productivity-driven changes in remote work rates.

Proposition 3 (Relative strength of changes in remote work)
Assuming internal optimal work from home rates, ω^*, exogenous changes in the parameters $\widetilde{f}$ and $\widetilde{g}$ have the following impact:

$$\frac{\partial \pi^*}{\partial \widetilde{g}} > \frac{\partial \pi^*}{\partial \widetilde{f}}$$

$$\frac{\partial \widetilde{z}}{\partial \widetilde{g}} < \frac{\partial \widetilde{z}}{\partial \widetilde{f}}.$$

The above proposition states that cost-driven changes are stronger, relative to those driven by efficiency changes. The intuition rests on the respective shapes of f and g. In particular, in order for businesses to optimally choose internal remote work rates, it must be that costs initially fall faster than productivity with higher ω. This, in turn, implies a larger effect on profits and the exit threshold for a given cost-driven change in optimal remote work rates compared to the same productivity-driven change.

Proof of $\frac{\partial \pi^*}{\partial \widetilde{g}} > \frac{\partial \pi^*}{\partial \widetilde{f}}$ and $\frac{\partial \widetilde{z}}{\partial \widetilde{g}} < \frac{\partial \widetilde{z}}{\partial \widetilde{f}}$. Using the previous results, we can prove the following equivalence relations:

$$\begin{aligned}
\frac{\partial \pi^*}{\partial \widetilde{g}} &> \frac{\partial \pi^*}{\partial \widetilde{f}} \\
\overset{(A9),(A11)}{\iff} -g_2(\omega^*;\widetilde{g})(\kappa_n n^* + \kappa_o) &> f_2(\omega^*;\widetilde{f}) z n^{*\alpha} \\
\overset{(A5)}{\iff} -g_2(\omega^*;\widetilde{g}) &> f_2(\omega^*;\widetilde{f}) \frac{g_1(\omega^*;\widetilde{g})}{f_1(\omega^*;\widetilde{f})} \\
\iff \frac{g_2}{g_1} + \frac{f_2}{f_1} &> 0
\end{aligned} \tag{A13}$$

Hence (A13) is the necessary and sufficient condition to obtain $\frac{\partial \pi^*}{\partial \widetilde{g}} > \frac{\partial \pi^*}{\partial \widetilde{f}}$. It states that the impact of $\widetilde{g}$ on profits is more significant than that of $\widetilde{f}$ if and only if (A13) holds.

Again we use the previous results to derive the equivalence relations:

$$\begin{aligned}
\frac{\partial \widetilde{z}}{\partial \widetilde{g}} &< \frac{\partial \widetilde{z}}{\partial \widetilde{f}} \\
\overset{(A10),(A12)}{\iff} -\frac{\frac{\partial \pi}{\partial \widetilde{g}}\big|_{z=\widetilde{z}}}{\frac{\partial \pi}{\partial z}\big|_{z=\widetilde{z}}} &< -\frac{\frac{\partial \pi}{\partial \widetilde{f}}\big|_{z=\widetilde{z}}}{\frac{\partial \pi}{\partial z}\big|_{z=\widetilde{z}}} \\
\iff \left.\frac{\partial \pi}{\partial \widetilde{g}}\right|_{z=\widetilde{z}} &> \left.\frac{\partial \pi}{\partial \widetilde{f}}\right|_{z=\widetilde{z}} \\
\iff 0 &< \left.\frac{g_2}{g_1}\right|_{z=\widetilde{z}} + \left.\frac{f_2}{f_1}\right|_{z=\widetilde{z}}
\end{aligned}$$

which is satisfied automatically by (A13).

Therefore, we show that the impacts of $\widetilde{g}$ on profits and cutoff productivity are more significant than those of $\widetilde{f}$ if and only if (A13) holds.

B Empirical Analysis: Additional Exercises and Robustness

In this Appendix, we consider various robustness checks to our empirical analysis of Section 3. We also provide a comparison between the BED and BDS data.

B.1 Working Outside the Workplace

As discussed in the main text, 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 (9), 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.

