Work from Home, Business Dynamism, and the Macroeconomy*

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Abstract

The COVID-19 pandemic catalyzed a surge in remote work. We propose a new macroeconomic model in which firms can employ workers off-site. Cheaper or more efficient remote work increases profitability and incentivizes firm entry. This, in turn, raises labor demand and wages which elevates business exit and lowers average firm size. We confirm all these predictions in the data. According to our model, the post-pandemic increase in remote work accounts for 1/3 of the observed surge in firm entry. Moreover, despite a shift towards smaller and less productive businesses, a greater number of firms increases aggregate output, consumption and welfare.

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1 Introduction

The COVID-19 pandemic sparked an unprecedented adoption of remote work arrangements. According to U.S. survey data, about one quarter of workdays occur remotely since the pandemic ended – more than five times that of the pre-pandemic average (see Barrero et al., 2023). While recent studies emphasize the implications of the large shift towards remote work for individual firms and workers, sectors or city structures (see e.g. Barrero et al., 2023; Decker and Haltiwanger, 2023; Hansen et al., 2023), in this paper we study its ***macroeconomic impact***.

We show that changes in remote work conditions impact the macroeconomy through their effect on business dynamism. Specifically, more attractive remote work raises firm profitability and encourages business entry. This part of our analysis, therefore, rationalizes the "surprising surge in applications for new businesses" (see Decker and Haltiwanger, 2023, p.1) in the U.S. following the COVID-19 pandemic. However, a greater mass of startups increases labor demand and with it the wage rate. This makes operation harder for all firms and business exit rates rise while average firm size drops. Connecting several micro-datasets, we document that all these patterns are consistent with the data.

At the aggregate level, more attractive work from home conditions improve welfare. This outcome, however, hides two opposing forces. On the one hand, more attractive remote work arrangements lead to a decline in productivity as the distribution of firms tilts towards smaller, less productive, businesses. This happens because smaller firms are more sensitive to (fixed) cost declines brought about by more attractive remote work. On the other hand, this effect is more than compensated for by stronger incentives to start new firms. A larger mass of businesses then leads to an increase in aggregate output, consumption and, ultimately, welfare.

To arrive at these results, we proceed in three steps. First, we develop a core theoretical framework to analytical show that changes in work from home arrangements impact business dynamism. Second, we link multiple micro-datasets and show that our model predictions hold empirically. Finally, we generalize our core model along several dimensions and ***quantify*** the extent to which increased work from home rates affect the macroeconomy.

In our core model, individual firms – which are heterogeneous 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 includes lower wage growth pressure, reductions in worker turnover and associated training and hiring costs, or lower fixed overhead costs because of a reduced need for office or production space (see e.g. Barrero et al., 2022, 2023; Bloom et al., 2023b). On the other hand, remote work may lower productivity. This occurs because of less efficient communication, mentoring and training or through reductions in worker motivation and self-control (see e.g. Battiston et al., 2021; Yang et al., 2022; Emanuel and Harrington, 2023; Gibbs et al., 2023).

Our core framework allows us to derive several analytical predictions about optimal remote work rates and business dynamism. Specifically, we show that exogenous increases (decreases) in the efficiency (cost) of remote work lead to, intuitively, a greater uptake of work from home arrangements and a rise in firm profitability. This, in turn, raises the incentives to start new businesses and more firms enter the economy. In general equilibrium, a greater number of startups push up labor demand and with it the wage rate. As a result, firm exit rates increase as operating a business becomes harder and the least productive firms shut down. The impact on firm size is a-priori unclear as it depends on the strength of the wage increase relative to the reductions in costs or improvements in efficiency of remote work.

Next, we test these model predictions empirically making 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 in all work days.[1] 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 Dynamcis (BED) data as a source of quarterly information on business entry, exit and sizes. Finally, we use the Quarterly Census of Employment and Wages (QCEW) to obtain industry-level information on wages.

Using our linked data, we 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 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 reductions in firm size. All of these patterns can be rationalized by our core theoretical framework as explained above.

The generalized framework extends our core model along several dimensions. All of the following extensions are important for a realistic quantification of the macroeconomic impact of changes to remote work. First, we endogenize the degree of long-run productivity differences across firms, allowing it to respond to changes in remote work conditions. Second, we also let persistent idiosyncratic shocks affect firm-level productivity. 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

[1]In the Appendix, we show that our results are very similar when considering remote work more generally, i.e. not necessarily "just" from home.

endogenously respond to remote work changes.[2]

We parameterize the generalized model to match key (pre-pandemic) features of U.S. data. Specifically, our model is made to match the strong "up-or-out" dynamics with high exit rates of young firms, but strong average growth of surviving business (see e.g. Haltiwanger et al., 2013). Next, to discipline the key margin of our framework – work from home decisions – we make our model match 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) – and an average pre-pandemic work from home rate of 4 percent which we estimate from ATUS data.[3] Note that the parameterized model also does well in matching a range of other ***untargetted*** empirical moments related to capital investment rates, firm-level productivity dynamics as well as the extent of cost savings of remote work.

To quantify the macroeconomic impact of increased work from home arrangements, we compare our baseline economy to a counterfactual which targets a higher level or remote work observed in the ***post-pandemic*** U.S. economy. This counterfactual model is identical to our baseline with the only exception being that remote work is cheaper and more efficient. When comparing results from the two economies, we focus on stationary steady states.[4]

Results from the generalized model confirm our qualitative predictions from our theoretical analysis. Since remote work – and thus production – becomes more efficient and cheaper, firms optimally choose higher rates of work from home, expand their output and enjoy larger profits. This, in turn, provides greater incentives for firm entry, raises labor demand and puts upward pressure on wages. Elevated labor costs make production more expensive, leading to higher firm exit rates and smaller firm sizes.

Recall that remote work allows firms to partly reduce their (fixed) costs. This effect is relatively stronger for smaller businesses for which fixed costs represent a larger chunk of their expenditures. Therefore, in the counterfactual economy, entry and exit decisions of heterogeneous firms ***endogenously*** tilt the distribution towards smaller, less productive, businesses. This change in the composition of firms lowers productivity, adding to the negative productivity impact brought about by a larger fraction of labor working (less efficiently) off-site.

As a final step in our analysis, we quantify the impact of these changes on aggregate outcomes. First, while average firm-level output falls because of an endogenous shift

[2]We also provide a discussion of other potential model features, including e.g. a fixed cost associated with starting remote work, or bargaining between employees and firms about remote work arrangements.

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

[4]We focus on steady states because while the pandemic period catalyzed the transition towards remote work (often through lock-downs), a sustainable increase in work from home rates must ultimately be supported by underlying, fundamental, changes in their cost and efficiency.

towards smaller firms and higher labor costs, greater business entry leads to a rise in the number of firms. The latter effect dominates and aggregate output rises, as does aggregate employment and capital.[5] Next, higher output leads to a rise in household consumption despite elevated entry costs. Finally, even though the positive effect of more consumption is dampened by the disutility from expanded labor supply, household welfare rises by about 0.2 percent.[6]

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 (see e.g. Barrero et al., 2022, 2023; Decker and Haltiwanger, 2023; Hansen et al., 2023). Complementary to our paper, Davis et al. (2024) and Richard (2024) study the household side of remote work trade-offs and the impact on house prices, household income, wealth and on city structure. In contrast to these studies, we focus on the implications of remote work for business dynamism with a primary goal of quantifying their *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 stylized 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 and provide our main quantitative results. 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 about how work from home influences choices of individual firms.

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.

[5] In the Appendix, we provide robustness checks with respect to the elasticity of firm entry.

[6] Note that our model is not particularly geared towards obtaining welfare gains from remote work. In particular, remote work decisions are made at the firm level and households take them as given. We also do not explicitly model additional benefits of remote work such as a decline in commuting time (i.e. increased leisure and/or work hours), benefits for home-production (see e.g. Barrero et al., 2023, for a discussion).

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 keep this part of the analysis concise, we defer the description of the household, aggregates and a formal definition of the equilibrium to the Appendix. Instead, in what follows we focus solely on firm decisions. To ease the exposition, we omit the (discrete) time index where possible and use upper-case letters to denote aggregates and lower-case letters for firm-level variables.

Production and costs. In our economy, output is produced by individual firms who 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 $\alpha \in (0, 1)$ denote 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 or various employee benefits.

Work from home. All firms have the possibility of having a fraction, $\omega \in [0, 1]$, of their employees work from home. There are both costs and benefits of remote work.[7]

On the one hand, work from home helps firms reduce their costs. This occurs 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 quite rates and associated turnover and training (Bloom et al., 2023b).[8] In addition, remote work also lowers overhead costs, κ_o, as firms require less production space and save on associated on-site production costs (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

[7]In this section, we assume that the household takes ω as given.The generalized model of Section 4, endogenizes the household response to work from home patterns by allowing for flexible labor supply.

[8]We abstract from direct impacts of work from home on wages – e.g. because businesses can recruit from low-wage areas. Our generalized model, however, allows for changes in remote work patterns to impact wages indirectly through general equilibrium effects.

worker motivation and self control (see e.g. Battiston et al., 2021; Yang et al., 2022; Emanuel and Harrington, 2023; Gibbs et al., 2023).[9] Therefore, we assume that firm productivity decreases as remote work rates increase according to $f(\omega) \in [0,1]$, with $f'(\omega) < 0$.

Firm entry and exit. 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.

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:

$$v(z) = \max_{n,\omega} \left\{ 0, \sum_{t=0}^{\infty} [\beta(1-\delta)]^t \pi(z) \right\} = \max_{n} \left\{ 0, \frac{\pi(z)}{1-\beta(1-\delta)} \right\}, \tag{2}$$

where $\beta \in (0, 1)$ is a discount factor and where $\pi(z) = f(\omega)y(z) - Wn - g(\omega)(\kappa_n n + \kappa_o)$ are per-period profits. The above gives rise to an exit rule – a cutoff productivity, $\widetilde{z}$, below which firms choose to shut down. This cutoff productivity is implicitly defined by

$$\pi(\widetilde{z}) = f(\omega(\widetilde{z}))y(\widetilde{z}) - Wn(\widetilde{z}) - g(\omega(\widetilde{z}))(\kappa_n n(\widetilde{z}) + \kappa_o) = 0, \tag{3}$$

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

Finally, assuming free entry, the mass of (entering) firms is implicitly given by the following condition

$$\kappa_e = \int v(z)h(z)dz. \tag{4}$$

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.

[9] 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.

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 rms 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.[10] 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 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. We will return to this point in our quantitative analysis, where it will play an important role for endogenous changes in the distribution of firms.

Changes to 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 at which productivity losses and cost savings accrue 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.[11] The following proposition describes how

[10]The Appendix provides conditions under which optimal remote work rates have interior solutions.
[11]Note that what is important for firms' decisions is the efficiency and price of remote work *perceived* by

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)
All else equal and assuming internal optimal work from home rates, ω^*, exogenous changes 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 pro ts:

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

c) Exit threshold:

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

Part a) of Proposition 3 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 – see Part b). Part c) directly follows. As firms become more profitable, even relatively less productive businesses can survive in operation, reducing the exit threshold, $\widetilde{z}$.

General equilibrium. In general equilibrium, however, the wage and the mass of firms adjust. In particular, more efficient or cheaper remote work provides incentives for businesses to hire more workers. In addition, higher firm-level profits brought about by cheaper or more efficient remote work make firm entry more attractive. Both these effects raise labor demand and with it the wage rate, see the free entry condition (15).

Moreover, since in equilibrium the mass of firms is stationary, a greater number of startups necessarily implies higher firm exit. Note that this overturns the partial equilibrium predictions about firm exit, see Proposition 3.

Finally, the impact of more attractive remote work conditions on firm employment is not clear a-priori. Specifically, firms optimally choose the number of workers to balance marginal productivity with marginal costs:

$$n = \left(\frac{z f(\omega) \alpha}{W + g(\omega)\kappa_n} \right)^{\frac{1}{1-\alpha}}. \tag{5}$$

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., 2023).

