Digital Prowess:
ICT Human Capital, Remote Work, and Asset Prices*

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Abstract

Using a novel measure of human capital associated with Information and Communication Technology (ICT), we show that ICT human capital explains a large portion of variations in several widely used measures of remote work flexibility and has a first-order effect in the variations of asset prices and labor policies during the recent Covid-19 pandemic. Post pandemic, there is a persistently high adoption of work from home practices in high-ICT human capital industries. A dynamic neoclassical model of firms operating multiple job tasks together with pandemic shocks captures the relationship between ICT human capital, remote work flexibility in labor force, and asset returns. The model mechanism highlights that i) job task flexibility enabled by ICT human capital is a key driving force of the cross-industry heterogeneity in firm value fluctuations, and ii) combining labor productivity (supply) and uncertainty shocks is crucial to generate large drop and persistent recovery in firm value and output.

Keywords: ICT human capital, Remote work, Return predictability, Multiple job tasks, Labor shocks, Uncertainty shocks, Pandemic.

JEL Classifications: G12, G17.

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1 Introduction

Remote work, which decentralizes work activities at traditional workplaces (Nilles (1975)), has gained significant prevalence since the onset of the Covid-19 pandemic (Barrero, Bloom, and Davis (2021)). Information and Communication Technology (ICT) plays a pivotal role in enabling a wide range of remote work activities (Autor (2001)). In this paper, we use the recent pandemic as a laboratory to show that, fundamentally, the human capital associated with ICT is crucial for maintaining production at relatively high levels during emergency situations that disrupt the traditional workplaces.

We provide a novel measure of ICT human capital and study the dynamic relationship between ICT human capital, remote work flexibility, and asset prices during and post pandemic. Empirically, we find that ICT human capital is the driving force behind firms' ability to adopt remote work. Firms with high ICT human capital experience higher employment and hours growth, higher asset returns during the pandemic, and have persistently higher remote work practices even after the pandemic. Theoretically, we develop a dynamic model economy wherein firms have multiple tasks. The central insight of our model is that job task flexibility enabled by ICT human capital is the key driver of firm value and output fluctuations.

Our measure for ICT human capital capitalizes the labor expenses related to ICT jobs. Specifically, we identify ICT jobs as those that score highly on five O*NET (Occupational Information Network) job characteristics associated with information and computers. We rely on the industry-job composition information from OES (Occupational Employment Statistics program) to measure the total labor expenses associated with ICT jobs in each NAICS-4 digit industry. Our industry-level ICT human capital measure, which is calculated as of 2019, has a strong positive correlation with several ex-ante measures of work from home that are widely used in the literature (e.g., Dingel and Neiman (2020); Mongey, Pilossoph, and Weinberg (2020), and Papanikolaou and Schmidt (2022)).[1] More importantly, we find that ICT human capital accounts for a significant share of variations in these work from home measures, especially within sectors. This suggests that ICT human capital is an integral factor that enables work from home for jobs that are identified as telework flexible in the literature.

Our first set of tests focus on the dynamics of asset returns during the pandemic across industries that are differentiated by their ICT human capital. We show that industries grouped as high-ICT human capital significantly outperform their low-ICT human capital peers in terms of asset returns throughout the first few months of the pandemic. Specifically, the stock return and bond return spreads between the two industry groups widen as the pandemic shapes to be a real threat to the U.S. public health, hence making it impossible to conduct most tasks in the economy on-site. This cumulative return spread between the high- and low-ICT human capital industries increases steadily towards the peak of the pandemic, suggesting that the relationship between ICT human capital and asst returns is persistent when the pandemic shock is still in effect. Furthermore, based on a regression analysis, we find that the ICT human capital component of WFH measures is the main driver of the cross-sectional WFH-return relation during the pandemic for both asset classes.

As an out of sample exercise, we then apply the industry-level ICT human capital scores from the U.S. sample to equities in other G-7 countries. Consistent with our findings in the U.S., there is a positive ICT human capital-return relationship in this sample during the pandemic. Additionally, the WFH-return spread is also fully explained by the variations in the ICT human capital component across these countries. Interestingly, when analyzing the ICT human capital-return relationship for a larger set of individual countries, we find that higher pandemic severity (e.g., the Covid-19 infection or death rates per 100,000 people) is associated with a stronger association of ICT human capital and stock returns.

Our second set of tests analyze the effect of ICT human capital on firms' labor policy

[1] We use remote work, telework, and work from home (WFH) interchangably in this paper.

during the pandemic. We compare cumulative employment and working hours growth across industries with high- and low-ICT human capital throughout the peak of the pandemic. We find that while there is a drop in employment and working hours in the first months following the pandemic across all industry groups, the rate of decline for these values is significantly smaller for industries with higher levels of ICT human capital during this period. This is also the case even when we only compare industries that belong to the the same sector. This is consistent with high-ICT human capital industries being able to maintain a higher level of their productions during the pandemic.

Post pandemic, we find that the employment and working hours reverted to the pre-pandemic levels as the effect of this shock wanes. The natural question that arises following this finding is to what extent firms maintained their work from home practices during this period, and whether ICT human capital influenced the extent of work from home practices across industries. Our third set of tests address this question. We compare the work from home practices, as surveyed by Barrero, Bloom, and Davis (2021), across ICT human capital groups in the period between June 2020 and April 2023. We find that while the work from home practice has declined since June 2020 across all ICT human capital groups, the drop has been significantly larger and more persistent for the low-ICT human capital group. For the high-ICT human capital group, on the other hand, the work from home practice has remained at a persistently high level since the ending of the pandemic (i.e., January 2022 to April 2023). As a result, the spread between work from home practices is largest in recent months. These results are consistent with the notion that workers with high ICT human capital are able to maintain a relatively high level of productivity in remote work while enjoying the cost saving benefits (such as the time for commuting to on-site work) of work from home.

To understand the driving forces for the empirical findings, we build a heterogeneous industry dynamic model. In the model, firms produce an output by operating two types of tasks: the in-person task which can only be performed on site, and the flexible task which allows for a remote work option at a cost. The in-person task only uses labor as inputs, while the flexible task makes use of both ICT human capital as well as physical capital. More important, labor productivity shocks directly affect the workers of the in-person task, while the workers of the flexible task can maintain their productivity if the firm chooses to switch to remote work for these tasks. In other words, depending on the states of the world, there could be productivity gains associated with switching to remote work, but this switch comes at a cost. In addition to the aggregate labor productivity (supply) shocks, firms also face aggregate uncertainty shocks and aggregate demand shocks. The aggregate time-varying uncertainty drives the expected recovery of the labor market and the demand conditions.

In the model, the industry heterogeneity is driven by two factors: 1) the fraction of the flexible job task in producing the output, and 2) the ICT human capital share in flexible tasks across industries. At each time, heterogeneous firms respond to aggregate shocks through their investment, hiring as well as work from home policy, depending on the level of the switching cost. The model generates heterogeneity in terms of policy responses to labor productivity shocks consistent with the data. Specifically, firms with ICT human capital share above a specific threshold find it optimal to switch to remote work in response to a labor productivity shock, while those below the threshold remain on-site. Intuitively, for a firm with a relatively high ICT human capital share, the benefits associated with maintaining labor productivity through switching to telework outweighs the fixed adoption cost. The level of this threshold is a function of the size of the aggregate productivity shocks as well as the switching cost, making firms' responses in our model consistent with firms' adoption of remote work in the pre-, during- and post-pandemic periods in the data.

Using impulse response analysis, we also show that our model generates a sizable spread in the firm value drop between industries with different ICT human capital in response to a combination of aggregate shocks, consistent with the data. Intuitively, the higher the fraction of the ICT human capital, the more flexible the industry is in smoothing the response to negative shocks by adopting remote work. Hence, the high-ICT human capital industry suffers less in terms of firm value drop because its output (cashflow) is less affected by these negative productivity shocks. On the firms' WFH adoption policies, we show that low-ICT human capital industries do not adopt remote work in response to the aggregate shock, while other firms adopt at least some degree of remote work. As the effect of the negative productivity shock dissipates, firms in the medium-ICT human capital revert back to the on-site mode, while those in the high-ICT human capital group still maintain their remote work policy as the productivity gain still outweighs the adoption costs once this adoption cost becomes lower in the post shock period.

Literature Review – This paper contributes to the fast-growing body of work on the impact of the Covid-19 pandemic on the economy and financial markets. On the economic impact of the pandemic,[2] Guerrieri et al (2020) study how negative supply shocks during a pandemic can trigger and amplify demand shocks; Chetty et al (2020) find that the drop of consumer spending in the pandemic is due to contraction in firms' ability to supply certain goods and services without health risks, rather than a reduction in consumer purchasing power (especially from the high-income households), implying that the pandemic shock is more likely to be a firm supply shock than a consumer demand shock. Our results complement their findings by showing that we can infer firms' ability to supply goods and services without health risks through the ICT that is accumulated in their human capital. In addition, our model highlights the importance of combining uncertainty shocks and labor productivity shocks in quantitatively capturing the drops in firm value and real activities observed in the data.