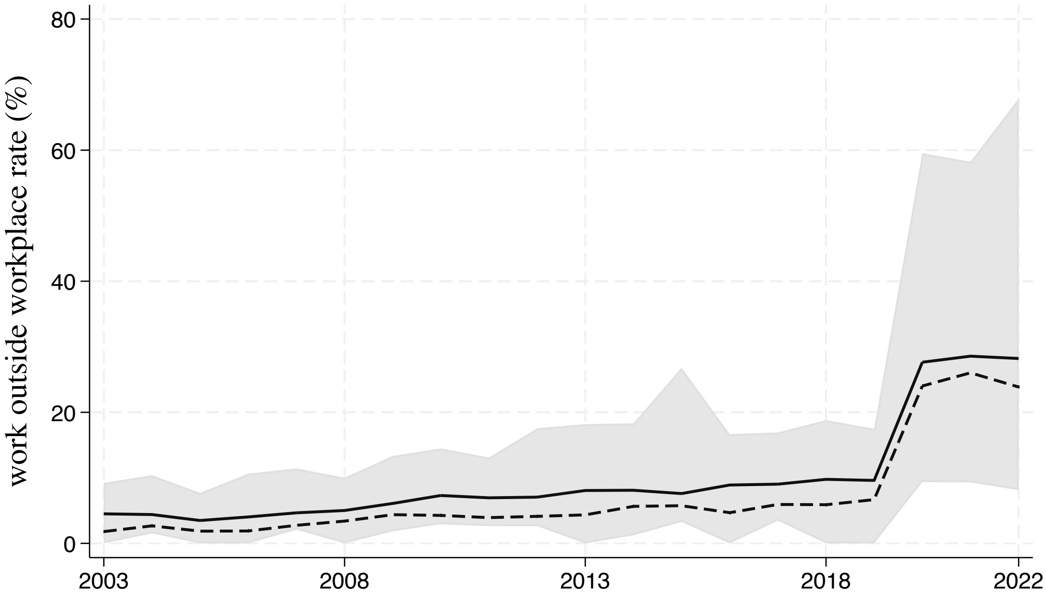
Figure A1 shows the evolution of working-outside-workplace rate from 2003 to 2022. In addition, Figure A2 plots how changes in remote work rates are connected to changes in establishment entry and exit across industries. Finally, Table A1 shows the associated panel regression results. All these are very similar to the outcomes presented in the main text which are based on work from home definitions.

Table A1: Working outside workplace and business dynamism: Regression results

	Entry	Exit	Wages	Entrant Size
A: Pre-pandemic sample (2003Q1-2019Q4)				
Work from home rate, β	0.832***	0.875***	0.323***	-0.519***
	(0.187)	(0.202)	(0.080)	(0.167)
R-squared	0.465	0.384	0.658	0.351
# observations	590	590	590	590
B: Full sample (2003Q1-2022Q4)				
Work from home rate, β	1.299***	0.924***	0.392***	-0.723***
	(0.116)	(0.115)	(0.048)	(0.104)
R-squared	0.685	0.538	0.709	0.463
# observations	710	700	710	710

Note: The table reports results from estimating (10). 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 A1: 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.