However, the overall effect cheaper or more efficient remote work conditions have on firm-level employment will depend on the strength of these changes relative to the wage increase.

Summary. To summarize our theoretical results, recall that cheaper or more efficient remote work conditions imply – in a new stationary general equilibrium – higher remote work rates, larger firm-level profits and, therefore, more incentives to start new businesses. With more entrants starting up, labor demand increases which pushes up the wage rate. This, in turn, makes it harder for businesses to operate which leads to higher firm exit. Finally, the impact of these changes on average firm size is unclear a-priori.

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. 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. We rely on the American Time Use Survey (ATUS) which is conducted by the Bureau of Labor Statistics and 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.[12]

For our purposes, we focus on individuals' time allocated to working and its reported location. In particular, following Barrero et al. (2023) 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.[13]

[12]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).

[13]To define our baseline measure of working from home, we focus on workers with minimum real annual earnings of \$20,000 (counted as 52 times average weekly earnings, deflated by the Personal Consumption Index). The Appendix shows that results are similar when considering "work-outside-workplace", i.e.

Analogously, we define days worked from 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. Towards this end, we complement 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:[14]

$$\omega_{i,t} = \frac{\sum_{j=1}^{J_{i,t}} d_{j,\tau}^{home}}{\sum_{j=1}^{J_{i,t}} d_{j,\tau}}, \tag{6}$$

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.[15] 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.[16]

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.

[14] Since the ATUS interviews individuals in outgoing waves of the CPS and asks time allocation information for only one day, counting days is the same as counting individuals.

[15] 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, 2023, 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.

[16] 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.

Finally, the BED does not report overall establishment size at a quarterly frequency. However, for establishment births and deaths it can be imputed using information on the number of entering or exiting establishments and their respective employment levels. Therefore, in our analysis we focus on the size of entrants and exiters instead of average size of all establishments.[17]

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.[18]

3.2 Empirical Analysis

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

Work from home: Heterogeneity across sectors and firm sizes. In the period between 2003 and 2019, the average work from home rate was just over 4% in the U.S. economy. However, this value hides a large amount of heterogeneity both across different sectors and over time.

Table 1 summarizes the heterogeneity in work from home across sectors for our pre-pandemic sample. Intuitively, Transportation and Warehousing or Construction have the lowest work from home rates. In contrast, service industries (Financial activities, Information, Profession and Business Services) have work from home rates as high as 14%, i.e. more than quadruple that of Construction or Transportation.[19]

In addition, linking information on individual work from home patterns from ATUS to the Current Population Survey (CPS) and, in particular, the Annual Social and Economic

[17] 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.

[18] 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).

[19] Work from home patterns differ across industries not only on average, but also in terms of the speed at which they change over time. For instance, while the Utility industry experienced more than a doubling in its work from home rate over the course of 2003-2019 (albeit from a very low starting point), work from home actually became *less* frequent over time in the Leisure and hospitality industry.

Table 1: Work from home rate: Industry heterogeneity

Industry	WFH	Industry	WFH
Construction	1.5	Other Services	4.6
Educational and Health Services	3.1	Professional and Business Services	8.6
Financial Activities	6.7	Public Administration	2.0
Information	8.8	Retail Trade	1.5
Leisure and Hospitality	1.3	Transportation and Warehousing	1.7
Manufacturing	2.9	Utility	0.8
Natural Resources and Mining	5.3	Wholesale Trade	5.0

Note: The table reports work from home rates (in %) across super-sectors for the period between 2003Q1 and 2019Q4.

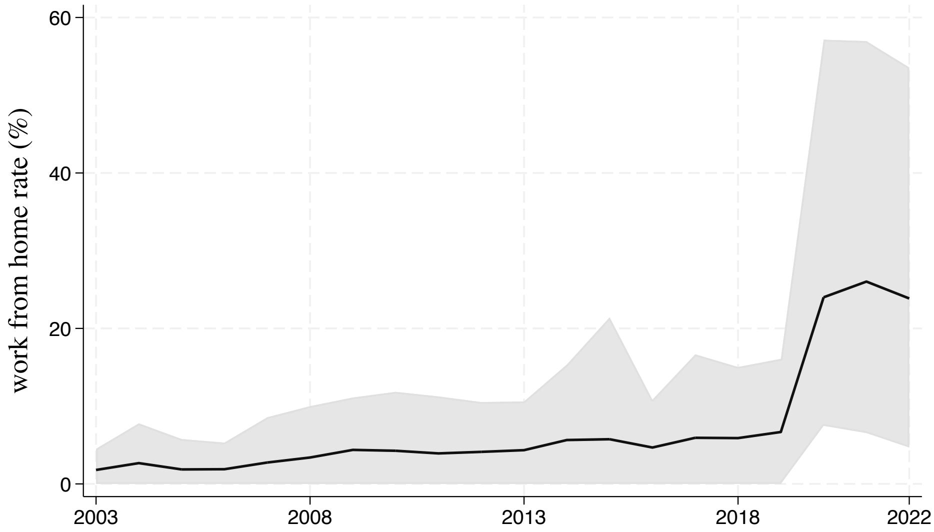
Supplement (ASEC) allows us to infer the size distribution of firms for which individuals in ATUS report working remotely. According to this data, remote work was somewhat less common in larger firms between 2003-2019. Specifically, while average work from home rates were about 4.1% among all businesses, they were 4.0% for firms with more than 100 employees. Recall that through the lens of our theory, this is consistent with the possibility of alleviating a fraction of firms' (non-zero) fixed costs through remote work.

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. 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. The shaded areas then indicate the range of work from home rates across industries. As is apparent from the figure, there is a large degree of sectoral heterogeneity throughout our sample.

Across all sectors, however, the COVID-19 pandemic had a profound impact on remote work, inducing a dramatic increase in such flexible work arrangements. 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., 2023a; Decker and Haltiwanger, 2023).

Business dynamism: Changes over time. It is well documented that business dynamism has been on a secular decline for several decades (see e.g. Decker et al., 2016b). This is true not only in the U.S. but also in many developed economies 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

Figure 1: Work from home rate: Changes over time



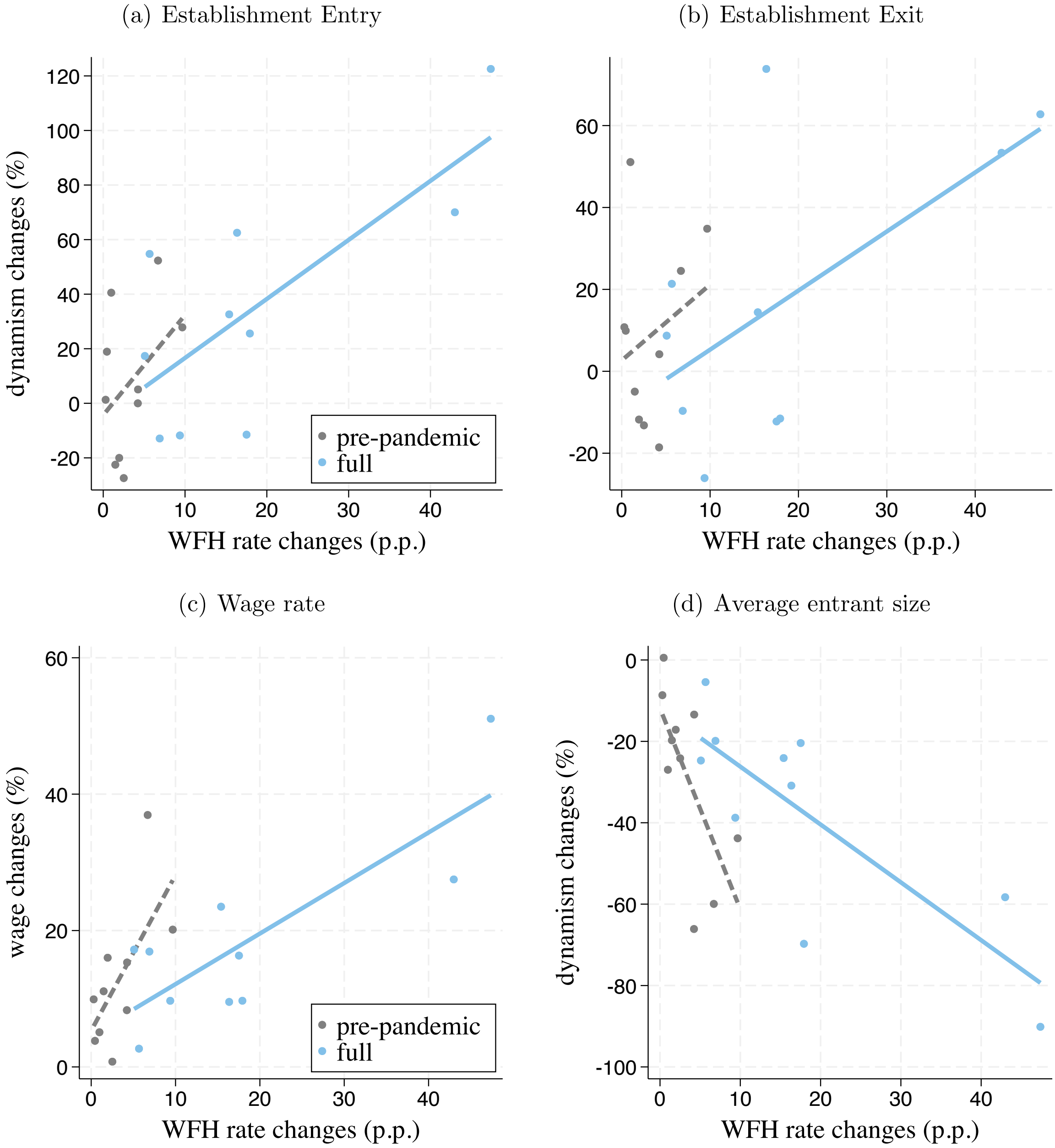
Note: The figure shows work from home rates – computed from ATUS as described in the main text – over time for the aggregate economy (solid black line) and the range of values across industries (shaded area).

older businesses. With these changes comes a drop 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, 2023, 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-

Figure 2: Work from Home and Business Dynamism: Changes across Industries



(a) Establishment Entry
(b) Establishment Exit
(c) Wage rate
(d) Average entrant 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 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).

pandemic period (2003-2019).[20]

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

[20]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).

Table 2: 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 (7). 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.

as with rises in wages. In addition, in our sample, increases in remote work rates are associated with declines in average entrant size.[21] Note that these patterns are note 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:

$$y_{i,t} = \delta_i + \delta_t + \beta \overline{\omega}_{i,t} + \Gamma X_{i,t} + \epsilon_{i,t}, \tag{7}$$

where $y_{i,t}$ is a measure 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 set of control variables and $\overline{\omega}^L_{i,t} = 1/(L+1)\sum_{l=0}^{L} \omega_{i,t-l}$ are time-varying moving averages of work from home rates. Coefficient β is the primary object of interest as it provides a concise summary of the potentially dynamic (lagged) effects of working from home rates on business dynamism.[22]

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.

[21] 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.

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

Table 2 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 lower 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

While the core model in Section 2 is useful for understanding why and how business dynamism is related to remote work conditions, it not well suited for a quantitative analysis. Towards this end, 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 in which to quantitatively evaluate how increases in work from home rates impacted the U.S. macroeconomy.

4.1 Environment

The generalized model retains the structure of our stylized framework, but extends it along several important dimensions. First, 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. Second, we introduce physical capital as a production factor, the accumulation of which is subject to adjustment costs. These extensions have an impact on the distribution of firms in the model and, therefore, the responsiveness of the economy to changes in parameters – including those governing remote work choices. 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 and which we describe in detail in the next section. Therefore, in the absence of business cycles, all aggregates will be fixed in the respective steady states. 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.