On the impact on financial markets,[3] Baker, Bloom, Davis, Kost, Sammon, and Vi-

[2] A non-exhaustive list of papers include Eichenbaum et al (2020a,b), Berger et al (2020), Alvarez et al (2020), Atkeson (2020a,b), Bethune and Korinek (2020), Bigio et al (2020), Caballero and Simsek (2020), Faria-e Castro (2020), Jones et al (2020), Jorda et al (2020), Kaplan et al (2020), Krueger et al (2020), Bodenstein et al (2020), Barrot et al (2020), Barro et al (2020), Fernandez-Villaverde and Jones (2020), Hall et al (2020), Glover et al (2020), Fornaro and Wolf (2020), Acemoglu et al (2020), etc.

[3] An incomplete list includes Alfaro, Chari, Greenland, and Schott (2020), Albuquerque, Koskinen, Yang, and Zhang (2020), Bretscher, Hsu, Simasek, and Tamoni (2020), Cejnek, Randl, and Zechner (2020), Gerding,

ratyosin (2020) study the stock price impact of infectious disease outbreaks over different periods based on text-based analysis of news, and identify a sizable impact associated with COVID-19 on stock prices relative to the previous outbreaks. Papanikolaou and Schmidt (2020) use the American Time Use Survey (ATUS) to measure the fraction of workers that cannot work from home and study the supply-side disruptions associated with Covid-19 across firms and workers. We complement these papers by showing that firms with greater ability to maintain their productivity through telework have outperformed their peers, as measured both in terms of their stock returns as well as bond returns. In addition, we provide a neoclassical model to understand the economic mechanism driving the empirical results.

This study is also related to the literature that studies work-from-home feasibility of US occupations and the implications of work-from-home for firms' real and financial policies during the pandemic. These papers typically use two sources of information to infer the telework feasibility, the American Time Use Survey (ATUS) and O*NET. For example, Alon, Doepke, Olmstead-Rumsey, and Tertilt (2020) use the data from ATUS in 2017 and 2018 to infer the fraction of US workers that can work from home. Dingel and Neiman (2020) use some job characteristics in O*NET surveys related to work context and work activities to construct the fraction of workers that cannot work from home. Note that ATUS captures the actual incidence of working at home but mostly reflects the practice before Covid-19 as is shown in Barrero, Bloom, and Davis (2021)). [4] In particular, the survey

Martin, and Nagler (2020), Haddad, Moreira and Muir (2020), Hassan et al (2020), Hong, Wang, and Yang (2020a,2020b), Hong et al (2020), Pettenuzzo, Sabbatucci, and Timmermann (2020), Ramelli and Wagner (2020), among others.

[4]The key differences between the ATUS and O*NET data are also noted in several papers (e.g., Dey, Frazis, Loewenstein, and Sun (2020), Mongey, Pilossoph, Weinberg (2020), Garrett and Danziger (2007)). For example, Dey et al (2020) note that O*NET job characteristics could reflect the ability to work from home while ATUS survey captures the incidence of working at home. In addition, they find that among the telework eligible workers (following the measure by Dingel and Neiman (2020)), only 11% of workers actually did telework (from ATUS), indicating a take-up rate of 25%. The comparison suggests that the ATUS survey results before the Covid-19 pandemic likely underestimate the fraction of teleworkers during the pandemic. Interestingly, Garrett and Danziger (2007) note that the BLS work at home surveys in 2004 and 2005 indicate about 15% of US non-agricultural workers work at home at least once a week but they find 37.5% of computer use workers in their survey sample did some work from home.

results by Barrero, Bloom, and Davis (2021) suggest that during the Covid-19 pandemic, 42% of US employees are full-time working from home, higher than the 15% of Americans having paid full work from home days in the 2017 and 2018 surveys before the pandemic. Barry, Campello, Graham and Ma (2021) show that the impact of the Covid-19 crisis on corporate activities varies with labor force flexibilities using the CFO survey data. Our measure of ICT human capital sheds new light on what determines firms' ability to switch to telework.

Furthermore, this paper is also related to the literature on other aspects of telework (see Bailey and Kurland (2002) for a survey). Some of the papers focus on how telework affects labor productivity. For example, Bloom, Liang, Roberts, and Ying (2014) use an experiment with Ctrip to document that working from home improves workers' performance and work satisfaction and reduces attrition rates. Viete and Erdsiek (2015) find that mobile ICT is associated with higher worker productivity in firms with more workplace flexibility. Angelici and Profeta (2020) use a randomized experiment to show flexible working space and time improves worker productivity, well-being, and work life balance. Although we do not assess the labor productivity directly, our results that high-ICT human capital industries' employment and hours do not decline as materially as low-ICT human capital peers suggest the workers in high-ICT human capital industries are able to maintain their labor productivity.

Lastly, our paper is related to the growing literature on the link between labor market frictions and financial markets.[5] Michaels, Page and Whited (2019) investigate how financing frictions affect the firm's labor decision in a structural model. Zhang (2019) studies the asset pricing implications of substitutability between automation and routine tasks. Donangelo, Gourio, Kehrig, and Palacios (2019) study the relations between operating leverage and expected stock returns. Our analysis contributes to this literature by highlighting how the

[5] The examples include Danthine and Donaldson (2002), Gourio (2007), Berk, Stanton and Zechner (2010), Berk and Walden (2013), Belo, Lin and Bazdresch (2014), Donangelo (2014), Li and Palomino (2014), Palacios (2015), Favilukis and Lin (2016a,b), Donangelo, Eiling and Palacios (2016), Belo, Li, Lin and Zhao (2017), Blanco and Navarro (2017), Donangelo (2018), Tuzel and Zhang (2019), Favilukis, Lin, and Zhao (2020), Favilukis, Lin, Wang, and Zhao (2020), Chen, Favilukis, Lin, and Zhao (2020), among others.

ICT human capital channel through remote work affects the work activities at the traditional workplace and the variations of asset returns across industries.

2 Data

In this section, we provide a description of the data used in our empirical analysis. We also explain how we construct the industry-level ICT human capital (ICTHumanCapital) measure and examine the properties of this measure.

2.1 Measuring ICT Human Capital

Our main variable of interest is an empirical measure of the firms' ICT human capital in its labor force (hereafter ICTHumanCapital), which captures the extent to which expenses associated with ICT human capital has been capitalized in the firm. Intuitively, a firm is less likely to face disruption in its production if it is more dependent on the job tasks of occupations that may be performed remotely, and ICT is an important enabler for remote exectuion of these tasts. Therefore, this measure depends on two important features of a firm's labor force: what types of occupations is the firm composed of, and to what extent the job tasks associated with each occupation depend on ICT.

Our data sources for the labor force characteristics are public datasets at the industry level. The first data source on the job composition of industries is the Bureau of Labor Statistics' Occupational Employment Statistics (OES) program, which contains information about the number of employees and their corresponding wages for each occupation for industries classified based on 4-digit NAICS industry codes. The data set is based on surveys of 200,000 establishments conducted every six-months, covering roughly 62% of non-farm establishments in the US over three-year periods.

The second data source on the job characteristics at the occupation level is the US

Department of Labor's Occupational Information Network (O*NET).[6] For each occupation, the dataset contains information about the relevance and importance of a large set of job characteristics. When merged with the OES data, we have a total of 810 occupations in 2019, classified according to the 2010 Standard Occupation Classification (SOC) taxonomy.[7]

The central component of telework is the infrastructure of information and communication technologies (ICT) that enable the work activities at alternative worksites (Garrett and Danziger (2007)).[8] We infer the ICT component of telework feasibility from the following five O*NET job characteristics that are associated with information and computers: (1) Computer and Electronics (2.C.3.a), (2) Telecommunications (2.C.9.a), (3) Programming (2.B.3.e), (4) Interacting with Computers (4.A.3.b.1), (5) Analyzing Data or Information (4.A.2.a.4).[9]

For each year, we combine the above five job characteristics that determine the ICT dependence of occupations to construct an ICT score for each occupation.[10] Of the five job characteristics that define ICT score, two are characteristics that are classified as work activities by O*NET. For each characteristic categorized as work activities, there are two categories of scores, one indicating the "importance" of the work activity for the job and the other indicating the "level" of the work activity associated with the job. The "importance" is categorized by five levels ranging from *not important, somewhat important, important* to *very important*, and *extremely important*. The "level" is typically categorized by the level of sophistication required by the work activity. We follow Blinder (2009) to use a Cobb-Douglas function to consolidate these two attributes of each work activity. Specifically, we assign a

[6]For each year, we use newly released O*NET to obtain occupation level job characteristics.