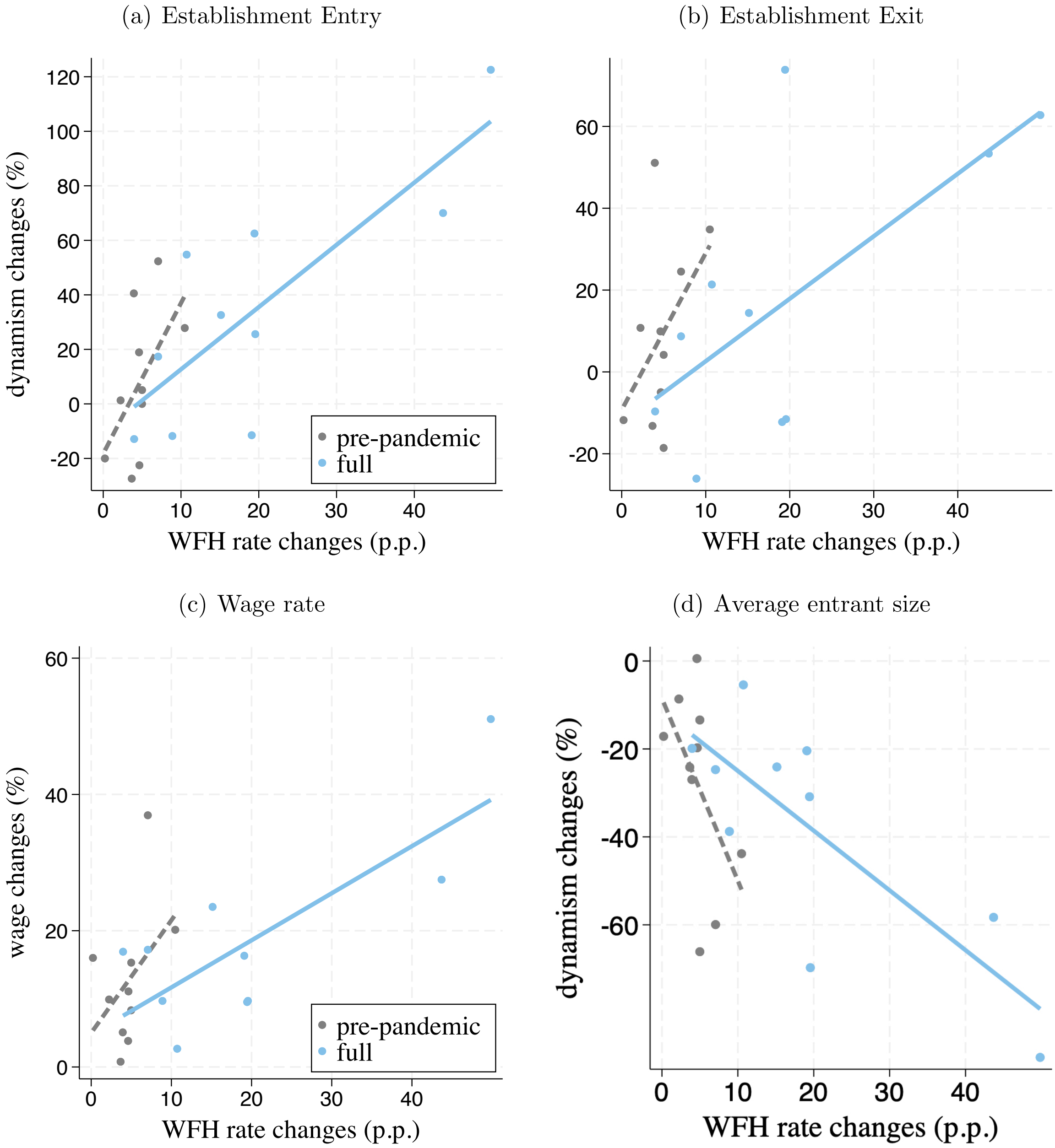
B.2 Robustness: Using Average Size and Exiter Size

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 and average exiter size from BED. Figure A3 shows the how the change in remote work is associated with changes in average establishment size and average exiter size. Table A2 shows the results of panel regression.

Table A2: Working from home and establishment size

	Average Size	Exiter Size
A: Pre-pandemic sample (2003Q1-2019Q4)		
Work from home rate, β	-0.604***	-1.235***
	(0.236)	(0.180)
R-squared	0.115	0.566
# observations	590	590
B: Full sample (2003Q1-2022Q4)		
Work from home rate, β	-0.605***	-0.408***
	(0.110)	(0.085)
R-squared	0.256	0.581
# observations	710	700

Figure A2: 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), wages (Panel c) and average entrant size (Panel d). All panels show data for the pre-pandemic sample (2003-2019) and the full sample (2003-2022).