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

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

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

All the above parameters are assumed to be common across businesses. The exception is $\underline{z}_j$ – the unconditional, long-run, mean of firm-level productivity – which is assumed to be heterogeneous across firms. We index this "type" heterogeneity by j and describe how it is determined below. Since the long-run level of productivity is important for all firm choices, in what follows firm-level variables will also be indexed by j.

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

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

where $\alpha \in (0,1)$ and $\theta \in (0,1)$ are common across all firms. In addition to z, the efficiency of production is also affected by firms' work from home choices. As in our stylized model, $f(\omega_{j,t})$, represents the efficiency losses associated with remote work.

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:

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

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

Finally, 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 in our stylized model, we assume that firms can affect the average level of their fixed overhead costs with work from home choices, summarized by the function $g(\omega_{j,t})$. 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 let work from home.

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 businesses in operation is given by

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

where $\pi_{j,t} = y_{j,t} - Wn_{j,t} - g(\omega_{j,t})(\kappa_n n_{j,t} + \mu_\kappa) - x_{j,t} - \zeta(x_{j,t}, k_{j,t})$ are per-period profits, $\beta \in (0,1)$ is the discount factor and $\delta \in [0,1)$ is an exogenous rate of exit. In the above, v_j^c is the continuation value given by

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

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

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

where firms obtain value from selling their stock of capital, but have to take into account the adjustment costs of doing so.

Firm Entry. Having described incumbent businesses, we now turn to entry decisions. Recall that firms differ, among other things, in terms of their long-run productivity mean, $\underline{z}_j$. We endogenize the distribution of these firm types by modelling entry along the lines of Sedláček and Sterk (2017).

In particular, for tractability we assume a finite number of different firm types, J. Potential startups are free to choose which type of 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 type, denoted by Ψ_j.

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 type, m_j, is determined by the following "entry function"

$$m_j = \Psi_j^\phi s_j^{1-\phi}, \tag{14}$$

where s_j is the mass of startup attempts of type j and $\phi \in (0,1)$ determines the degree of crowding out which is common across business types. Assuming free entry, this gives rise to the following entry conditions

$$\kappa_e = \frac{m_j}{s_j} \int_z v_j(z_j, 0) dH_z(z). \tag{15}$$

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 $M = \sum_j m_j$. Notice that in equilibrium, potential startups are indifferent between business types. This happens because business types with high expected payoffs (v_j) attract more startup attempts. This, however, lowers the chances of successfully starting up.

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

$$\ln C - \upsilon N, \tag{16}$$

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:

$$C = WN + \Pi, \tag{17}$$

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:

$$W = \upsilon C. \tag{18}$$

Aggregation. Using $\mu(z,k)$ to denote the distribution of firms, the following conditions describe goods and labor market clearing:

$$Y = \int\int y\mu(z,k) dz dk, \tag{19}$$

$$N = \int\int n\mu(z,k) dz dk. \tag{20}$$

Finally, the aggregate resource constraint is given by

$$Y = C + S\kappa_e + \int\int \left[\zeta(x,k) + g(\omega)(\kappa_n n + \mu_\kappa) + \widetilde{\kappa}_o\right]\mu(z,k)dzdk, \tag{21}$$

where $S = \sum_j s_j$ 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 and overhead costs. 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 3. The next section describes in detail how we quantitativley isolate the macroeconomic impact of changes in work from home arrangements.

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

As explained in Section 2, in order to allow for interior solutions to optimal work from home rates, we require that $f'' \leq 0$ and $g'' \geq 0$. Therefore, we assume the following functional forms:

$$f = \exp\left(\widetilde{f}\omega^2\right), \tag{22}$$

$$g = \exp\left(-\widetilde{g}\omega\right). \tag{23}$$

In addition to allowing for internal remote work solutions, the above specification ensures several important properties. First, fully on-site production entails no productivity losses or cost savings, $f(0) = g(0) = 1$. Second, changes in either $\widetilde{f}$ or $\widetilde{g}$ make remote work more attractive, i.e. $\frac{\partial f}{\partial \widetilde{f}} > 0$ and $\frac{\partial g}{\partial \widetilde{g}} < 0$.

In addition to specifying how remote work affects production, we also make a stand on the form of capital adjustment costs, $\zeta(x,k)$. In particular, we follow Cooper and Haltiwanger (2006) and assume

$$\zeta(x,k) = \zeta_0(x)k + \frac{\zeta_1}{2}\left(\frac{x}{k}\right)^2 k, \tag{24}$$

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. For tractability, we assume two types of firms and we denote them as $j = \{L, H\}$. Associated with these types are two long-run productivity levels, $\underline{z}_L$ and $\underline{z}_H$, and the respective masses of business opportunities of each type, Ψ_L and Ψ_H.

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 $M = 1$. Finally, we take the parametrization of ϕ in the entry function from Sedláček and Sterk (2017) and provide robustness checks with respect to this parameter in the Appendix.

Indirect inference. The remainder of the parameters are set to match a range of business dynamism and work from home moments in the data. For the former, we make use of BED data on establishment size and exit rates. For the latter, we employ our remote work rate measures from ATUS.

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 13 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 ($\widetilde{f}$, $\widetilde{g}$) and the level of non-wage labor costs (κ_n).

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

Table 3: 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)		
$\widetilde{f}$	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	0.089	Average work from home rate, ATUS	4.1%	4.2%
κ_n	Non-wage labor costs	0.25	Average work from home rate of 100+ firms, ATUS & ASEC	4.0%	3.5%
Ψ_L	Mass of "low" business opportunities	0.00011	Share of small (< 50) businesses, BED	95%	94%
Ψ_H	Mass of "high" business opportunities	0.000016	Startup success rate, BED	21%	24%
$\underline{z}_H$	Mean "high" productivity	0.130	Average establishment size, BED	15.4	15.1
$\underline{z}_L$	Mean "low" productivity	0.104	Average establishment size of small (< 50) businesses, BED	6.8	7.7
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	0.64	Establishment size life-cycle profile, BED	see Figure 3	
μ_κ	Overhead costs, mean	0.78	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.

to capital adjustment costs are closely linked to business growth rates. Therefore, we target the 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.[23]

Next, overhead cost parameters are tied to patterns of firm exit. Therefore, using the same data source as for establishment size, we target the 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 and 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. The last parameter determines the level of non-wage labor costs, κ_n. To pin this parameter down, we target the work from home rates of large firms (with more than 100 employees).[24]

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

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

where j indicates a given moment. Note that our model is over-identified as we are estimating 10 parameters using 23 moments (12 firm size moments, 8 firm exit moments and 3 work from home moments).

Model performance. Table 3 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, while we targeted average establishment size and its life-cycle growth in terms of employment, our model is also consistent with capital investment patterns. In particular, Cooper and Haltiwanger (2006) estimate average investment rates at around 12% and

[23]Since the BED starts in 1992, the fife-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.

[24]Intuitively, given all other parameters, κ_n controls the relative importance of reductions in fixed costs when choosing remote work rates (e.g. with $\kappa_n = 0$ remote work only reduces fixed costs). As explained in Section 2, fixed cost reductions are key for generating heterogeneity in remote work rates across the firm size distribution.

average inaction rates (investment rates between -1% and 1%) of about 8%. Our model predicts these values to be, respectively, 14% and 7%.[25]

Second, in addition to matching average patterns, our model also does reasonably 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 0.35.[26]

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).

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% of its employees working remotely faces an efficiency loss of just 0.02%. On the other hand, this average firm saves 0.4% 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 pressures by about 1 percent (see Barrero et al., 2022).

5 Macroeconomic Impact of Work from Home

In this section, we use ourmodel to quantitatively evaluate how changes in work from home patterns impact business dynamism and, in turn, the macroeconomy. In particular, we take our generalized model (parameterized to the pre-pandemic period) as a starting point. Then, we compare it to a counterfactual economy which is identical to our starting point with one difference: we adjust the parameters governing the efficiency and cost of remote work ($\widetilde{f}$ and $\widetilde{g}$) to mimic the higher remote work rates observed after COVID-19.

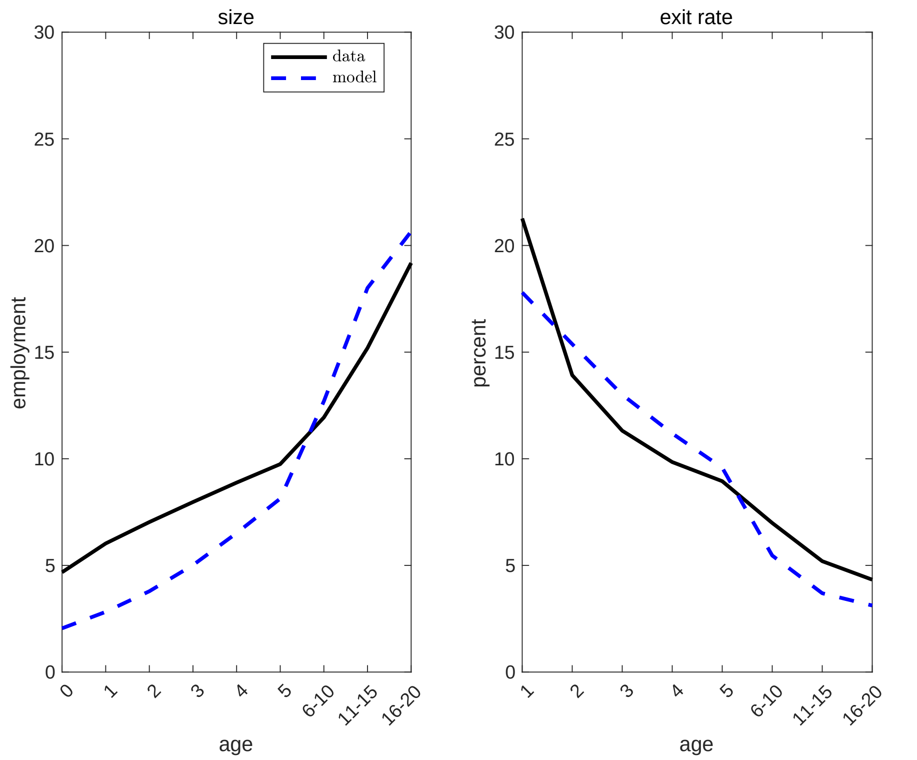
Note that in doing so, we leave out the COVID-19 period of 2020 and 2021.[27] In-

[25] The sample of firms and time period used in Cooper and Haltiwanger (2006) differs from that of the BED. Nevertheless, we view the consistency of our model predictions with the estimated moments as an encouraging sign for our parametrization strategy.

[26] Note, however, that our model fails to replicate (by about a half) a fat enough tail of the firm size distribution; a common issue in firm dynamics models with log-normal productivity shocks. The Appendix provides an exercise in which we use the share of very large firms as an additional target showing that the results are not fundamentally affected.

[27] We do so because we are interested in structural shifts in remote work patterns *not* driven by lockdowns which we view as truly extraordinary events. While the latter may have sped up the transition towards remote work, a sustainable increase in work from home rates must ultimately be supported by underlying, fundamental, changes in the cost and efficiency of remote work arrangements.

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.

stead, we focus on the difference between two stationary steady state equilibria: our pre-pandemic baseline described above and a counterfactual economy designed to match post-pandemic remote work moments. We describe the latter in detail below and discuss the question of transition dynamics at the end of this section.

The post-pandemic economy. There are two reasons that can induce firms to conduct more of their production remotely – either work from home becomes more efficient (a decline in $\widetilde{f}$), or it becomes cheaper (a rise in $\widetilde{g}$). Moreover, as explained in Section 2, the impact of these two sources of remote work changes is quantitatively different. Therefore, a key pre-requisite for our quantitative exercise is to determine the relative importance of efficiency and cost changes in driving up remote work rates in the post-pandemic period. Towards this end, we change $\widetilde{f}$ and $\widetilde{g}$ such that the resulting new general equilibrium features two important characteristics.