[7]We consolidate all the occupations at the 6-digit occupation codes. We merge job characteristics from O*NET to OES industry-occupation data based on the occupation code. Note that the SOC taxonomy used by O*NET and OES is not always the same and can vary over years. For datasets that do not use the 2010 SOC system, we first convert the occupation code to the 2010 SOC taxonomy using crosswalks provided by the BLS before merging O*NET to OES.

[8]In practice, an alternative worksite can be home, a telework center, or some other mobile locations.

[9]Appendix B lists the detailed survey questions used by O*NET to generate scores for each attribute.

[10]Such top-down approach of combining job characteristics and work attributes has also been used in other contexts, such as Blinder (2009), Acemoglu and Autor (2011), Jensen and Kletzer (2010), among others.

Cobb-Douglas weight of one-third to the "level" and two-thirds to the "importance" scores provided by the O*NET to achieve a single score for that job characteristic associated with a certain occupation. We then standardize the score associated with each job characteristic across all occupations.

To construct the occupation-level ICT score, we sum over all five standardized characteristic scores for each occupation and scale the resulting score to values between 0 and 10. To examine the validity of the occupation-level measure of ICT dependence, we list in Table 1 occupations with the highest and lowest ICT scores in 2019. Occupations with high ICT scores, as expected, are those such as "Computer Network Architects" or "Computer Programmers" which typically have as requirements extensive work with computers and data, an attribute that naturally enables remote execution of the tasks associated with occupations. In contrast, occupations with low ICT scores are those such as the "Models", or "Tapers", which do not have much reliance on computers and its related technologies.

[Table 1 about here]

We construct the industry-level measure for the stock of ICT human capital by first cumulating the labor expenditure associated with ICT occupations for each industry using the perpetual inventory method. To this end, for each year we classify those occupations that are in the upper 10% of all occupations in that year in terms of ICT score as "ICT occupations".[11].

We then merge this ICT occupation identifier, denoted by $\mathbb{1}_{(ICT_{j,t})}$, with the OES industry-occupation data in that year, and apply the perpetual inventory method to find the ICT human capital ($ICTHumanCapital_{i,t}$) for each industry i and year t. This process involves

[11] Our main results are robust to alternative thresholds for this classification. Moreover, there is a 65% overlap between our set of ICT occupations and those defined by Tambe, Hitt, Rock and Brynjolfsson (2020), implying the consistence between or classification and the classifications used in other studies. Importantly, when constructing our ICTHumanCapital measure based on the occupation-level classification of ICT jobs proposed by Tambe et al (2020), the results are consistent with our main results.

recursively constructing the stock of ICT human capital for each industry-year by cumulating the deflated ICT labor expenditure over the previous years. More specifically, for each industry i in year t, $ICTHumanCapital_{i,t}$ is calculated as

$$ICTHumanCapital_{i,t} = (1 - \delta_0) \times ICTHumanCapital_{i,t-1} + \frac{ICTLaborExp_{i,t}}{cpi_t} \quad (1)$$

where δ_0 is the depreciation rate of ICT human capital, cpi_t is the consumer price index in year t, and $ICTLaborExp_{i,t}$ is the labor expenditure associated with ICT occupations in industry i in year t. That is,

$$ICTLaborExp_{i,t} = \sum_j \mathbb{1}_{(ICT_{j,t})} \times LaborExp_{i,j,t} \quad (2)$$

where $LaborExp_{i,j,t}$ is the aggregate labor expenditure associated with ICT occupations in industry i and year t. Throughout our analysis, we use a value of 25% for the depreciation rate δ_0. [12]

For each industry i, the initial stock of ICT human capital is calculated following Eistfeldt and Papanikolou (2013) based on

$$ICTHumanCapital_{i,0} = \frac{ICTLaborExp_{i,1}}{g + \delta_0} \quad (3)$$

where g is the average rate of growth in real ICT wage expenditure over the entire sample across all industries.[13] The above recursive procedure then obtains the value of ICT human capital in each year. Our final measure of $ICTHumanCapital$ is created by scaling each year's $ICTHumanCapital$ for each industry by the number of employees in that industry.

[12] Our results are robust to alternative values of δ_0.

[13] The starting year in our sample is 2003. One reason is that O*NET data before and after 2002 were collected using different methodology. The other reason is that the year 2002 is the year that BLS started using NAICS codes to classify industries in the OES dataset. This choice is to maintain consistency across years over which we define ICT jobs and calculate industry-level ICT labor expenditure.

This is to make sure that the cross-sectional variations in ICT human capital is not driven by the size of the industry.

Table 2 shows the list of industries with the highest and lowest values of ICTHuman-Capital in 2019. Consistent with intuition, industries such as the "computer and peripheral equipment manufacturing" and "software publisher" are ranked among those with the highest ICT human capital in their labor force, as these are industries in which there is a great concentration of human capital associated with ICT. Conversely, the resulting ICTHuman-Capital score for industries such as "gasoline stations" and "restarants" is among the lowest, consistent with our intuition that there is minimal reliance on ICT related tasks, and hence, relatively low accumulation of ICT human capital in these industries.

[Table 2 about here]

2.2 Asset Returns and Employment

Daily stock returns are from the Compustat North America Security Daily data file. Our benchmark analysis focuses on the US firms (FIC = "USA") that have common shares (TPCI= 0), and are traded on NYSE, AMEX, and NASDAQ (EXCHG= 11, 12, or 14). We keep the primary issue of each company (IID = PRIUSA), and exclude firms in the financial (NAICS = 52) and energy (NAICS = 21) sectors.[14] The security data for Canada is also from Compustat North America daily file. The data for the other G-7 countries (Germany, France, United Kingdom, Italy and Japan) is from Compustat Global Security Data file. We use similar filters for the other G-7 countries as in the US sample. The data on the daily bond returns are obtained from Enhanced TRACE and the data cleaning process follows Dickerson, Philippe and Robotti (2023). We derive information on workers' employment, hours and earnings at the monthly frequency from the Current Employment Statistics (CES)

[14]We remove energy sector from our analysis to minimize the impact of the oil price war in March 2020 that was started not necessarily because of the Covid-19 pandemic.

dataset at the BLS.

2.3 Work From Home Measures

Throughout our study, we explore the extent to which ICT human capital explains variations in work from home and its relationship with asset returns. To this end, we utilize several WFH measures from the literature as benchmarks, and analyze the correlation between the pre-pandemic values of these measures with that of our ICT human capital measure.

We start by constructing Dingel and Neiman's (2020) WFH measure, which is based on a set of occupation-level attributes that the authors ascribe to the possibility of the tasks associated with a job to be performed remotely. Specifically, the occupation-level measure of tele-workability is obtained by taking the weighted average of the scores associated with 7 "Work Context" and 8 "Generalized Work Activity" job attributes from the O*NET. We define WFHDN for each industry as the employment-weighted average of the teleworkability measure across occupations within the industry. Next, we construct WFHPS following Papanikolaou and Schmidt (2021), as the industry exposure to Covid based on the American Time Use Survey. Occupations are identified as "able to work from home" based on their response to two related questions in the ATUS. The industry-level measure of work from home is constructed by aggregating the individual-level responses within industries. A number of manual adjustments are executed to account for the forced closure of a number of industries during the pandemic. Our last alternative WFH proxy is constructed following Mongey, Pilossoph and Weinberg (2020) who also use the ATUS microdata. The aggregate based on this method is defined using share of work hours that are spent at home form the survey.

In addition to the above mentioned three pre-pandemic WFH measures, we also explore how ICT human capital affected WFH policies during and post-pandemic across industries depending on their ICT human capital. For this purpose, we take advantage of the updated survey results published by Barrero, Bloom and Davis (2021), which provide insights into the practice of WFH across industries in the economy.[15]

3 Empirical Results

In this section we document the relationship between ICTHumanCapital and other WFH measures, and present our main findings on the cross-sectional relationship between ICTHumanCapital and industry equity and bond returns in the wake of the Covid-19 pandemic and its aftermath. We also investigate if the differential effect of the shock is explained by other components of WFH than its ICT component. Moreover, we extend the ICTHumanCapital-return analysis to other G-7 countries as an out-of-sample exercise. Finally, we show that the ICTHumanCapital explains variation in the practice of work from home across industries even after the Covid-19 pandemic.