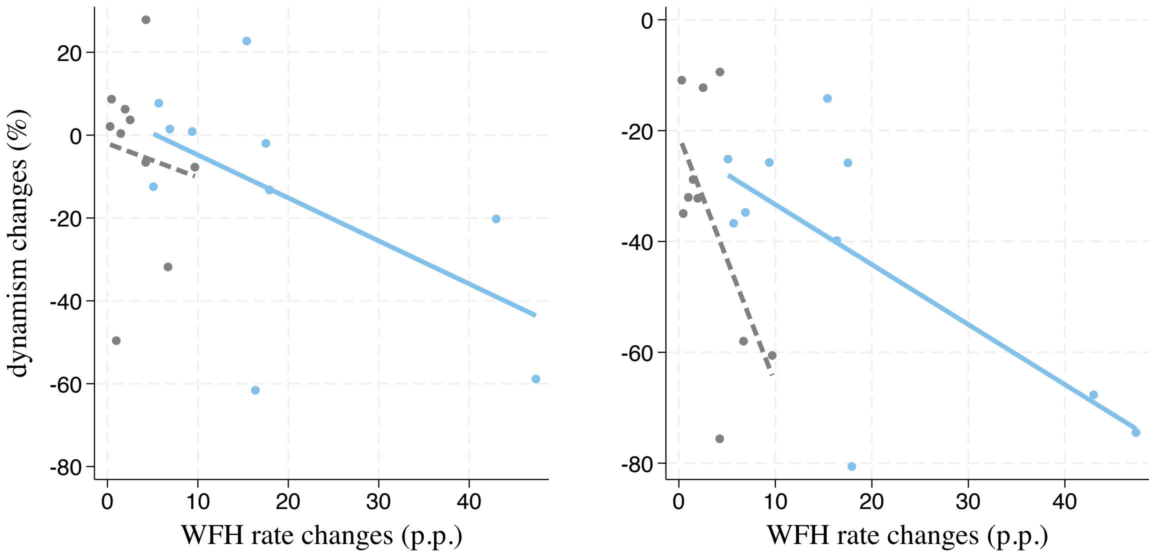
B.3 Robustness: 2-digit Sectors

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 A3: Work from home and establishment size: Changes across industries

(a) QCEW average size

(b) BED average exiter size



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 (Panel a) and average exiter size (Panel b). All panels show data for the pre-pandemic sample (2003-2019) and the full sample (2003-2022).

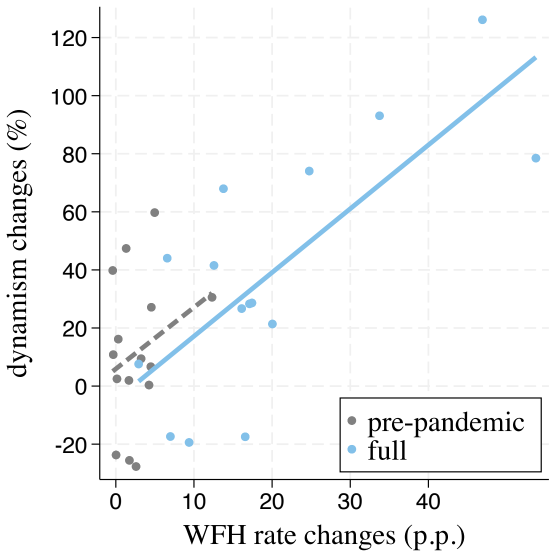
temporary closings and reopening. We dropped "Agriculture, forestry, fishing, and hunting", "Mining, quarrying, and oil and gas extraction" and "Management of companies and enterprises", due to limited observations in ATUS. Besides, "Finance and insurance" sector is excluded, consistent with the previous analysis at the super sector level. Figure A4 shows the linkage between work from home rates and business entry. Table A3 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 A3: Working from home and business entry: 2-digit sectors