First, a work from home rate of 24%. This corresponds to the post-pandemic average across all firms computed using the ATUS data. Second, we target the relative increase in work from home rates of large firms (with more than 100 workers) compared to all businesses. Specifically, according to the ATUS-ASEC information, remote work rates in large firms increased by 1.04 times more than in all businesses.[28] The intuition for why this moment provides information about the relative strength of changes in $f(\omega)$ vs $g(\omega)$ rests on Proposition 1. In particular, in the presence of non-zero fixed costs, changes in cost savings of remote work, $g(\omega)$, affect small and large firms differently.

Using these two targets, our model suggests that – compared to the pre-pandemic average – $\widetilde{f}$ decreased by half while $\widetilde{g}$ increased about 3 times.[29] To put these changes into perspective, consider a typical firm with 4 percent of its employees working remotely. Holding the rate of remote work fixed, these changes imply that productivity losses would go from 0.02% to 0.01% and that cost savings would increase form 0.4% to 1.0%. Therefore, while these changes are large proportionally, their levels remain very modest.

In what follows, we first describe how work from home rates changed across the firm size and age distributions. Next, we investigate how increased remote work rates affected the macroeconomy, including household welfare. Details of our computational strategy can be found in the Appendix.

5.1 Work from Home and Business Dynamism

In this subsection, we first describe heterogeneity in remote work rates implied by our model. Next, we quantify the connection between work from home decisions and business dynamism.

Work from home at the worker- and firm-level. Table 4 shows descriptive statistics of work from home rates in the baseline economy. It does so for various groups of firms and, importantly, for an size- (employment-) and un-weighted sample.[30] 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 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 column). This holds true even within subgroups of firms. Second, work from home rates are skewed to higher values with averages being above medians. Finally, as predicted by our theory, small firms are characterized by higher work from home rates. This is because they benefit relatively more from the associated labor and fixed cost reductions.

[28] Note that when computing these relative changes, we hold the employment distribution across firm size classes fixed at the pre-pandemic levels (both in the data and model). This allows us to isolate the firm-level responses to changes in remote work conditions from any composition effects.

[29] Davis et al. (2024) use a model of household decisions about remote work and also find that productivity of working from home increased substantially in the post-pandemic period.

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

Table 4: Remote work rates in the model (%)

	Size-weighted	Un-weighted		
	Mean	Mean	Median	Std
All	4.1	9.0	5.6	13.3
High-type	4.0	8.0	5.0	11.8
Low-type	4.4	9.8	6.0	14.4
Small (< 50 workers)	4.7	9.4	5.8	13.7
Young (< 6 years)	6.0	29.7	12.0	32.5
Gazelles (> 25%)	4.0	7.3	5.1	8.6

Note: The first column of the table reports the ATUS-ASEC comparable, i.e., size- (employment-)weighted, average work from home rates. The remaining columns compute unweighted mean, median and standard deviation ("std") across all firms. The rows indicate different firm groups: "all", "high-type" ($\underline{z}_H$), "low-type" ($\underline{z}_L$), "small" (less than 100 workers), "young" (less than 6 years of age) and "gazelles" (with growth rates exceeding 25%). We excluded non-employers (i.e., firms with employees less than one) in the calculation.

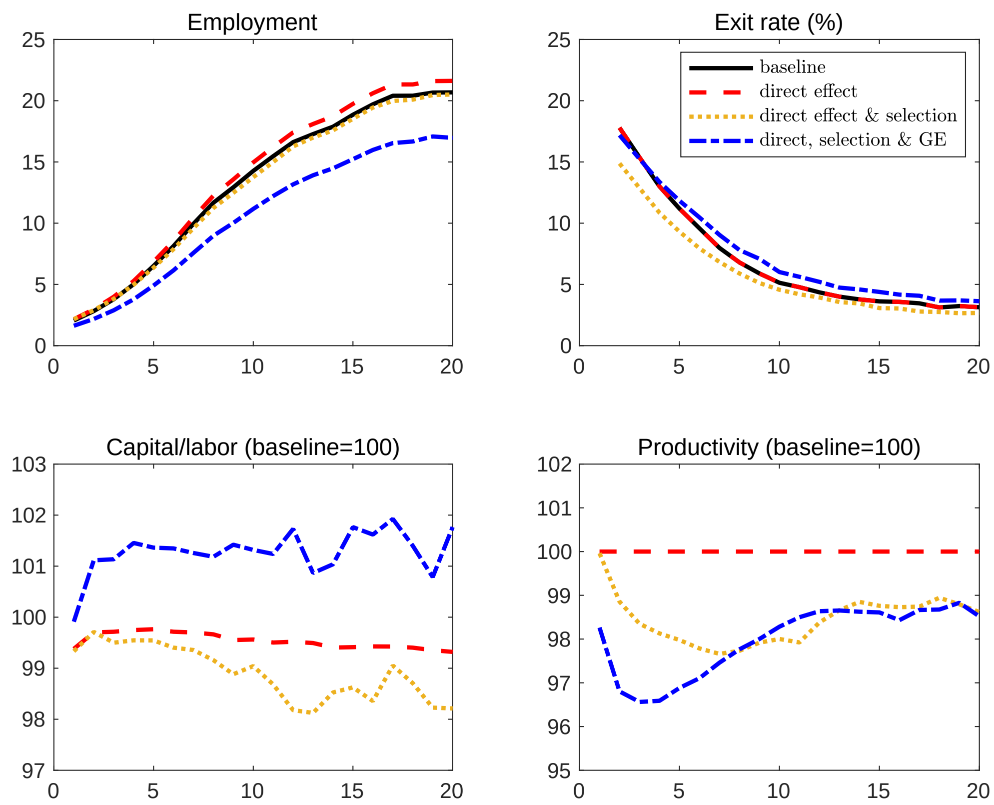
Several other patterns follow from the above. For instance, un-weighted (firm-based) averages are considerably higher than their employment-weighted (worker-based) counterparts. This is because large firms – which wield a greater employment share – choose lower work from home rates. Similarly, young businesses, which are typically small, are characterized by higher remote work rates. Finally, the same is true for fast growing firms ("gazelles"), which are typically young.

Firm growth and selection. Next, 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 firms' life-cycles.

In addition to our baseline specification (black solid line), we consider 3 different scenarios, all based on our counterfactual (post-pandemic) 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 post-pandemic 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 reduce their capital-labor ratios as they take advantage of the relatively cheaper production factor (bottom left panel). By construc-

Figure 4: Firm-level effects of cheaper and more efficient 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.

tion, average TFP 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 stylized model 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 stronger. 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 average firm size (top left panel).

Finally, with increased entry and lower exit, the number of firms expands which raises labor demand and 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 relative to 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 for small firms they remain below the respective baseline levels (top right panel). Because of such weaker firm selection among young firms, average firm-level productivity remains below the baseline. However, higher exit rates among older firms eventually lead to a catching up of average productivity to its baseline levels (bottom right panel).

Note that underlying all the above effects is an endogenous change in the composition of firms. Recall that our framework includes permanent firm heterogeneity in long-run productivity. Since low-productivity firms are on average smaller, as explained above they can benefit relatively more from cheaper work from home. For this reason, the post-pandemic economy features an endogenously lower share of high-productivity firms.

In particular, the share of high-type firms drops by more than one quarter. Note that this is a combination of both an endogenous shift towards low-type startups, but also a relative change in exit rates. Specifically, high-type firms are on average larger and, therefore, benefit relatively less from the (fixed) cost reduction associated from remote work. Therefore, their exit rates increase ***relatively*** more compared to those of low-type firms, further exacerbating the shift towards smaller, less productive, businesses.[31]

Overall impact on entry and exit. In the data, increases in remote work rates are associated with increases in both firm entry and exit and with the decline in average size – overall as well as sizes of startups and exiting businesses. Recall that our core theoretical results can reconcile all these relationships. We now turn to investigating them quantitatively.

Table 5 quantifies the impact of changes in remote work rates on business entry, exit and establishment size in the data and the model. As explained above, the latter is done by comparing steady state values in the pre- and post-pandemic economies.

As discussed in Decker and Haltiwanger (2023), 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, 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 36 percent of the entry rate increase and about 67 percent of the exit rate.

In addition, the last two columns report that our model also explains much of the decline in firm sizes of entering and exiting businesses. As explained, above, this is a combination of lower average firm productivity but also a higher equilibrium wage rate.

[31]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.

Table 5: Model Results: Remote work and business entry and exit

	Rate		Size	
	Entry	Exit	Entrants	Exiters
Data	+28%	+15%	−24%	−22%
Model	+10%	+10%	−21%	−20%

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

	Output (Y)		Consumption (C)			Welfare ($\mathcal{W}$)	
Overall	2.5		3.5			0.2	
Components	Ω	$\overline{y}$	Y	I	Costs	C	N
	26.1	−23.6	3.7	−0.6	0.4	0.2	−0.0

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.

Therefore, our quantitative framework suggests that the observed reversal of some of the business dynamism patterns of the past decades may not be that surprising in light of the increased uptake of remote work arrangements.

5.2 Work from Home and the Macroeconomy

In this subsection we quantify the macroeconomic impact of increases in work from home arrangements.

Firm-level production and the mass of firms. We begin by summarizing how changes in remote work impact average firm-level production and the number of firms in the economy. In particular, the first two columns of Table 6 show the change in aggregate output and its decomposition into the contributions of changes in the number of firms, Ω, and average firm-level production, $\overline{y}$.

As can be seen from the Table, aggregate output increases by 1.3 percent. This, however, is entirely driven by a higher number of firms which more than compensates for the drop in average firm-level production.[32] The latter is a combination of two forces.

[32]While large, the model-predicted changes in the number of businesses and average output are not unrealistic. In particular, the number of establishments is about 20 percent higher in the post-pandemic BED data relative to the pre-pandemic average. Even the growth rate of the number of establishments (which is positive on average over our sample) is more than twice as high in 2022 compared to the pre-pandemic period (3.1 percent in 2022 relative to 1.4 on average in 2003-2019). Finally, while output data is not available in the BED, average size of entrants and exiting firms is also in the realm of 20 percent.

First, smaller scales of production stemming from higher equilibrium wages – as discussed in Figure 3. Second, lower average firm-level productivity as the firm distribution shifts towards less productive businesses.[33]

Aggregate output and consumption. The next three columns of Table 6 investigate the change in aggregate output and its sources ($Y = Z(N^{1-\alpha}K^{\alpha})^{\theta}$). In general equilibrium, aggregate output increases by about 2.5 percent. This is driven primarily by the rise in TFP discussed above, but also by an increase in employment and capital. Notice that capital rises by more than labor, reflecting firm-level choices discussed in the previous subsection. Note, however, that both the increases in aggregate capital and labor are entirely driven by a greater number of firms in the economy. Indeed, individual businesses operate at a smaller scale on average (see Figure 4).

Next, Table 6 shows how consumption changes between the counterfactual and baseline economies and splits this effect into the contributions of output, investment and costs ($C = Y - I - Costs$). The latter encompass capital adjustment costs, fixed operation costs and entry costs. Overall, consumption increases strongly, predominantly driven by a rise in aggregate output. In contrast, higher investment (consistent with the increased aggregate capital stock) dampens consumption. This effect is compensated for by a decline in paid costs, as spending on overhead costs and non-wage labor costs falls due to increased remote work, more than compensating for higher entry costs.

Welfare. Finally, the last two columns of Table 6 investigate the impact of increased remote work arrangements on household welfare ($\mathcal{W} = \log(C) - \upsilon N$). Note that our model is not particularly geared towards generating welfare benefits of work from home. First, remote work decisions are made at the firm level and households take them as given. Second, we do not explicitly model additional benefits of remote work such as a decline in commuting time (i.e. increased leisure and/or work hours), benefits for home-production (see e.g. Barrero et al., 2023, for a discussion).

Nevertheless, our model predicts that welfare increases slightly by about 0.2 percent when moving towards more flexible remote work arrangements. This is entirely driven by the strong consumption increase. As discussed before, aggregate employment rises slightly, but this has a negligible quantitative effect on welfare.