3.1 Relationship between ICT human capital and WFH

A key observation from the results in the Table 2 is that most tasks associated with the occupations in these industries can effectively be fulfilled through telework, particularly in response to a pandemic. Similarly, job tasks in the lowest-ICT human capital group are much more difficult, if not impossible, to perform through telework. Therefore, it would be interesting to examine how strongly ICTHumanCapital is related to the ex-ante measures of work from home, and more importantly, to what extent does ICT human capital explain variations in these WFH measures. In this regard, we conduct a cross-sectional regression of WFH, as measured based on Dingel and Neiman (2020), Papanikolaou and Schmidt (2021), and Mongey, Pilossoph and Weinberg (2020), on our ICT human capital measure:

[15] We thank the authors for making the data publicly available.

$$WFH_i = b_0 + b_1 \cdot ICTHumanCapital_i + f_s + \epsilon_i \quad (4)$$

The results are provided in Table 3. Across all specifications with different WFH measures, we find that the coefficient associated with ICTHumanCapital is positive and significant, indicating that higher ICT human capital is associated with more likelihood of working from home across industries. One standard deviation in ICTHumanCapital is associated with 29.6% (=20.996×0.005/0.355) rise in WFHDN, 16.7% (=20.996×0.010/1.258) rise in WFHPS and 19.8% (=20.996×0.001/0.106) rise in WFHATUS (columns 2, 4 and 6). Moreover, the R^2 resulting from this regression is quite significant, ranging from 0.408 to 0.482. This translates to univariate correlation coefficients between 0.6 and 0.7, suggesting that for the commonly used WFH measures used in previous studies, a large part of variations are driven by ICT human capital.

[Table 3 about here]

Importantly, this relationship is even stronger when we control for the sector fixed effect, with sectors being defined based on the 2-digit NAICS industry codes. This suggests that this positive relationship is unlikely to be driven by variations in characteristics that differentiate firms at the sector-level.

3.2 ICT human capital and firm dynamics during the pandemic

Did firms' ICT human capital influence how firms and their asset prices reacted to the pandemic shock? We address this question by studying U.S. firms' equity and bond returns in the few months of the pandemic. We then extend this analysis to international equity markets. Lastly, we examine firms' employment policy as the pandemic unfolded.

3.2.1 ICT Human Capital and Stock Returns during the Pandemic

In this section, we study how prices of assets vary across firms with different levels of ICT human capital during the height of the pandemic. Based on our hypothesis, firms that entered the pandemic while possessing greater ICT human capital were allowed an option to telework for their subset of tasks that could be done remotely. This allowed them to maintain their productivity at the pre-pandemic levels for this subset of tasks, resulting in a higher valuation for stocks and bonds for these firms relative to firms with lower levels of ICT human capital in response to the pandemic shock. We verify if this is indeed the case by first comparing the cumulative returns of portfolios of stocks for the set of industries with the various levels of ICTHumanCapital. Specifically, we form industry portfolios by grouping firms based on their 4-digit NAICS codes while excluding those industries with fewer than five publicly-traded firms to mitigate the effect of firm-level idiosyncratic risks. For the remaining industries, we calculate the daily return for each industry as the value-weighted average of the returns of its constituent firms using most recent end-of-day market capitalization as weights. We then calculate each industry's cumulative returns from January 1, 2020 until May 31, 2020. We sort the industries into three groups within each 2-digit NAICS industry based on the value of their ICTHumanCapital scores at the end of 2019: those in the highest ICTHumanCapital quintile, those in the lowest ICTHumanCapital quintile, and those in the middle 60% of industries in terms of ICTHumanCapital. We compare the average cumulative returns across these industry groups over time. The results are illustrated in Figure 1. We find that the return spread between high- and low-ICTHumanCapital quintiles is small in the month of January 2020. Consistent with our hypothesis, this spread, however, becomes sizable starting in late February 2020 when it became more evident that the Covid-19 is likely to be a real threat to the US public health, suggesting the return spread is largely due to the Covid-19 shock. Then we see a steady increase in the cumulative return spread between the high-ICTHumanCapital and low-ICTHumanCapital quintiles, clearly suggesting that industries in high-ICTHumanCapital outperformed their low-ICTHumanCapital peers when the pandemic shock was still in effect.

[Figure 1 about here]

Given the positive correlation between ICTHumanCapital and other WFH measures that we identified in Section 3.1, a potential concern with the above interpretation is that the observed return spread is driven by other components of WFH that also facilitate the remote exectuion of tasks. To the extent that the scores associated with these non-ICT job attributes are correlated with the ICT score across occupations, we could still see this positive relationship between ICTHumanCapital and cumulative returns. To address this concern, we run a cross-sectional regression of cumulative returns during this period on industries' ICTHumanCapital while controlling for the component of WFH that is driven by industry properties other than ICTHumanCapital that contribute to WFH. In particular, we run a regression of the form

$$CumRet_i = b_0 + b_1 \cdot ICTHumanCapital_i + b_2 WFH_i(res) + f_s + \epsilon_i \tag{5}$$

where $CumRet_i$ is the cumulative stock returns for industry i over the period between January 1, 2020 and May 31, 2020, and f_s is the sector fixed effect. The term $WFH(res)$ is obtained by regressing WFH on ICTHumanCapital, where WFH is based on the three measures discussed in Section 2.3:

$$WFH_i = c_0 + c_1 \cdot ICTHumanCapital_i + f_s + WFH_i(res). \tag{6}$$

The results are presented in Table 4. Consistent with the results in Figure 1, the coefficient associated with ICTHumanCapital shown in columns (1) and (2) are positive and significant, suggesting that higher ICTHumanCapital positively predicts cumulative stock returns in the cross-section of industry portfolios over this period. The magnitude of the coefficient suggests that one standard deviation increase in ICTHumanCapital is associated with a sizeable 6% increase in the cumulative stock returns over this 5-month period. More importantly, this coefficient remains positive and significant even after we control for the residual component of WFH (i.e. $WFH(res)$) in this regression. In particular, the results in columns (3) through (8) show that in the bivariate regression with ICTHumanCapital and the residual components of the WFH measure, the coefficient associated with ICTHumanCapital remains significant and positive. This suggests that the predictive relationship between WFH and stocks returns that has been identified in previous studies is largely driven by ICT human capital. The predictive power of the residual component in this specification varies depending on the WFH measure used in the regression. Interestingly, when WFH measure is constructed based on Dingel and Neiman (2020) and Mongey, Pilossoph and Weinberg (2020), the coefficient associated with WFH loses its significance as a positive coefficient (as shown in columns (3)-(4) and (7)-(8), respectively). This is the case in the presence or absence of a control for the sector fixed effect, implying that the results are not driven by cross-sector variations in ICT human capital and WFH.

[Table 4 about here]

3.2.2 ICT Human Capital and Bond Returns during the Pandemic

Do the relationship between ICT human capital and cumulative stock returns during the pandemic extend to other asset classes? We answer this question by examining the cumulative bond returns for industries with different values of ICT human capital. To the extent that the pandemic shock has had differential effects on firms' ability to maintain their productivity, it should also affect the likelihood that they will meet their financial obligations, and hence it should deferentially impact value of their bonds. To show this, we repeat the analysis conducted in Section 3.2.1 by sorting industries within their corresponding sectors into groups based on the level of their ICT human capital and comparing their cumulative bond returns over the period between January 2020 and May 2020. The results are provided in Figure 2. Similar to our findings on how stock returns behaved during this period, we find that the bonds associate with the group of industries in the highest 20% of ICTHumanCapital outperformed their peers in the lowest quintile by 143.5% (=(0.030-(-0.069))/0.069) in the end of May 2020 in terms of the cumulative return since January 2020. This spread has only started to become significant during March 2020 when the market recognized the pandemic as a risk to the creditworthiness of companies, and has persisted at almost the same level until May 2020.

[Figure 2 about here]

Next, we examine if the extent to which ICT human capital explains cumulative bond returns is driven by other components of WFH. To this end, we use the estimated residuals from Equation 6 as control variables in a regression of cumulative bond returns from January 2020 to May 2020 on ICTHumanCapital. The results are presented in Table 5. Similar to our results on the predictive relationship between ICTHumanCapital and stock returns, regressing $CumRet_i$ on the ICTHumanCapital confirms that the positive ICTHumanCapital-return relationship holds in the regression setting, consistent with our previous portfolio analysis. In columns (3) to (8), we show the results of regressing $CumRet_i$ on ICTHumanCapital as well as the residual component of WFH. Across all specifications based on the three different WFH measures, we find that the coefficient associated ICTHumanCapital remains significant, while the residual WFH term remains insignificant. For example, when we use WFH measure based on Dingel and Neiman (2020), the coefficient for ICTHumanCapital is 0.0005 (t-ratio= 2.31) without controlling for the sector fixed effects, and 0.0016 (t-ratio= 2.06) when controlling for the sector fixed effects. In columns (5)-(6) as well as (7)-(8), we find similar results when using Papanikolaou and Schmidt's (2021) and Mongey, Pilossoph and Weinberg's (2020) WFH measures, respectively. The results confirm that the ICT component of WFH is the main driver of the cross-sectional industry bond returns during the Covid-19 pandemic.