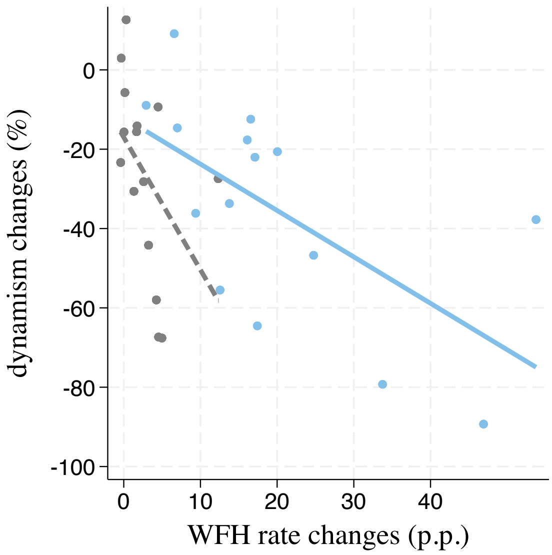
	Entry	Entrant Size
A: Pre-pandemic sample (2003Q1-2019Q4)		
Work from home rate, β	1.118***	-1.169***
	(0.415)	(0.328)
R-squared	0.524	0.361
# observations	225	225
B: Full sample (2003Q1-2022Q4)		
Work from home rate, β	2.079***	-1.147***
	(0.199)	(0.156)
R-squared	0.718	0.521
# observations	270	270

Figure A4: 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).

B.4 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 A4 reports the results. In Table A5, we further investigate the 2-digit scenario.

B.5 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 A6 and A7 report the results.

Table A4: 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 (10). 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 A5: 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 (10). 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.

B.6 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 A5, life-cycle profiles of size and exit rates of BED establishments are close to those of BDS firms.

Table A6: 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

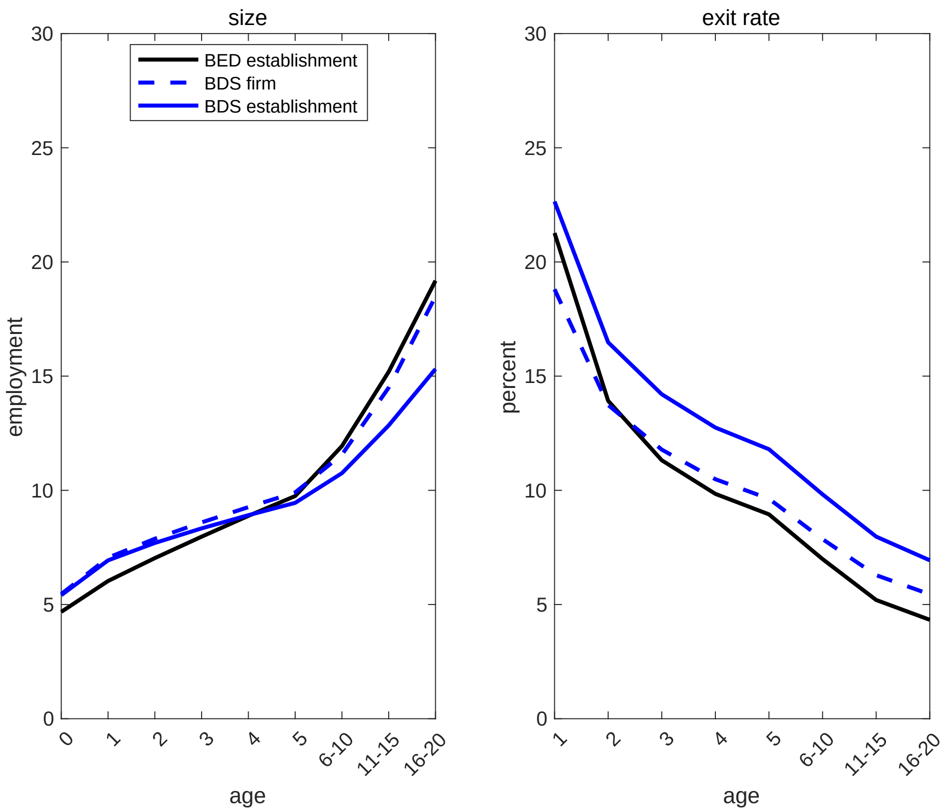
Note: The table reports results from estimating (10). Panel A reports estimates using the pre-pandemic period (2003Q1-2019Q4) only, while Panel B report results for our entire sample period (2003Q1-2022Q4). All specifications include industry and time fixed effects as well as lagged values of the dependent variable and industry-level real output growth rates. Standard errors are reported in brackets – all estimates are significant at the 1 percent level.