5.3 Discussion

This paper studies how expanded work from home practices can impact the macroeconomy. Our quantitative analysis is based on a new model in which heterogeneous

[33] Note that "aggregate" productivity, measured as $Z = Y/((N^{\alpha}K^{1-\alpha})^{\theta})$, increases slightly. Intuitively, this happens because in the presence of decreasing returns to scale a larger number of firms operating at lower scales of production improves the allocation of resources.

businesses optimally choose the extent of remote work. In this section, we discuss some features of the current model and sketch potential extensions.

Heterogeneous responses of firms. A key mechanism in our theory is that smaller – and, therefore, younger – businesses are more responsive to changes in work from home conditions since they benefit relatively more from reductions in the associated fixed costs. A direct implication of this feature of the model is that exit rates increase relatively more for older businesses in our framework, see Figure 4. We now confront this prediction with the data.

Using the age breakdown of exit rates in the BED, we are able to compute the relative changes in exit rates for young and old businesses in the data. In particular, while average exit rates of old firms (between 11-20 years) increased by about 1/5 percent (from 4.8 to 5.8 percent), they remained essentially unchanged for young firms (less than 6 years of age). Our model predicts virtually the same changes with an increase of 21 percent for old firms and a 0.1 percent decline for young businesses. Given that the heterogeneity in responsiveness by firm age and size is an important feature of our model, these (untargeted) results are reassuring for the rest of our quantitative analysis.

Fixed costs of starting remote work. In the baseline model, we assume that any business can employ some of its workforce remotely without incurring any setup costs. In reality, there may be costs associated with obtaining the necessary hard- or soft-ware for remote work, as well as putting in place processes for efficient use of remote work. The Appendix extends our baseline model to allow for such fixed setup costs.

The presence of fixed setup costs gives rise to an interesting additional "extensive margin" channel. In particular, changes in the conditions of remote work would impact the share of firms engaging in work from home arrangements. However, our baseline model with its endogenous composition of low- and high-productivity firm already contains some of these features. Moreover, a careful quantitative evaluation of the relative strengths of the intensive vs extensive margins requires more detailed information on the characteristics of firms engaging in remote work. To the best of our knowledge, such data is currently lacking and, therefore, we defer this extension to the Appendix.

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 investment and resulting growth.[34]

[34]See e.g.Akcigit and Kerr (2018); Acemoglu et al. (2018) for recent examples of frameworks with heterogeneous firms and endogenous 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.

Other factors, their interaction and transition dynamics. Our model predicts that more than a third of the entry rate spike during and in the aftermath of the COVID pandemic can be explained by increased remote work arrangements. We are well aware of other factors that likely 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, 2023).

Similarly, aside from the presence of capital adjustment costs, our model does not feature other frictions which firms may face in reality. It may be interesting for future research to concentrate on the interaction of remote work with other factors and frictions, or to consider bargaining about remote work between workers and firms.

Finally, let us note that the patterns of remote work are still evolving with – what seems to have been – an "overshooting" of remote work rates during the pandemic which is slowly settling down to a new equilibrium. 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 about one third of the firm entry rate increase since the COVID-19 pandemic. It also leads to an increase in output, consumption and welfare. These effects occur despite a shift towards smaller and less productive firms, entirely driven by a larger number of firms. To the best of our knowledge, we are the first to analyze how work from home practices impact the macroeconomy.

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 rm-level*** – is needed to better understand the aggregate impact of the increasing trend of remote work.

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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, aggregation and formally define the equilibrium.

Household Problem. A representative household owns all businesses in the economy and optimally chooses aggregate consumption, C, and labor, N, to maximize:

$$\ln C - \upsilon N,$$

subject to a budget constraint:

$$C = WN + \Pi,$$

where $\upsilon > 0$ is the disutility of labor supply, the aggregate price is normalized, and Π is the real aggregate profits.

Aggregation. In our framework, the distribution of surviving firms is then given by

$$\mu(z) = \begin{cases} 0 & z < \widetilde{z}, \\ \frac{h_z(z)}{1-H_z(\widetilde{z})} & \text{if } z \geq \widetilde{z}. \end{cases} \tag{A1}$$

Using this notation, the following conditions describe goods and labor market clearing:

$$Y = \int y_t \mu(z) dz,$$

$$N = \int n_t \mu(z) dz. \tag{A2}$$

Finally, the aggregate resource constraint is given by

$$Y = C + M\kappa_e + \int g(\omega_t)(\kappa_n n_t + \kappa_o)\mu(z) dz,$$

where aggregate output is used for consumption and all paid costs, including entry costs, non-wage labor costs and overhead costs.

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 entrants $M \geq 0$, and a measure of incumbents $\mu(z)$, such that:

- $v(z)$, $n(z)$, $\omega(z)$ and $\widetilde{z}$ solve the incumbent's problem (2) and satisfy the exit threshold (3),
- the free entry condition (4) is satisfied with equality if $M > 0$,
- the labor and goods markets clear (A2),
- and the distribution of firms satisfies (A1).

A.2 Proofs

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

Interior Solutions. Start with the FOCs:

$$\begin{aligned} f'(\omega)zn^{\alpha} - g'(\omega)(\kappa_n n + \kappa_o) &= 0 && \text{(A3)} \\ f(\omega)z\alpha n^{\alpha-1} - W - g(\omega)\kappa_n &= 0 && \text{(A4)} \end{aligned}$$

Solve optimal employment, n^*, from equation (A4):

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

Substituting n^* into equation (A3), we have

$$\frac{zf'(\omega^*)}{g'(\omega^*)} - \kappa_n n^{*1-\alpha} - \kappa_0 n^{*-\alpha} = 0 \tag{A5}$$

Define the followings for simplicity:

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

Then we can rewrite equation (A5) 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:

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

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

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

b) if $\kappa_o > 0$, differentiating equations (A3) and (A4) 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:

$$(\frac{f''g' - g''f'}{g'^3})f\alpha(\alpha-1) > [\frac{f'}{g'}(\alpha-1) + \frac{\kappa_o}{zn^{*\alpha}}]^2 \tag{A6}$$

We can further derive the necessary condition from (A6):

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

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 (A3) and (A4) as:

$$f_1(\omega^*;\widetilde{f})zn^{*\alpha} - g_1(\omega^*;\widetilde{g})(\kappa_n n^* + \kappa_o) = 0 \tag{A7}$$

$$f(\omega^*;\widetilde{f})z\alpha n^{*\alpha-1} - W - g(\omega^*;\widetilde{g})\kappa_n = 0 \tag{A8}$$

Proof of $\frac{\partial\omega^*}{\partial\widetilde{f}} > 0$. Differentiating Equations (A7) and (A8) 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 (A6) holds, $\frac{\partial\omega^*}{\partial\widetilde{f}} > 0$ if and only if the RHS is positive:

$$\frac{f_1f_2 - f_{12}f}{g_1^2}\alpha(\alpha-1) + \frac{f_2}{g_1}\frac{\alpha\kappa_o}{zn^{*\alpha}} > 0 \tag{A9}$$

We can further obtain the necessary condition for $\frac{\partial\omega^*}{\partial\widetilde{f}} > 0$ from (A9):

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

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

Proof of $\frac{\partial \omega^*}{\partial \widetilde{g}} > 0$. Differentiating Equations (A7) and (A8) 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 (A6) holds, $\frac{\partial \omega^*}{\partial \widetilde{g}} > 0$ if and only if the RHS is positive:

$$\frac{g_{12}f_1 f}{g_1^3}\alpha(\alpha-1) - \frac{g_2\kappa_n}{g_1 zn^{*\alpha-1}}(\frac{\alpha f_1}{g_1} - \frac{\kappa_n}{zn^{*\alpha-1}}) > 0 \tag{A10}$$

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

$$\frac{\partial \pi^*}{\partial \widetilde{f}} = f_2(\omega^*; \widetilde{f})zn^{*\alpha} > 0 \tag{A11}$$

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

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

As $\frac{\partial \pi^*}{\partial \widetilde{f}} > 0$ from (A11) and by the envelope theorem $\frac{\partial \pi^*}{\partial z} = f(\omega^*; \widetilde{f})n^{*\alpha} > 0$, we have:

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

Alternative proof of $\frac{\partial \pi^*}{\partial \widetilde{f}} > 0$ and $\frac{d\widetilde{z}}{d\widetilde{f}} < 0$. Consider an increase in velocity of productivity loss, from $\widetilde{f}_0$ to $\widetilde{f}_1$. Assume Conditions (A6) and (A9) hold, so that the optimal wfh rate increases from $\omega_0^*(z)$ to $\omega_1^*(z)$, given productivity z. The optimal employment changes from $n_0^*(z)$ to $n_1^*(z)$. We have:

$$\begin{aligned}
\pi^*(z, \widetilde{f}_1) &\equiv f(\omega_1^*; \widetilde{f}_1)zn_1^{*\alpha} - Wn_1^* - g(\omega_1^*)(\kappa_n n_1^* + \kappa_o) \\
&> f(\omega_0^*; \widetilde{f}_1)zn_0^{*\alpha} - Wn_0^* - g(\omega_0^*)(\kappa_n n_0^* + \kappa_o) \\
&> f(\omega_0^*; \widetilde{f}_0)zn_0^{*\alpha} - Wn_0^* - g(\omega_0^*)(\kappa_n n_0^* + \kappa_o) \equiv \pi^*(z, \widetilde{f}_0)
\end{aligned}$$

The first inequality is because $(\omega_1^*, n_1^*) \succ (\omega_0^*, n_0^*)$ when $\widetilde{f} = \widetilde{f}_1$. The second inequality is because $\frac{\partial f(\omega; \widetilde{f})}{\partial \widetilde{f}} > 0$ as defined.

Intuitively, it states the envelope theorem that with an increase in $\widetilde{f}$, profits increase under the original bundle (ω_0^*, n_0^*). Given that firms can choose optimally, the preferred bundle (ω_1^*, n_1^*) generates even higher profits than (ω_1^*, n_1^*).

Denote the new cutoff as $\widetilde{z}_1$ and the old cutoff as $\widetilde{z}_0$. Note that $\forall z$, $\pi^*(z, \widetilde{f}_1) > \pi^*(z, \widetilde{f}_0)$.

We then have:

$$0 \equiv \pi(\widetilde{z}_1, \widetilde{f}_1) > \pi(\widetilde{z}_1, \widetilde{f}_0)$$

Note that $\frac{\partial \pi}{\partial z} > 0$ and $\pi(\widetilde{z}_0, \widetilde{f}_0) \equiv 0$, we have $\pi(\widetilde{z}_0, \widetilde{f}_0) > \pi(\widetilde{z}_1, \widetilde{f}_0)$. Therefore,

$$\widetilde{z}_1 < \widetilde{z}_0$$

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

$$\frac{\partial \pi^*}{\partial \widetilde{g}} = -g_2(\omega^*; \widetilde{g})(\kappa_n n^* + \kappa_o) > 0 \tag{A13}$$

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

$$0 \equiv \frac{d\pi^*(\widetilde{z}(\widetilde{g}))}{d\widetilde{g}} = \frac{\partial \pi^*}{\partial \widetilde{g}}|_{z=\widetilde{z}} + \frac{\partial \pi^*}{\partial \widetilde{z}} \frac{d\widetilde{z}}{d\widetilde{g}} \tag{A14}$$

As $\frac{\partial \pi^*}{\partial \widetilde{g}} > 0$ from (A13) and $\frac{\partial \pi^*}{\partial z} > 0$, we have

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

Alternative proof of $\frac{\partial \pi^*}{\partial \widetilde{g}} > 0$ and $\frac{d\widetilde{z}}{d\widetilde{g}} < 0$. Consider an increase in velocity of cost saving, from $\widetilde{g}_0$ to $\widetilde{g}_1$. Assume Conditions (A6) and (A10) hold, so that the optimal wfh rate increases from $\omega_0^*(z)$ to $\omega_1^*(z)$, given productivity z. The optimal employment changes from $n_0^*(z)$ to $n_1^*(z)$. We have:

$$\begin{aligned} \pi^*(z, \widetilde{g}_1) &\equiv f(\omega_1^*) z n_1^{*\alpha} - W n_1^* - g(\omega_1^*; \widetilde{g}_1)(\kappa_n n_1^* + \kappa_o) \\ &> f(\omega_0^*) z n_0^{*\alpha} - W n_0^* - g(\omega_0^*; \widetilde{g}_1)(\kappa_n n_0^* + \kappa_o) \\ &> f(\omega_0^*) z n_0^{*\alpha} - W n_0^* - g(\omega_0^*; \widetilde{g}_0)(\kappa_n n_0^* + \kappa_o) \equiv \pi^*(z, \widetilde{g}_0) \end{aligned}$$

The first inequality is because $(\omega_1^*, n_1^*) \succ (\omega_0^*, n_0^*)$ when $\widetilde{g} = \widetilde{g}_1$. The second inequality is because $\frac{\partial g(\widetilde{g}, \omega)}{\partial \widetilde{g}} < 0$ as defined.