[Table 5 about here]

3.2.3 International Evidence of ICT Human Capital-Return Relationship

Our benchmark empirical analysis focuses on the US firms based on a ICTHumanCapital measure using the occupational composition of industries in the US. Do these findings hold in other countries that were economically affected by the pandemic? Are there differences in the magnitude of the identified return spread depending on the severity of the shock caused by the pandemic? To answer these questions, we evaluate industry returns in the G-7 countries (other than the US) in an out-of-sample analysis, where we utilize the ICT human capital measure based on the US occupational composition of industries. In other words, we evaluate the relation between equity returns for industries in these countries and their corresponding ICT human capital, assuming that the ICT human capital value for each industry is the same as its US counterpart. To this end, for each country we find the equity returns for each 4-digit NAICS classified industry portfolio by calculating the market cap-weighted average of the equity returns for firms in that industry and merge it with the ICT human capital of the same industry in the US. Similar to our analysis for the US, sectors are also defined as firms with common 2-digit NAICS code.

We begin by comparing the stock performance of firms in industries with different values of ICT human capital. To this end, we run regression of the industry cumulative returns on their ICT human capital. In particular, we run the regressions for each individual country to understand the potential impact of the pandemic severity on the ICTHumanCapital-return relationship. The regressions take a similar form to the one used in the US analysis:

$$CumRet_{i,c} = b_0 + b_1 \cdot ICTHumanCapital_i + f_s + f_{c,s} + \epsilon_i \tag{7}$$

where $CumRet_{i,c}$ is the cumulative return of industry i in country c, and $ICTHumanCapital_i$ is the ICT human capital for industry i using corresponding measures from the US sample.

The countries in this regression include the G-7 countries other than the US: Canada, Germany, France, United Kingdom, Italy and Japan. We also control for various fixed effects. In particular, f_s is the sector fixed effect (if included) and $f_{c,s}$ is the country-sector fixed effect (if included).

We first report the results of combining all countries in the same regressions in Panel A of Table 6. Starting with a specification with no fixed effects in column (1), we find that b_1 has a positive value of 0.002 with a t-ratio of 3.29, suggesting that industries with higher ICTHumanCapital, on average, have had a better performance relative to their low-ICTHumanCapital counterparts. Our results remain very similar when we include country-sector fixed effects in column (2) to address the concern that this relationship might be driven by outperforming sectors in countries with greater concentration of high-ICTHumanCapital industries.

[Table 6 about here]

Consistent with our results of the U.S. indsutries, we find that controlling for the residual component of WFH relative to ICT human capital does not make anu significant change to our regression results. Specifically, as presented in Columns (3) to (8), for each of the three WFH measure, the coefficient associated with the residual term is hardly positive and significant, while the predictive relation between industry portfolio returns and ICTHumanCapital remains positive and significant. Altogether, these results suggest that the ICT human capital is the main driving force behind the positive WFH and return relationship not only in the U.S., but also in other countries.

In Panel B of Table 6, we compare the ICTHumanCapital-return relation across countries by running the above regression on subsample of industries belonging to each country. Among the western countries, we find that the ICTHumanCapital-return relation is weaker for Canada, UK, Japan and Germany and much stronger in France and Italy. This pattern is consistent with the pandemic severity measured by death rate per 100,000 people. Germany and Canada have the lower death rate among the western G-7 countries whereas France and Italy have much higher death rate.[16] These results suggest that the pandemic severity affects the labor supply disruption which amplifies the return spread associated with the ICT human capital.[17]

We further investigate how the return spread associated with the ICT human capital was affected by the pandemic severity. To this end, we run the following regression:

$$b_{ICT,c} = b_0 + b_1 \cdot Intensity_c + \epsilon_i$$

where $Intensity_c$ is the intensity of the pandemic in country c, measured as the logarithm of the infection rate (death rate) per hundred thousand population. The left-hand side variable in this regression, i.e.$b_{ICT,c}$, is obtained from the regression in equation 7 for each country c. The results are presented in Table 7.

[Table 7 about here]

Consistent with our finding in Table 6, we find that the return spread associated with the ICT human capital, as represented by $b_{ICT,c}$ is positively related to the severity of the pandemic across countries.[18] Specifically, when the $b_{ICT,c}$ is estimated without sector fixed effect, the coefficient associated with the infection rate (death rate) is equal to 0.023 (0.025) with a t-statistics that equals 1.75 (2.62). When controlling for the sector fixed effect, the coefficient associated with the death infection rate (death rate) increases to 0.049 with a t-statistics of 1.95 (0.043 with a t-statistics of 2.23). Overall, the results corroborate our previous findings on the importance of labor market disruptions that result from the

[16] This is based on the BBC news article (https://www.bbc.com/news/business-53222182) that reports the Covid-19 death rate in the 11-week periods for each nation as the virus hit its peak in each country.

[17] The pandemic severity could affect the labor supply either due to the corresponding government lock down policies or infection uncertainty faced by the labor force.

[18] We obtain the pandemic death and infection data from Our World in Data by Oxford University (https://ourworldindata.org/).

pandemic as a determinant of the magnitude of the return spread associated with the ICT human capital.

3.2.4 ICT human capital and Labor Policy during Pandemic

Our analyses above suggest a significantly positive ICTHumanCapital-return relationship. In this subsection, we analyze the effect of ICT human capital on firms' labor policy including changes in employment, hours worked and weekly earnings. To this end, we compare the changes in these measures between the January 2020 and May 2020. In particular, we run the following cross-sectional regression of the industry-level labor outcomes on ICTHumanCapital, and present the results in Table 8:

$$Y_i = b_0 + b_1 \cdot ICTHumanCapital_i + f_s + \epsilon_i \tag{8}$$

where Y_i is the labor outcome, including cumulative growth in employment (columns (1) and (2)), growth in hours worked (columns (3) and (4)), and growth in weekly earnings (columns (5) and (6)). We see that industries with higher ICT human capital experienced higher employment growth and hours worked during this period. This is consistent industries with higher ICT human capital have an option to maintain their productivity, and hence labor as a production factor, by switching to work from home for a larger fraction of their tasks.

[Table 8 about here]

3.2.5 Further analysis

To further establish that the effect of ICT human capital on stock returns is through its impact on the work from home capability of a firm's workforce, we use a staggered difference-in-differences design and study how firm stock returns are affected when the on-site operation of its tasks is deemed unsafe. We then compare this effect for firms with different levels of

ICTHumanCapital. To the extent that ICT human capital enables telework for the firm, a higher level of ICT human capital results in a less severe loss of productivity, and hence a smaller drop in its stock price when the risk of on-site work escalates. Following Hsu, Bretscher, Simasek and Tamoni (2020), we consider event day in this setting to be the date of the first confirmed case of the infection in the county in which the firm's headquarter is located, where the information on the number of cases for each county in the U.S. is obtained from the *New York Times*. Locations of firms' headquarters are obtained from Compustat (*addzip*). Specifically, we run the following difference-in-differences regression

$$log(Return)_{ijct} = b_0 + b_1 Treat_{ct} * ICTHumanCapital_{jt} + b_2 Treat_{ct} + f_i + f_t + \epsilon_{it}. \quad (9)$$

where $Return_{ijct}$ is the daily (gross) stock return of firm i from industry j headquarter in county c at time t. Our sample period is from January 1, 2020 to May 30, 2020. To make sure that we do not capture the impacts of events other than Covid-19, for each treated firm, we exclude the data 10 days after the county the firm is located in is first hit by Covid-19. In this regression, b_1 is the coefficient we are interested in. The results are reported in Table 9. Column (1) shows that, on average, a firm experiences a negative return when its host county is affected by Covid-19. This is expected, since the implication of this news is that the firm's workforce are likely to have to shelter in place, leading to a loss of productivity for the firm. More interestingly, the coefficient b_1 in Column (2) is positive and significant, suggesting that for firms with higher ICT human capital, the drop in firm value is more moderate.

[Table 9 about here]

A potential concern with our results so far is that the identified effect of ICT human capital is driven by the possibility that industries with higher ICT human capital are also those with better internet connection. Therefore, it is really the better internet connection that drives our results, as opposed to the ICT human capital that is embedded in the firm's workforce. To address this concern, we add a proxy for the internet quality as a control variable in our baseline regression in Equation 7 for the stock returns. The internet quality is measured as the fraction of the time that internet works, which is obtained from the U.S. Survey of Working Arrangements and Attitudes (SWAA) (Barrero, Bloom and Davis, 2021). We aggregate the survey questions to the sector-state level and take the average across months within each year.

The results, presented in Panel A of Table 10, show that after controlling for the internet quality, ICT human capital remains positive and significant across all specifications with the three alternative WFH measures.[19]. Similarly, when we construct the cumulative returns (the left-hand-side variable) based on U.S. bond returns over this period, the results are similar as reported in Panel B. Lastly, Panel C shows that the results also extend to international equity market. Overall, we find the results in this table shows that the variations in cumulative asset returns in response to the pandemic is unlikely to be driven by the internet quality.