Table A7: 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 (10). 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 A5: 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 Generalized Model: Additional Details and Results

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

C.1 Equilibrium Definition in Generalized Model

A stationary equilibrium consists of (i) a value function $v(z,k)$ and policy functions $n(z,k)$, $\omega(z,k)$, $\widetilde{r}(z,k)$, $\widetilde{z}(k)$, $x(z,k)$ and (ii) a 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:

- $v(z,k)$, $n(z,k)$, $\omega(z,k)$, $\widetilde{r}(z,k)$, $\widetilde{z}(k)$, $x(z,k)$ solve the incumbent's problem (14);
- the free entry condition (20) is satisfied;
- the goods and labor markets clear (24), (25);
- 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 (11) 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.

C.2 Computational Strategy

- Given $\widetilde{f}$ and $\widetilde{g}$, guess the equilibrium 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:

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

- 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:

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

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

$$
M = \sum_i m_i
$$

C.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 a equilibrium wage such that the consumption FOC is satisfied.

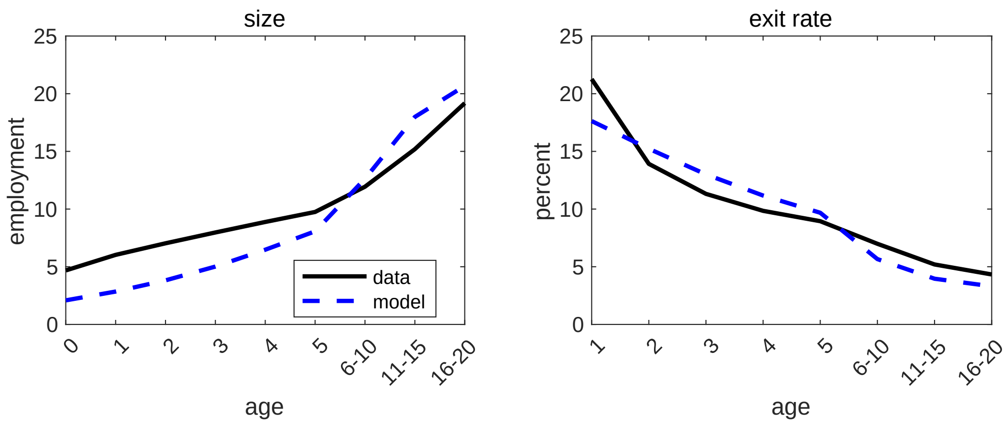
C.4 Robustness: Elasticity of Entry Function

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 A8 and A11 show the calibrated parameters, respectively. Table A9 to A13 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 A6: 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 A8: 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	0.0178	Normalization, $W = 1$		
κ_e	Entry cost	0.72	Normalization, $s_H + s_L = 1$		
ϕ	Elasticity of entry function	0.1	Sedláček and Sterk (2017)		
κ_L^ω	"Low" remote work setup costs	0.00	Normalization, minimum remote work setup cost of 0		
$\widetilde{f}$	Speed of remote work productivity losses	-0.151	Productivity loss of fully remote work, Battiston et al. (2021)	14%	14%
$\widetilde{g}$	Speed of remote work cost savings	0.325	Average work from home rate, ATUS	4.1%	3.9%
κ_n	Non-wage labor costs	0.255	Avg wfh rate of 100+ over 100− firms, ATUS & ASEC	1.12	1.12
κ_H^ω	"High" remote work setup costs	5.3	Share of large firms conducting remote work, BLS	30%	29%
Ψ_ω	Share of "low" remote work setup costs	0.195	Share of firms conducting remote work, BLS	23%	23%
Ψ_L	Mass of "low" business opportunities	$8e-7$	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 A6	
σ_z	Productivity shock dispersion	0.208	Establishment size life-cycle profile, BED	see Figure A6	
ζ_0	Capital adjustment costs, fixed	0.001	Establishment size life-cycle profile, BED	see Figure A6	
ζ_1	Capital adjustment costs, variable	0.61	Establishment size life-cycle profile, BED	see Figure A6	
μ_κ	Overhead costs, mean	0.795	Establishment exit life-cycle profile, BED	see Figure A6	
σ_κ	Overhead costs, dispersion	2.49	Establishment exit life-cycle profile, BED	see Figure A6	