Intuitively, it states the envelope theorem that with an increase in $\widetilde{g}$, profits increase under the original bundle (ω_0^*, n_0^*). Given that firms can choose optimally, the preferred bundle (ω_1^*, n_1^*) generates even higher profits than (ω_1^*, n_1^*).

Denote the new cutoff as $\widetilde{z}_1$ and the old cutoff as $\widetilde{z}_0$. Note that $\forall z$, $\pi^*(z, \widetilde{g}_1) > \pi^*(z, \widetilde{g}_0)$. We then have:

$$0 \equiv \pi(\widetilde{z}_1, \widetilde{g}_1) > \pi(\widetilde{z}_1, \widetilde{g}_0)$$

Note that $\frac{\partial \pi}{\partial z} > 0$ and $\pi(\widetilde{z}_0, \widetilde{g}_0) \equiv 0$, we have $\pi(\widetilde{z}_0, \widetilde{g}_0) > \pi(\widetilde{z}_1, \widetilde{g}_0)$. Therefore,

$$\widetilde{z}_1 < \widetilde{z}_0$$

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:

$$\begin{aligned}
& \frac{\partial \pi^*}{\partial \widetilde{g}} & > & \quad \frac{\partial \pi^*}{\partial \widetilde{f}} \\
\overset{(A11),(A13)}{\Longleftrightarrow} & -g_2(\omega^*;\widetilde{g})(\kappa_n n^* + \kappa_o) & > & \quad f_2(\omega^*;\widetilde{f}) z n^{*\alpha} \\
\overset{(A7)}{\Longleftrightarrow} & -g_2(\omega^*;\widetilde{g}) & > & \quad f_2(\omega^*;\widetilde{f}) \frac{g_1(\omega^*;\widetilde{g})}{f_1(\omega^*;\widetilde{f})} \\
\Longleftrightarrow & \frac{g_2}{g_1} + \frac{f_2}{f_1} & > & \quad 0 \qquad (A15)
\end{aligned}$$

Hence (A15) 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 (A15) holds.

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

$$
\begin{aligned}
\frac{\partial \widetilde{z}}{\partial \widetilde{g}} &< \frac{\partial \widetilde{z}}{\partial \widetilde{f}} \\
\overset{(A12),(A14)}{\Longleftrightarrow} -\frac{\frac{\partial \pi}{\partial \widetilde{g}}\big|_{z=\widetilde{z}}}{\frac{\partial \pi}{\partial z}\big|_{z=\widetilde{z}}} &< -\frac{\frac{\partial \pi}{\partial \widetilde{f}}\big|_{z=\widetilde{z}}}{\frac{\partial \pi}{\partial z}\big|_{z=\widetilde{z}}} \\
\Longleftrightarrow \left.\frac{\partial \pi}{\partial \widetilde{g}}\right|_{z=\widetilde{z}} &> \left.\frac{\partial \pi}{\partial \widetilde{f}}\right|_{z=\widetilde{z}} \\
\Longleftrightarrow 0 &< \left.\frac{g_2}{g_1}\right|_{z=\widetilde{z}} + \left.\frac{f_2}{f_1}\right|_{z=\widetilde{z}}
\end{aligned}
$$

which is satisfied automatically by (A15).

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 (A15) 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 (6), 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.

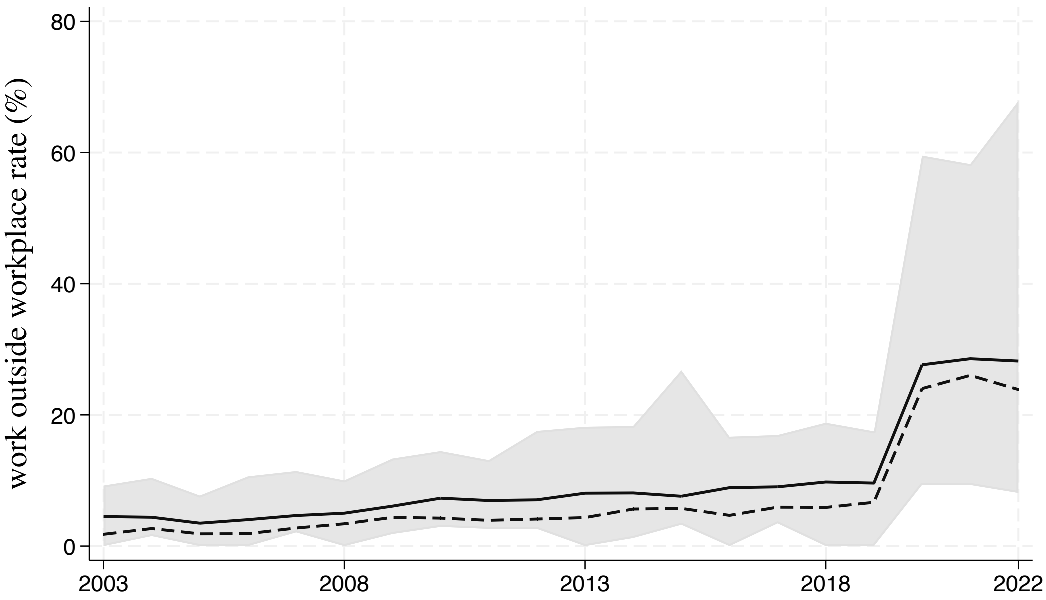
Figure A1 shows the evolution of working-outside-workplace rate from 2003 to 2022. In addition, Figure A2 plots how changes in remote work rates are connected to changes in establishment entry and exit across industries. Finally, Table A1 shows the associated panel regression results. All these are very 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 (7). 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.

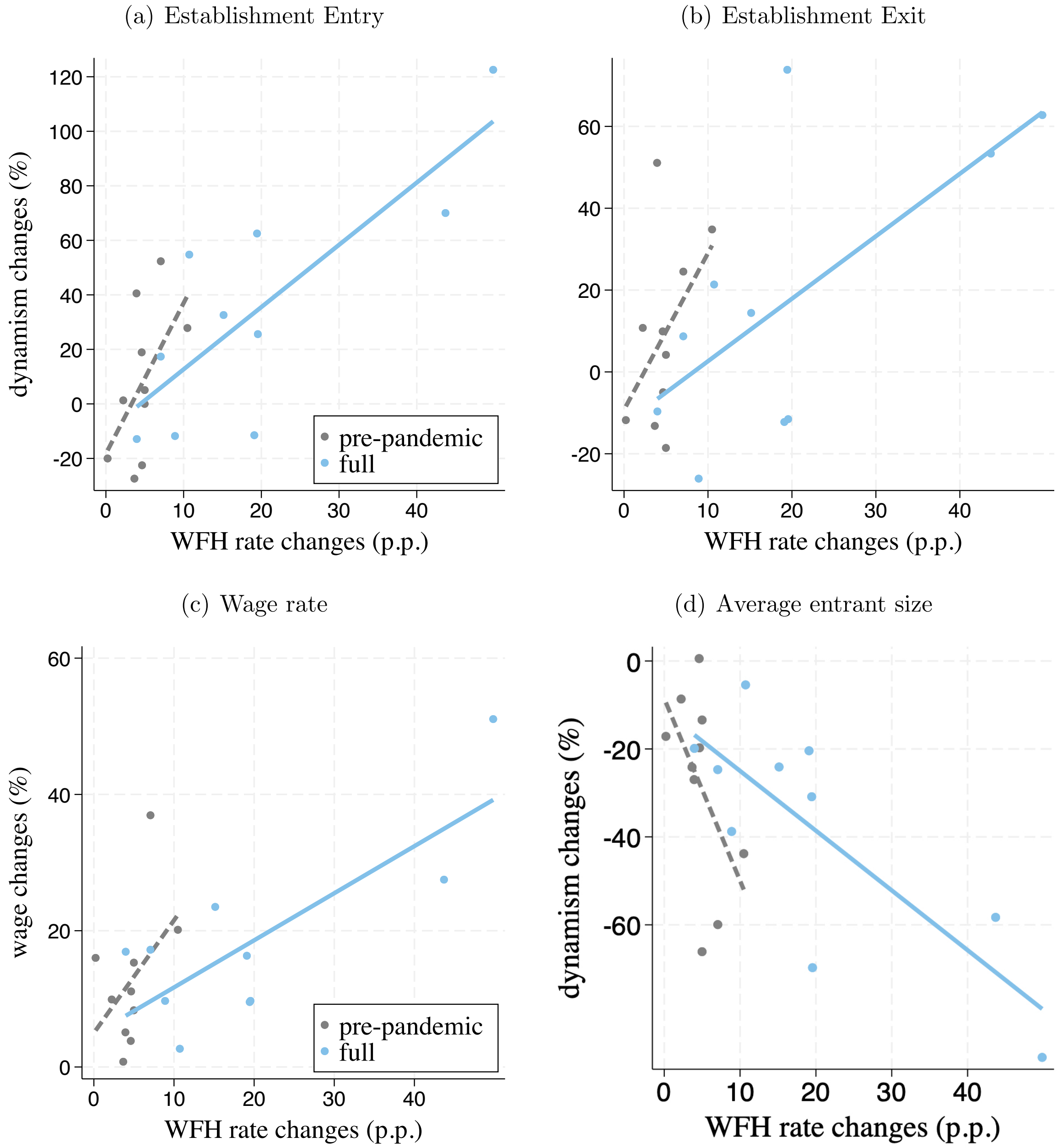
B.2 Robustness: Using Average Size and Exiter Size

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



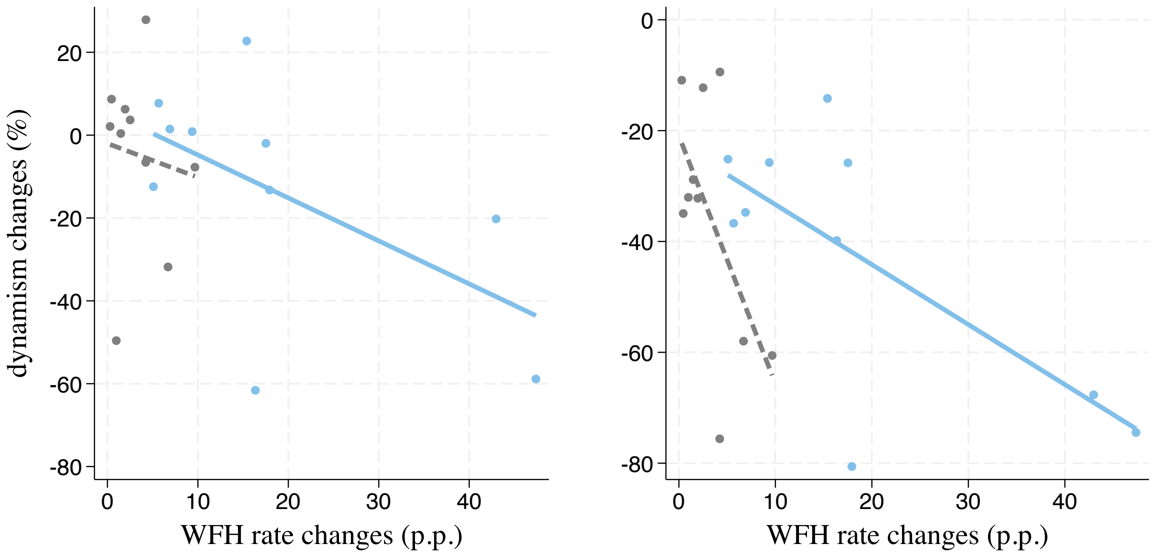
Note: The figure depicts super-sector changes in work outside workplace rates on the horizontal axis (in p.p.) and (percent) changes in the number of entrants (Panel a), exiters (Panel b), wages (Panel c) and average entrant size (Panel d). All panels show data for the pre-pandemic sample (2003-2019)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