[Table 10 about here]

3.3 ICT human capital and Firms' Behavior in post-Pandemic

In the previous section, we studies how ICT human capital shaped firms' employment policy and asset prices during the course of the pandemic. This was to show how ICT human capital enables firms to switch to performing their tasks remotely in response to emergency shocks that hamper productivity of labor on-site. In this section, we study the extent to which firms employment policy and asset returns were affected by ICT human capital when the economy started to shifted away from the health risks associated with in-person contact.

We start by examining the time series variations in the cumulative employment and hours growth across basket of industries in the high- and low-ICTHumanCapital quintiles.

[19]The sample size decreases compared to our main specification where we do not control for the internet quality because internet quality data is not available for all industries.

In Section 3.2.4, we found that the growth in firms' employment and hours had a positive relationship with their ICT human capital in the first 5 months of 2020. This is what we observe in Figure 3, which presents the variations in firms' hiring behavior for the three groups of industries sorted by their ICT human capital. In the period from January to May 2020, employment and hours were reduced across all groups of industries. This reduction was less pronounced for the high-ICT human capital industries, as they could maintain a large part of their productivity by adopting telework. As the health risk associated with the pandemic subsided, employment and hours started to revert back to their pre-pandemic levels, although the gap between high-ICTHumanCapital and low-ICTHumanCapital industries never shrank to zero. In light of the trends observed in this figure, an important question is that to what extent are the tasks associated with this recovered employment performed remotely across industries with different levels of ICT human capital.

[Figure 3 about here]

To answer this question, we study the extent to which the work-from-home practice was sustained in the months following the pandemic. While there are benefits associated with telework even after the pandemic, firms would have to incur a cost in order to switch to telework for their tasks. As a result, firms face a tradeoff between this adoption cost and the benefits associated with telework. For firms with relatively higher ICT human capital, benefits are more likely to outweigh the costs. Therefore, post-pandemic, we expect that WFH practice is more persistent for high-ICTHumanCapital firms relative to their low-ICTHumanCapital peers.

Our first set of results in support of this prediction is based on a portfolio sort of industries into groups based on their ICT human capital and tracking their WFH practice over time. To this end, we take advantage of the updated SWAA survey data provided by Barrero, Bloom, and Davis (2021), which includes information about the percentage of full days worked from home. The survey data starts in May 2020 and is updated every month since then (except for June 2020). In order to match WFH measure with ICTHumanCapital, we aggregate respondents' responses to the state-sector level for each month (the most detailed industry information provided by SWAA survey is at the NAICS sector level). The way to construct state-sector level ICT human capital is the same as before, except for that here we need to capitalize labor expenses at the state-sector level. The state-sector level employment and labor expense data are obtained from OES as before.

In particular, similar to our tests in Section 3.2.1, we rank each combination of states and sectors into three groups based on their ICT human capital measured at the end of the previous year: high-ICTHumanCapital, which consists of state-sectors that are in the highest 20%, low-ICTHumanCapital, which consists of state-sectors that are in the lowest 20%, and the remaining middle 60% state-sectors that we name medium-ICTHumanCapital. Then, for each group, we calculate the average percentage of paid full days worked from home in each month from May 2020 until April 2023. We take a 4-month moving average of the work from home measure (current month and previous three months) to avoid the noises in measurement[20]. The results are presented in Figure 4. Consistent with our hypothesis, work from home practice varies quite substantially even in the post-pandemic period. In particular, comparing the percentage of paid full days worked from home in the high-ICTHumanCapital (solid blue line) with that of the low-ICTHumanCapital (green dashed line), we find that there is a sizeable difference of as much as 27% (44% vs 17%) between the WFH practice between the two groups at the end of our sample period. This suggests that while the practice has receded for all group of industries as the health risk associated with the pandemic has eased, firms in the high-ICTHumanCapital have maintained this practice to a relatively larger extent. Moreover, comparing the trends over the period after December 2021 (post-pandemic) with those before that time (during the pandemic), we find that

[20] In particular, the survey question about WFH changed in November 2020. Before November 2020, the question was "Currently (this week) what is your work status?", and in November, the survey switched to a three-question structure that yields more granular data on the extent of WFH (Barrero, Bloom and Davis, 2021).

the WFH practice has been relatively stable at a high level for the high-ICTHumanCapital group post-pandemic, whereas for the low-ICTHumanCapital group, there is a downward trend in this practice during this period. This is because for the latter group of firms that have lower ICT human capital, the benefits associated with WFH practice dwindles in the post-pandemic period.

[Figure 4 about here]

To make sure that the observed gap in WFH across ICTHumanCapital groups are not driven by unobserved heterogeneities across sectors or states, and that it is stable across all months in the sample, we formally test the relationship between ICTHumanCapital and work from home practice in the following regression setting:

$$WFHBBD_{it} = b_0 + b_1 \cdot ICTHumanCapital_{it} + f_s + f_{st} + f_t + \epsilon_i \tag{10}$$

where $WFHBBD_{it}$ is the proxy for the realized WFH, measured as the percentage of paid full days worked from home for each month t over the period from May 2020 to April 2023 for the state-sector i, while $ICTHumanCapital_i$ is the the ICTHumanCapital in the same state-sector. Also, f_s is used to represent the state, the 1-digit NAICS sector or the 1-digit NAICS sector-state fixed effect, while f_t represents month fixed effect. The results are reported in Panel A of Table 11. Column (1) presents the results when we include no fixed effect in the specification, equivalent to comparing state-sector groups across their entire pools. We find that the coefficient associated with ICTHumanCapital is 0.497 with a t-ratio of 17.98, implying 21% increase in work from home practice for each standard deviation increase in ICTHumanCapital (note that the average value for this value in our sample is only 35%). When we control for sector (sector-month) fixed effects in columns (2) and (3), the coefficient drops to 0.229 (0.199) while still remaining statistically significant with a t-ratio that equals 7.84 (7.04). This suggests that while part of the predictive power of ICTHumanCapital for the WFH practice stems from heterogeneities across sectors, this relationship still remains positive and significant when comparing such practice across states within sectors. This observation also holds when we include the state fixed effect, state-month fixed effect, 1-digit NAICS sector-state fixed effect, and even 1-digit NAICS sector-state. Overall, the conclusion that we can derive from this experiment is that even after the pandemic had peaked in May 2020, firms with higher ICT human capital have found it optimal to maintain their telework practices to a greater extent relative to their peers that have a lower ICT human capital.

[Table 11 about here]

Next, we examine the extent to which the observed gap between the WFH practice between high- and low-ICTHumanCapital industries is compared in the period post-pandemic period relative to the period when the risk associated with the pandemic was still current. For this purpose, we interact ICTHumanCapitalin 10 with a dummy variable ($Post_t$) that is equal to one for periods after December 2021. The results reported in Panel B of Table 11 indicate that the coefficient associated with the interaction term is positive and significant. This corroborates the observed patterns in Figure 4 which imply that the WFH practice in industries with higher ICTHumanCapital has consistently surpassed those of industries with lower ICTHumanCapital, with a notable escalation in this difference during the post-pandemic period. In light of our hypothesis, this is exactly what we expect: for firms with high ICTHumanCapital the benefits associated with enhanced productivity resulting from WFH exceeds the costs associated with this practice. As a result, industries with higher ICTHumanCapital maintain WFH at a relatively higher level, while those with lower ICTHumanCapital switch back to the on-site mode for a greater share of their tasks.

In our last set of tests, we evaluate the dynamics of asset prices in the post-pandemic period. Admittedly, studying the asset price dynamics over a long period is a rather difficult task, as there could be many factors other that the pandemic that can have a differential effect on prices of assets. As shown before, the effect of the pandemic was strongest from

January to May 2020. Following this period, when the initial effect of the pandemic waned, firms started to regain their productivity through hiring. This, altogether resulted in greater revenue for these firms in the future, an effect that was reflected in their asset prices.

[Figure 5 about here]

For bonds, we see that post-pandemic, the values associated industries in the three ICT human capital groups started to converge, mainly driven by the improvements in the low-ICT human capital firms' likelihood of default as they gained productivity.

[Figure 6 about here]

4 A Model with Multiple Tasks

In this section, we develop a stochastic dynamic firm model with aggregate labor productivity shocks, uncertainty shocks, demand shocks and multiple production tasks to understand the empirical findings, and perform counterfactual analyses.

4.1 Setup

There are two types of tasks: the first type requires in-person contact (denoted as in-person task), while the second type of task is flexible task (denoted as flexible task) which provides firms a choice to switch from the current work mode to remote work. The ability to switch to remote work depends on the technology of the task. If a task uses ICT (digital) human capital in the production technology, which is portable, then this task allows for an option to switch to remote work. For simplicity, the in-person task only requires labor as the input to produce an output, hence it is not able to switch to remote work. The flexible task uses both ICT human capital and physical capital in the production technology, and hence are able to switch to remote work if necessary, but this option incurs fixed switching costs, which capture all kinds of costs that are associated with switching to remote work.