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 A9: 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%

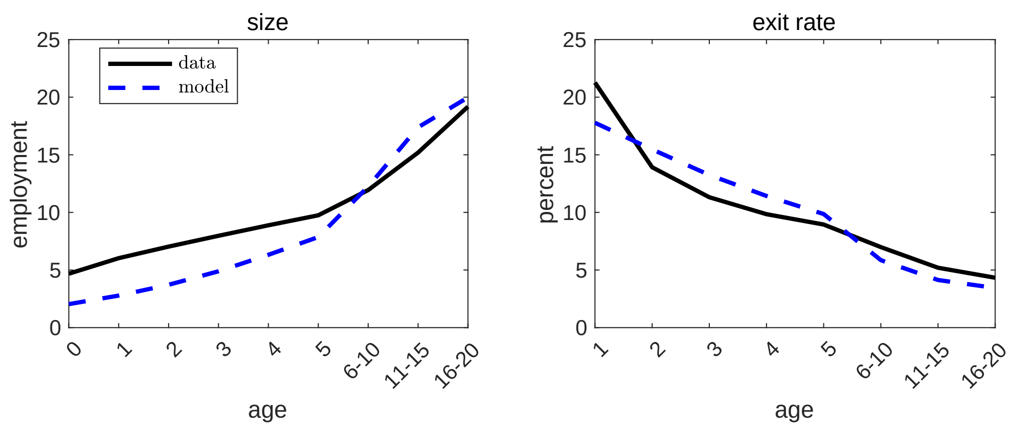
Note: The table shows changes in entry and exit rates (first two columns) and changes in average of entrants and of exiting businesses (last two columns). The top row shows changes in the BED data, while the bottom row shows the model-predicted changes.

Table A10: 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 A7: 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.

C.5 Robustness: Share of Large Establishments

In this Appendix, we provide results for the case when we target the share of large firms instead of the share of small firms. Table A14 presents the calibrated parameters. In particular, the calibrated share accounts for almost 65% of that in the data. We replicate the model results of business dynamism and aggregates as shown in Table A15 and A16. The model results in both business dynamism and aggregates are not fundamentally

Table A11: 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	0.0220	Normalization, $W = 1$		
κ_e	Entry cost	0.63	Normalization, $s_H + s_L = 1$		
ϕ	Elasticity of entry function	0.2	Sedláček and Sterk (2017)		
κ_L^ω	"Low" remote work setup costs	0.00	Normalization, minimum remote work setup cost of 0		
$\widetilde{f}$	Speed of remote work productivity losses	-0.151	Productivity loss of fully remote work, Battiston et al. (2021)	14%	14%
$\widetilde{g}$	Speed of remote work cost savings	0.325	Average work from home rate, ATUS	4.1%	3.9%
κ_n	Non-wage labor costs	0.255	Avg wfh rate of 100+ over 100− firms, ATUS & ASEC	1.12	1.12
κ_H^ω	"High" remote work setup costs	5.3	Share of large firms conducting remote work, BLS	30%	29%
Ψ_ω	Share of "low" remote work setup costs	0.195	Share of firms conducting remote work, BLS	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 A7	
σ_z	Productivity shock dispersion	0.208	Establishment size life-cycle profile, BED	see Figure A7	
ζ_0	Capital adjustment costs, fixed	0.001	Establishment size life-cycle profile, BED	see Figure A7	
ζ_1	Capital adjustment costs, variable	0.61	Establishment size life-cycle profile, BED	see Figure A7	
μ_κ	Overhead costs, mean	0.795	Establishment exit life-cycle profile, BED	see Figure A7	
σ_κ	Overhead costs, dispersion	2.49	Establishment exit life-cycle profile, BED	see Figure A7	

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 A12: 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.