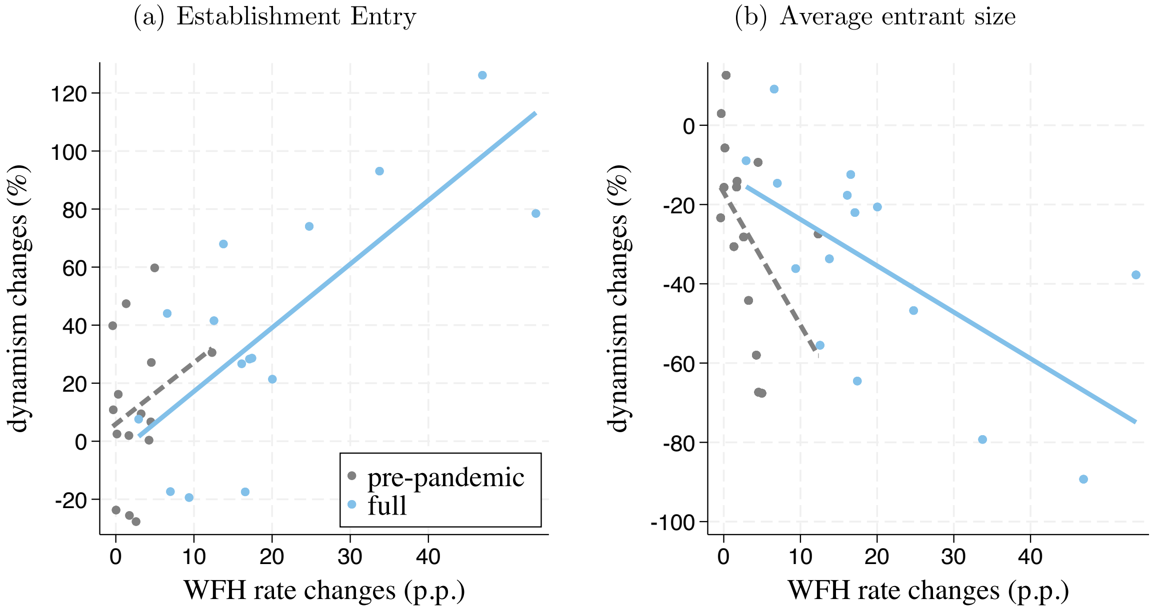
Note: The figure depicts super-sector changes in work from home rates on the horizontal axis (in p.p.) and (percent) changes in the average establishment size (Panel a) and average exiter size (Panel b). All panels show data for the pre-pandemic sample (2003-2019) and the full sample (2003-2022).

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



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 (7). 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 (7). 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

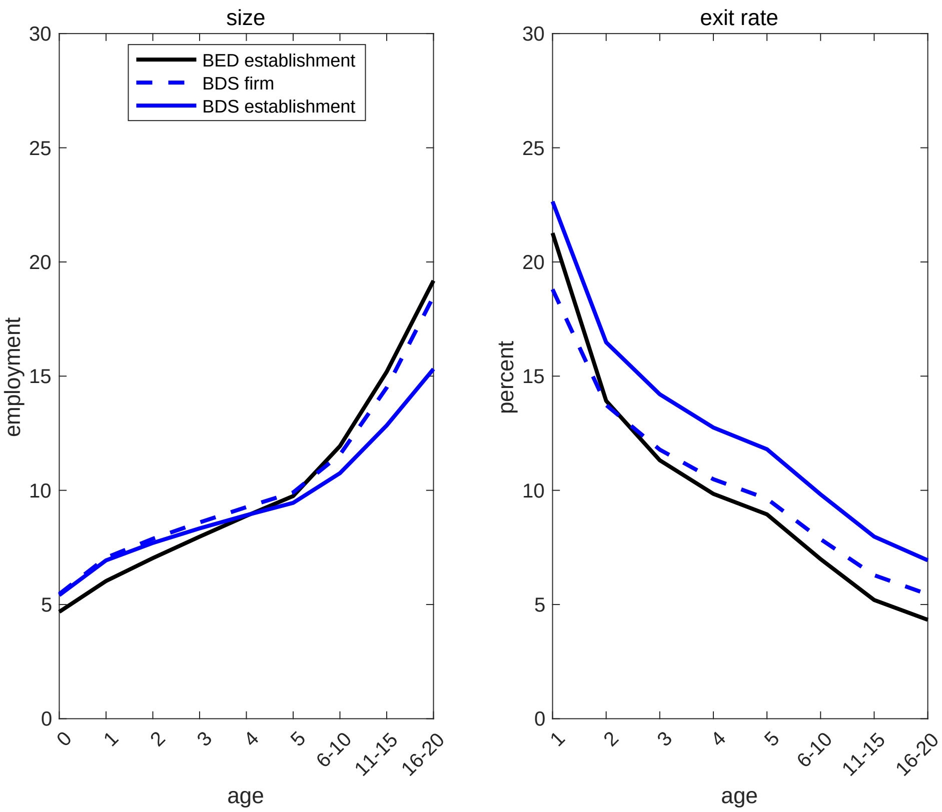
Note: The table reports results from estimating (7). Panel A reports estimates using the pre-pandemic period (2003Q1-2019Q4) only, while Panel B report results for our entire sample period (2003Q1-2022Q4). All specifications include industry and time fixed effects as well as lagged values of the dependent 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 (7). 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 and sketches an extension of our model for fixed costs of setting up remote work.

C.1 Equilibrium Definition in Generalized Model

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

- $v(z,k)$, $n(z,k)$, $\omega(z,k)$, $\widetilde{z}(k)$, $x(z,k)$ solve the incumbent's problem (11);
- the free entry condition (15) is satisfied
- the labor and goods markets clear (20)
- the distribution of firms satisfies

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

  where

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

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

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 choice of $(n_{j,t}, \omega_{j,t}, x_{j,t})$ is the solution to the following problem:

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

- Using the free entry condition and the entry function, compute the success probability p_j, the mass of startup attempts, s_j, and successful startups, m_j:

$$\begin{aligned} \kappa_e &= p_j \int_z v_j(z_j, 0) dH_z(z) \\ s_j &= \Psi_j p_j^{-\frac{1}{\phi}} \\ m_j &= \Psi_j^{\phi} s_j^{1-\phi} \end{aligned}$$

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

$$\begin{aligned} Y &= C + S\kappa_e + \int\int \left[\zeta(x_t, k_t) + g(\omega_t)(\kappa_n n_t + \mu_\kappa) + \widetilde{\kappa}_o\right] \mu(z,k) dz dk \\ W &= \upsilon C \end{aligned}$$

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

$$M = \sum_j m_j$$

C.3 Model with Fixed Setup Cost

In this Appendix, we extend our generalized model to include fixed costs of setting up remote work.

Firm Values and Optimal Decisions. Based with the model in the main text, we further consider a setup cost for working from home, κ_ω.

In particular, the beginning-of-period value of a businesses in operation which has not yet decided to conduct production remotely is given by

$$v(z_{j,t}, k_{j,t}) = \max_{n_{j,t}, x_{j,t}} \left\{ \pi_{j,t} + \beta(1-\delta) \int \max\left[\mathsf{E}_t v_j^x(z_{j,t+1}, k_{j,t+1}), \mathsf{E}_t v_j^c(z_{j,t+1}, k_{j,t+1}) - \widetilde{\kappa}_o\right] dH_\kappa(\widetilde{\kappa}_o) \right\},$$

where $v_j^c(z,k)$ is the continuation values, given by

$$v_j^c(z_{j,t}, k_{j,t}) = \max\left[v_j(z_{j,t}, k_{j,t}), v_j^\omega(z_{j,t}, k_{j,t}) - \kappa_\omega\right].$$

The above shows that the value of continuation depends on whether or not firms decide to begin remote work. Choosing to do so, requires firms to pay κ_ω. Then, the beginning-of-period value of a business which can conduct part of its production remotely is given by

$$v_j^\omega(z_{j,t},k_{j,t}) = \max_{n_{j,t},x_{j,t},\omega_{j,t}} \left\{ \pi_{j,t} + \beta(1-\delta) \int \max\left[\mathsf{E}_t v_j^x(z_{j,t+1},k_{j,t+1}), \mathsf{E}_t v_j^\omega(z_{j,t+1},k_{j,t+1}) - \widetilde{\kappa}_o\right] dH_\kappa(\widetilde{\kappa}_o) \right\},$$

Firm Entry. We assume that startups enter with no workers, but they do have the choice of immediately choosing to conduct some remote work.

Assuming free entry, the following condition implicitly pins down the mass of entrants, M:

$$\kappa_e = \frac{m_j}{s_j} \int_z \max\left[v_j(z_j,0), v_j^\omega(z_j,0) - \kappa_\omega\right] dH_z(z).$$

Aggregation. Finally, the aggregate resource constraint is given by

$$Y = C + S\kappa_e + \int\int \left[\zeta(x,k) + g(\omega)(\kappa_n n + \mu_\kappa) + \widetilde{\kappa}_o\right] d\mu(z,k) + T\kappa_\omega,$$

where the costs of setting up remote work are included. S is the total mass of startup attempts, and T is the mass of firms starting to conduct a fraction of their production remotely.

Model Results. We use κ_ω to calibrate the pre-pandemic economy such that the fraction of firms conducting remote work is around 70%. To the best of our knowledge, there is no information on remote work at the firm- or establishment-level. Therefore, it is not possible to infer the fraction of businesses conducting remote work. Our target of is, instead, based on the establishment size distribution and our result that smaller businesses have greater incentives to conduct remote work. In particular, in the BED about 70% of establishments have fewer than 10 employees and, therefore, we use this fraction as a target for the share of businesses conducting remote work in the baseline steady state.

We then calibrate the post-pandemic economy using the same strategy as in the main text. Besides, the average work-from-home rate of firms with 100-499 employees is 20%, close to the ATUS-ASEC data (21%). Table A8 and A9 show the model results. Because setup cost is constant among firms, smaller and less productive ones are less likely to arrange remote work pre-pandemic. When remote work becomes cheaper or more efficient, small firms are attracted to invest in remote work facilities, pay the setup cost and implement remote work arrangement.

Table A8: Model Results with κ_ω: Remote work and business entry and exit

	Rate		Size	
	Entry	Exit	Entrants	Exiters
Data	+28%	+15%	−24%	−22%
Model	+10%	+10%	−25%	−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 A9: Impact of increased remote work with κ_ω: Changes in aggregates (in %)

	Output (Y)		Consumption (C)			Welfare ($\mathcal{W}$)	
Overall	3.0		4.2			0.2	
Components	Ω	$\overline{y}$	Y	I	Costs	C	N
	31.9	−29.0	4.4	−0.7	0.5	0.3	−0.0

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

C.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 A10 and A13 show the calibrated parameters, respectively. Table A11 to A15 show the results.