Furthermore, there are two sources of heterogeneity in the model: the first is the cross-time differences in the transition dynamics and the magnitudes of aggregate shocks, and the adoption cost of remote work before, during and post the pandemic; the second is the difference in ICT human capital share in the flexible task and the share of the flexible task in the output production function.

The cross-time heterogeneity captures the fact that dynamics of aggregate shocks and the cost of remote work change through the course of pandemic. The cross-group heterogeneity captures the fact that firms have different technology in terms of the role of ICT human capital and the importance of flexible task in the production process. We identify the cross-time and cross-firm heterogeneity by using both asset pricing and quantity moments across firms and over time.

4.2 Technology

In this section, we discuss the details of the technology of in-person and flexible tasks.

In-person task

The technology for the in-person task for an industry j is given by

$$Y_{j,t}^{In} = S_t L_{j,t}, \tag{11}$$

where Y_t^{In} is the output of in-person task, $L_{j,t}$ is labor. We will suppress the industry index j whenever no confusion is resulted. The variable S_t is the aggregate labor productivity, and its dynamic process will be detailed in Section 4.3

The law of motion of labor is given by

$$L_{t+1} = (1 - \delta_l) L_t + H_t, \tag{12}$$

where δ_l are labor exit rate, and H_t labor hiring in in-person task.

Flexible task

Flexible task allows for an option to remote work but with a fixed adoption cost. If firms switch to remote work, their labor productivity will remain high and not be affected by the pandemic shock (the low state of the labor productivity in the model). Let $\phi_t = 1$ denote switching to remote work and $\phi_t = 0$ denote not switching, the technology of the flexible task is as follows:

$$Y_t^{Fl} = \begin{cases} \left(\mu\left(\hat{S}_t N_t\right)^{\xi} + (1-\mu)\left(K_t\right)^{\xi}\right)^{\frac{1}{\xi}}, & \text{if } \phi_t = 1 \\ \left(\mu\left(\check{S}_t N_t\right)^{\xi} + (1-\mu)\left(K_t\right)^{\xi}\right)^{\frac{1}{\xi}}, & \text{if } \phi_t = 0 \end{cases} \tag{13}$$

where Y_t^{Fl} is the output of task 2, N_t is the ICT human capital and K_t is the physical capital, μ is the share of the ICT human capital and ξ determines the elasticity of substitution between ICT human capital and ICT physical capital in task 2. $\hat{S}_t$ and $\check{S}_t$ are productivities of ICT associated with switching and non-switching.

To switch to remote work, the firm needs to pay adoption costs of f. The switching cost is

$$\Psi_t = \begin{cases} f & \text{if } \phi_t = 1 \\ 0, & \text{if } \phi_t = 0 \end{cases}. \tag{14}$$

The law of motion for ICT human capital and physical capital follows

$$N_{t+1} = (1 - \delta_n)\, N_t + O_t, \tag{15}$$

$$\text{and } K_{t+1} = (1 - \delta_k) K_t + I_t, \tag{16}$$

where O_t and I are the investments in ICT human and physical capital, respectively.

Revenue

Firms use both the in-person and the flexible tasks to produce the output (Y_t). The production function is a Constant-Elasticity of Substitution (CES) technology, given by

$$Y_t = \left[(1 - \varphi) \left(Y_t^{In}\right)^{\rho} + \varphi^{j} \left(Y_t^{Fl}\right)^{\rho}\right]^{\frac{1}{\rho}}, \tag{17}$$

where the parameter $0 < \varphi < 1$ is a constant that determines the fraction of output produced by the flexible task, and $1/(1 - \rho)$ determines the elasticity of substitution between the two tasks. Note that the fraction of output produced by different tasks varies across industries, which captures a key heterogeneity in the model in addition to industry-specific shocks. The firm faces an isoelastic demand curve with elasticity (ε),

$$Y_t = X_t \left(P_t\right)^{-\varepsilon}, \tag{18}$$

where X_t is the stochastic demand condition, which captures demand changes during the pandemic, e.g., workers lose their jobs and hence cut their expenditures in services and products, which leads to a demand drop for the output of the affected industry. These can be combined into a revenue function $E_t = X_t^{1/\varepsilon} \left(Y_t\right)^{1-1/\varepsilon}$ given by,

$$E_t = X_t^{1/\varepsilon} \left[(1 - \varphi) \left(Y_t^{In}\right)^{\rho} + \varphi \left(Y_t^{Fl}\right)^{\rho}\right]^{\frac{1-1/\varepsilon}{\rho}}. \tag{19}$$

Firms' maximization problem

Firms' dividend in the industry is defined as revenue in excess of wage expenses in the in-person task, investments in ICT human capital and physical capital in flexible task, and the costs associated with switching to remote work, which is given by the following,

$$D_t = E_t - W_t L_t - O_t - I_t - \Psi_t, \tag{20}$$

The firm takes as given the stochastic discount factor $M_{t,t+1}$ which is used to value the cash flows arriving in period $t+1$ (and subsequent periods). We specify the stochastic discount factor to be a function of the three aggregate shocks in the economy (to be detailed in the next section):

$$M_{t,t+1} = \frac{1}{1+r_f} \frac{e^{-\gamma_s \Delta \log S_{t+1} - \gamma_\sigma \Delta \log \sigma_{t+1} - \gamma_X \Delta \log X_{t+1}}}{\mathbb{E}_t \left[e^{-\gamma_s \Delta \log S_{t+1} - \gamma_\sigma \Delta \log \sigma_{t+1} - \gamma_X \Delta \log X_{t+1}} \right]}, \tag{21}$$

where r_f is the risk-free rate. We determine the sign of the risk factor loading parameters following the literature. Specifically, Baqaee and Fahri (2020) show the supply and demand shocks during the Covid crisis lead to drops in aggregate output and consumption, so we set γ_s and γ_B to be positive. In addition, we follow Bansal, Kiku and Yaron (2012) who show an increase in macroeconomic volatility is associated with a decline in consumption and set γ_σ to be negative. The risk-free rate is set to be constant. This allows us to focus on risk premiums as the main driver of the results in the model as well as to avoid parameter proliferation.

Firm's maximization is given by

$$V_t = \max_{\phi_t, L_{t+1}, N_{t+1}, K_{t+1}} \left[D_t + \mathbb{E}_t \left(M_{t,t+1} V_{t+1} \right) \right] \tag{22}$$

4.3 Dynamics of labor productivity and remote work adoption policy

This section details the dynamic evolution of labor productivity throughout the pandemic and the determinants of firms' remote work adoption policy.

Before pandemic Because there is no health risk before pandemic, labor productivity $s_t = log(S_t)$ follows a normal AR(1) process. If workers choose to stay on-site working, there is no productivity decrease, hence $\check{S}_t = S_t$; if firms choose to remote work, we assume that there is an increase in productivity, that is, $\hat{S}_t = (1+\zeta)S_t$, with with $\zeta > 0$, which captures all kinds of benefit associated with WFH including less commuting time, cost reduction in office rental costs, etc.

During pandemic Health risk concern becomes first-order during the pandemic. We assume S_t follows a two-state Markov process with S_L being the pandemic state, and S_H being the normal state. Consequently S_L becomes a pandemic shock. If firms choose to work from home, workers are able to keep the productivity at the normal state regardless of states, hence $\hat{S}_t = (1+\zeta)S_H$; if firms choose to stay on-site, there is significant infection risk, hence the labor productivity will fall, so $\check{S}_t = S_t$, that is if the pandemic state S_L occurs, workers' productivity will fall significantly.

Post pandemic After the pandemic, health risk becomes second order, so labor productivity follows a the same AR(1) process as before pandemic, ie., $\check{S}_t = S_t$ while $\hat{S}_t = (1+\zeta)S_t$. We assume the remote work adoption cost f is smaller compared to before pandemic, because as it is easier to adopt remote work with more advanced and widely-used technologies.

Next we turn to the model implied remote work policy. Proposition 1 characterizes the determinants of the remote work policy in the model.

Proposition 4.1 *Remote work policy is determined by the following equation*

$$\left(\mu\left(\hat{S}_t N_t\right)^{\xi}+(1-\mu)\left(K_t\right)^{\xi}\right)^{\frac{1}{\xi}}-f>\left(\mu\left(\check{S}_t N_t\right)^{\xi}+(1-\mu)\left(K_t\right)^{\xi}\right)^{\frac{1}{\xi}}.$$

1. Before and post pandemic, if $\zeta = 0$, firms do not adopt WFH policy as the benefit is strictly less the adoption cost. 2. During the pandemic, firms adopt WFH when $S_t = S_L$. 3. WFH probability is increasing in μ, which measures the cross sectional heterogeneity in ICT human capital intensity.