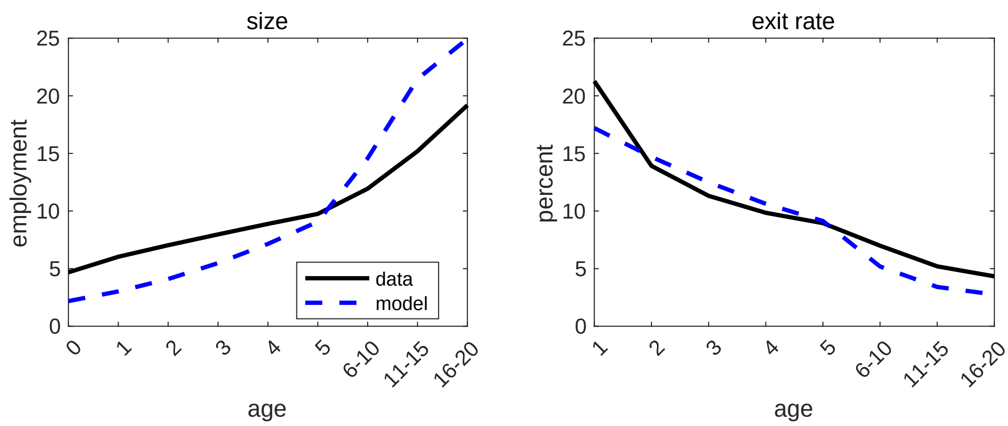
Table A13: Impact of increased remote work: Changes in aggregates ($\phi = 0.2$)

	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.

affected.

Figure A8: 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 A14: 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	0.0134	Normalization, $W = 1$		
κ_e	Entry cost	0.72	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	0.00	Normalization, minimum remote work setup cost of 0		
$\widetilde{f}$	Speed of remote work productivity losses	-0.151	Productivity loss of fully remote work, Battiston et al. (2021)	14%	14%
$\widetilde{g}$	Speed of remote work cost savings	0.325	Average work from home rate, ATUS	4.1%	3.9%
κ_n	Non-wage labor costs	0.255	Avg wfh rate of 100+ over 100− firms, ATUS & ASEC	1.12	1.20
κ_H^ω	"High" remote work setup costs	5.3	Share of large firms conducting remote work, BLS	30%	30%
Ψ_ω	Share of "low" remote work setup costs	0.195	Share of firms conducting remote work, BLS	23%	23%
Ψ_L	Mass of "low" business opportunities	$1.1e-4$	Share of small (< 50) businesses, BED	95%	92%
Ψ_H	Mass of "high" business opportunities	$1.1e-5$	Startup success rate, BED	21%	22%
$\underline{z}_H$	Mean "high" productivity	0.134	Average establishment size, BED	15.4	18.7
$\underline{z}_L$	Mean "low" productivity	0.094	Average establishment size of small (< 50) businesses, BED	6.8	8.5
ρ	Productivity persistence	0.723	Establishment size life-cycle profile, BED	see Figure A8	
σ_z	Productivity shock dispersion	0.208	Establishment size life-cycle profile, BED	see Figure A8	
ζ_0	Capital adjustment costs, fixed	0.001	Establishment size life-cycle profile, BED	see Figure A8	
ζ_1	Capital adjustment costs, variable	0.61	Establishment size life-cycle profile, BED	see Figure A8	
μ_κ	Overhead costs, mean	0.795	Establishment exit life-cycle profile, BED	see Figure A8	
σ_κ	Overhead costs, dispersion	2.49	Establishment exit life-cycle profile, BED	see Figure A8	

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 A15: Model Results: Remote work and business entry and exit (targeting large firms)

	Rate		Size	
	Entry	Exit	Entrants	Exiters
Data	+28%	+15%	−24%	−22%
Model	+16%	+16%	−16%	−21%

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 A16: Impact of increased remote work: Changes in aggregates (targeting large firms)

	Output (Y)		Consumption (C)			Welfare ($\mathcal{W}$)	
Overall	2.5		4.2			0.2	
Components	Ω	$\overline{y}$	Y	I	Costs	C	N
	23.3	−20.8	3.8	−0.7	1.2	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.