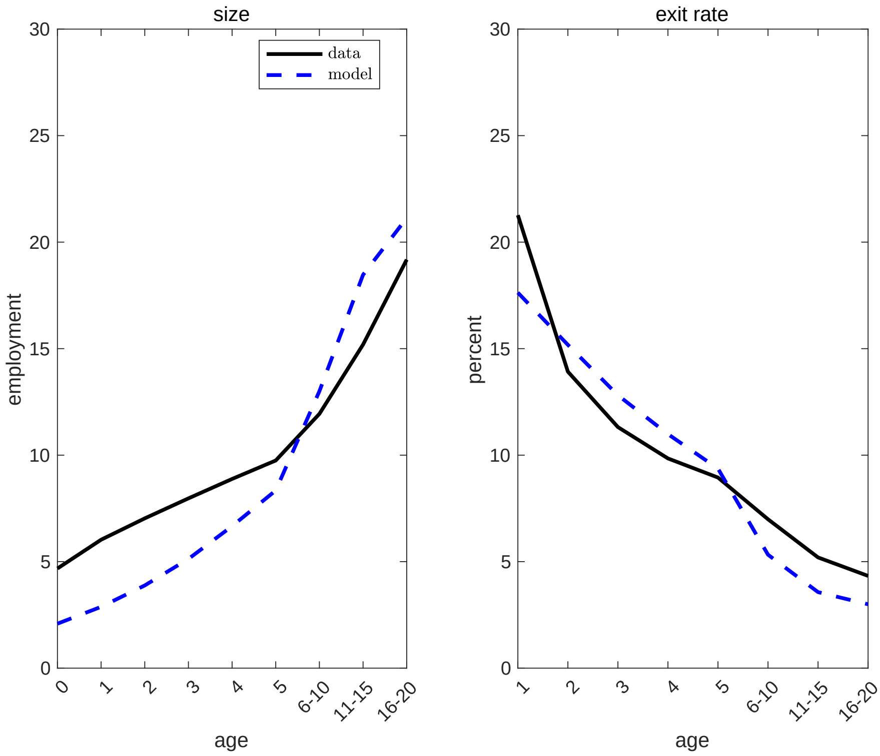
While the elasticity of entry matters for the strength of the entry response, it matters less for changes in firm sizes and aggregates. The reason is that a shallower (stronger) entry response is compensated for by a stronger (weaker) change in firm selection. Therefore, aggregate outcomes are effectively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

Table A10: 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	0.0171	Normalization, $W = 1$		
κ_e	Entry cost	0.64	Normalization, $s_H + s_L = 1$		
ϕ	Elasticity of entry function	0.1	Robustness check		
$\widetilde{f}$	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	0.089	Average work from home rate, ATUS	4.1%	4.1%
κ_n	Non-wage labor costs	0.25	Average work from home rate of 100+ firms, ATUS & ASEC	4.0%	3.5%
Ψ_L	Mass of "low" business opportunities	0.0000006	Share of small (< 50) businesses, BED	95%	93%
Ψ_H	Mass of "high" business opportunities	0.00000004	Startup success rate, BED	21%	23%
$\underline{z}_H$	Mean "high" productivity	0.130	Average establishment size, BED	15.4	15.6
$\underline{z}_L$	Mean "low" productivity	0.104	Average establishment size of small (< 50) businesses, BED	6.8	7.8
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	0.64	Establishment size life-cycle profile, BED	see Figure A6	
μ_κ	Overhead costs, mean	0.78	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.

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 A11: Model Results: Remote work and business entry and exit ($\phi = 0.1$)

	Rate		Size	
	Entry	Exit	Entrants	Exiters
Data	+28%	+15%	−24%	−22%
Model	+13%	+13%	−20%	−22%

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 A12: Impact of increased remote work: Changes in aggregates ($\phi = 0.1$)

	Output (Y)		Consumption (C)			Welfare ($\mathcal{W}$)	
Overall	2.4		3.2			0.2	
Components	Ω	$\overline{y}$	Y	I	Costs	C	N
	27.5	−25.1	3.6	−0.6	0.2	0.2	−0.0

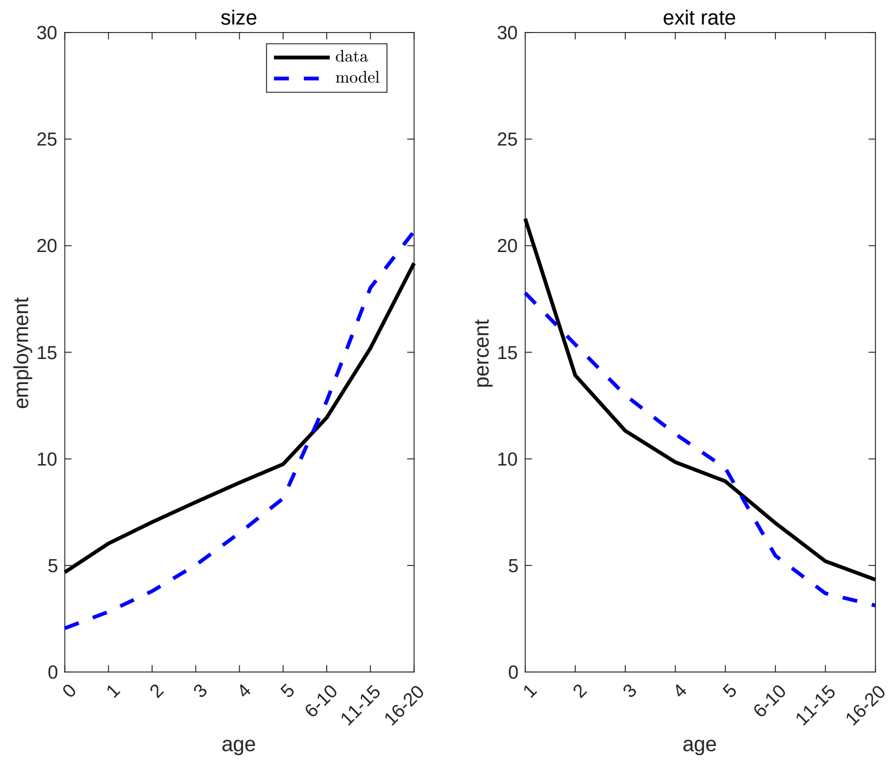
Note: The first row of the table shows log-changes in aggregate Output (Y), Consumption (C) and Welfare ($\mathcal{W}$). The second row then split the overall changes into the contributions of the various components. All values are reported in percent changes from the pre-pandemic baseline.

Table A13: 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	0.66	Normalization, $s_H + s_L = 1$		
ϕ	Elasticity of entry function	0.2	Robustness check		
$\widetilde{f}$	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	0.089	Average work from home rate, ATUS	4.1%	4.1%
κ_n	Non-wage labor costs	0.25	Average work from home rate of 100+ firms, ATUS & ASEC	4.0%	3.5%
Ψ_L	Mass of "low" business opportunities	0.0007	Share of small (< 50) businesses, BED	95%	94%
Ψ_H	Mass of "high" business opportunities	0.00015	Startup success rate, BED	21%	24%
$\underline{z}_H$	Mean "high" productivity	0.130	Average establishment size, BED	15.4	15.2
$\underline{z}_L$	Mean "low" productivity	0.104	Average establishment size of small (< 50) businesses, BED	6.8	7.7
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	0.64	Establishment size life-cycle profile, BED	see Figure A7	
μ_κ	Overhead costs, mean	0.78	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.

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.

Table A14: Model Results: Remote work and business entry and exit ($\phi = 0.2$)

	Rate		Size	
	Entry	Exit	Entrants	Exiters
Data	+28%	+15%	−24%	−22%
Model	+9%	+9%	−23%	−23%

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 A15: Impact of increased remote work: Changes in aggregates ($\phi = 0.2$)

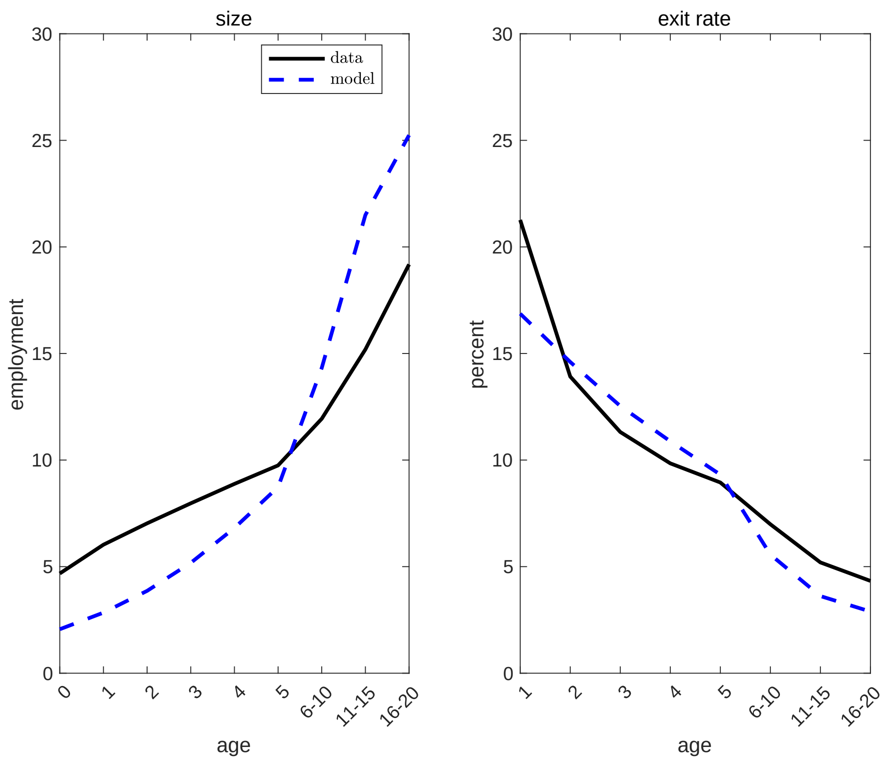
	Output (Y)		Consumption (C)			Welfare ($\mathcal{W}$)	
Overall	2.9		4.3			0.2	
Components	Ω	$\overline{y}$	Y	I	Costs	C	N
	29.3	−26.4	4.3	−0.6	0.6	0.3	−0.0

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

C.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 A16 presents the calibrated parameters. In particular, the calibrated share accounts for more than 80% of that in the data. We replicate the model results of business dynamism and aggregates as shown in Table A17 and A18. The model results in both business dynamism and aggregates are not fundamentally 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 A16: 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	0.0147	Normalization, $W = 1$		
κ_e	Entry cost	0.68	Normalization, $s_H + s_L = 1$		
ϕ	Elasticity of entry function	0.156	Sedláček and Sterk (2017)		
$\widetilde{f}$	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	0.091	Average work from home rate, ATUS	4.1%	4.3%
κ_n	Non-wage labor costs	0.27	Average work from home rate of 100+ firms, ATUS & ASEC	4.0%	3.8%
Ψ_L	Mass of "low" business opportunities	0.0000821	Share of large (≥ 500) businesses, BED	0.30%	0.25%
Ψ_H	Mass of "high" business opportunities	0.0000075	Startup success rate, BED	21%	24%
$\underline{z}_H$	Mean "high" productivity	0.130	Average establishment size, BED	15.4	18.6
$\underline{z}_L$	Mean "low" productivity	0.086	Average establishment size of small (< 50) businesses, BED	6.8	8.2
ρ	Productivity persistence	0.726	Establishment size life-cycle profile, BED	see Figure A8	
σ_z	Productivity shock dispersion	0.212	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	0.78	Establishment exit life-cycle profile, BED	see Figure A8	
σ_κ	Overhead costs, dispersion	2.67	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 A17: Model Results: Remote work and business entry and exit (targeting large firms)

	Rate		Size	
	Entry	Exit	Entrants	Exiters
Data	+28%	+15%	−24%	−22%
Model	+15%	+15%	−24%	−29%

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 A18: Impact of increased remote work: Changes in aggregates (targeting large firms)

	Output (Y)		Consumption (C)			Welfare ($\mathcal{W}$)	
Overall	2.3		3.5			0.2	
Components	Ω	$\overline{y}$	Y	I	Costs	C	N
	31.3	−28.9	3.5	−0.5	0.6	0.2	−0.0

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.