5 Quantitative results

This section presents the quantitative results of the model. We first describe the calibration of the model, then we discuss the model implied policy functions, and lastly we present the model implied results on asset prices and real quantities during and after the pandemic.

5.1 Calibration

We calibrate the model at the weekly frequency, which is consistent the rapid change of the stock market and firms' decisions during the Covid pandemic. Table 12 reports the parameter values of the baseline calibration.

Common parameters We assume the subjective discount factor β is 0.999. We set the physical capital depreciation rate, ICT human capital depreciate rate and the labor exit rate at 0.2/52, 0.4/52 and 0.36/52, respectively, consistent with the annual values estimated in the literature. We normalize the wage rate $W_t = 1$ which is also consistent with the fact that aggregate wage rate did not move significantly during the pandemic. The elasticity of substitution between physical capital and ICT human capital and the elasticity between the in-person task and flexible task do not have readily available estimates in the data, so we follow Krusell, Ohanian, Rios-Rull and Violente (2000) by setting ξ and ρ to be -0.5 and 0.4 which are consistent with the elasticity between physical capital and skilled worker, and the elasticity between unskilled labor and equipment capital. We set the price elasticity for the revenue function $\varepsilon = 4$ consistent with Hall (1988) and Bloom (2009). Given the calibrated technology parameters and stochastic processes calibrated below, we set the price of risks for aggregate labor productivity shocks, uncertainty shocks and demand shocks $\gamma_s = 10$, $\gamma_\sigma = -10$, and $\gamma_x = 10$ such that the drop of the firm value of an average industry is 10% following combined shocks, roughly consistent with the average weekly drop of all industry returns of 12% on average for the first 4 weeks of the pandemic from Feb 19 to March 23, 2020.[21]

[Table 12 about here]

Before and post pandemic We assume that aggregate labor productivity and aggregate demand condition follow AR(1) processes (in log terms) before and post the pandemic, namely, $s_{t+1} = \rho_s s_t + \sigma_s \varepsilon^s_{t+1}$, and $x_{t+1} = \rho_x x_t + \sigma_x \varepsilon^x_{t+1}$, where $s_t = log(S_t)$ and $x_t = log(X_t)$. In particular, we calibrate the persistence and the conditional volatilities of $\rho_s = \rho_x = 0.983$ and $\sigma_s = \sigma_x = 0.003$ so that they are consistent with the annual values used in the literature.

During pandemic We specify a two-state Markov process for the aggregate uncertainty process σ_t,

$$\sigma_t \in \{\sigma_L, \sigma_H\}, \text{where } \Pr(\sigma_{t+1} = \sigma_i | \sigma_t = \sigma_k) = \pi^{\sigma}_{k,i}. \tag{23}$$

We calibrate the volatilities σ_L and σ_H to match the bottom and peak of the stock market volatility during the four weeks period from Feb 19 to March 23, 2020. This implies $\sigma_L = 5\%, \sigma_H = 20\%$. There is no direct estimate of the transition probabilities of the aggregate uncertainty process for the Covid crisis period, as such, we use the estimates from Bloom et

[21] Note that the quantitative result is not sensitive to the price of risk of demand shocks because the volatility of demand shocks is low. We have experimented different values of γ_s and γ_σ and found both are quantitatively important for the fit of the model.

al (2018).[22]

We specify two-state Markov processes for S_t and S_t^j as follows,

$$S_t \in \{S_L, S_H\}, \text{where } \Pr(S_{t+1} = S_i | S_t = S_k) = \pi_{k,i}^S(\sigma_t), \tag{24}$$

in which the transition probability matrix of S_t and S_t^j varies with the aggregate uncertainty σ_t. We set $S_H = 1$ and $S_L = 0.95$, implying a negative aggregate labor shock of 4%, consistent with the drop of the aggregate labor force in March, 2020. Since there is no readily available empirical estimate, determining the transition probabilities of labor shocks due to pandemic is more challenging. We first set the transition probabilities of labor productivities from H to L to capture the probability of the pandemic occurrence. Specifically, we set $\pi_{H,L}^S(\sigma_L) = 0.001$, sand $\pi_{H,H}^S(\sigma_L) = 0.999$, which imply that the Covid-type pandemic only occurs once every 19 years in expectation, roughly matching with the time length between the SARS outbreak in 2003 and the Covid in 2020. Moreover, we assume that the change in aggregate uncertainty does not change this probability of pandemic occurrence.

Next, we determine the recovery time through specifying the probability of labor productivities from L state back to H state. We assign different probabilities in low and high uncertainty state to capture the uncertainty on when the labor productivities could recover from the pandemic. Specifically, for low uncertainty state, we set $\pi_{L,H}^S(\sigma_L) = 0.25$ and $\pi_{L,L}^S(\sigma_L) = 0.75$ which implies a fast recovery, i.e., the negative labor shock lasts in expectation for about 1 month. In contrast, for high uncertainty state, we set $\pi_{L,L}^S(\sigma_H) = 0.987$, and $\pi_{L,H}^S(\sigma_L) = 0.0417$, which implies a much higher persistence of the negative labor shock; in particular the recovery can be as long as more than 18 months. The transition matrix is detailed in the table below. Since there is no estimate for the transition probabilities of the industry-specific labor productivity, we set them the same as the aggregate labor productivity.

[22] We have also experimented other values of the transition probability matrix and find quantitative result robust to these variations.

Turning to demand shocks, we specify two-state Markov processes for X_t as follows,

$$X_t \in \{X_L, X_H\}, \text{where } \Pr(X_{t+1} = X_i | X_t = X_k) = \pi^B_{k,i}(\sigma_t), \tag{25}$$

in which the transition probability matrix of X_t varies with the aggregate uncertainty σ_t. This also captures the fact that the recovery of the aggregate demand conditions is uncertain. Given that there is no readily available data for the transition probabilities for demand shifters, we set them the same as those of labor productivities for simplicity, i.e., $\pi^X_{k,i} = \pi^S_{k,i}$ for all k and i.[23] Lastly we set $X_H = 1$ and $X_L = 0.94$, implying a negative aggregate demand shock of 4%, consistent with the estimate of Brinca, Duarte and Castro (2020).

Parameters varying across industries To capture the heterogeneity of ICT human capital portfolios in the data. We focus on two main sources of industry heterogeneity: 1) the fraction of ICT human capital μ in the flexible task, and 2) the fraction of the flexible task in output φ^j. We calibrate these two parameters to match the ICT human capital to assets ratio and the ICT human capital to revenue ratio for 5 portfolios before the pandemic. Table 13 reports the results. We see that the model matches the data reasonably well.

[Table 13 about here]

5.2 Policy functions

To illustrate the intuition of the model mechanism we analyze the policy functions implied by the model with multiple tasks and ICT human capital. Figure 7 plots the remote work policy against the ICT human capital share in the flexible task with low and high labor productivity. Recall that the remote work policy is an extensive margin decisoin with 1 indicating remote work and 0 otherwise. We see that the remote work adoption likelihood is increasing the share of ICT human capital in the flexible task because the gain from remote

[23] We experiment different transition probabilities for demand shocks and find the result is not sensitive to these changes.

work is increasing ICT human capital. In addition, the remote work likelihood also increases in low labor productivity state, which represents the pandemic state in the model. This is also intuitive, as the benefit of remote work is higher when labor productivity is low, e.g., due to the health risk.

[Figure 7 about here]

Figures 8a, 8b and 8c plot the remote work policy before, during and after pandemic in the model. In 8a, the benefit of remote work before pandemic is less than the switching cost, hence the likelihood of adopting remote work is low and close to zero regardless of the values of ICT human capital or physical capital. In 8b, productivity gain of remote work outweighs the switching cost, and hence the likelihood of remote work is much higher, especially when ICT human capital is high. In 8c, switching cost of remote work is lower compared to the pre-pandemic level, as a result the likelihood of remote work adoption is higher but still less than the level of during pandemic model.

[Figure 8 about here]

Overall, this shows two results. First, remote work likelihood increases in the ICT human capital share of the firm. Second, the remote work likelihood varies overtime which is driven by the variations of labor productivity and the cost/benefit of remote work.

5.3 ICT human capital, asset prices and quantities

We examine the quantitative result of the baseline model on the relation between ICT human capital, asset prices and firm policies. We simulate the model with combined labor productivity shock, aggregate demand shock and uncertainty shock for different ICT human capital intensity groups. Table 14 presents the result. We see that the model generates significant cross-sectional differences across ICT human capital groups that are consistent with the data. Specifically, low ICT human capital group has larger decreases in revenue growth, employment growth and stock returns than high ICT human capital group, with the spread (Low-High) at 10.7%, 7.8% and 10.7%, respectively, close to 8.7%, 8.3% and 10.8% in the data. Moreover, the model implied average decrease in revenue growth, employment growth and stock returns are -9.3%, -10.8% and -9.9%, close to the data counterparts of -8.2%, -7.5% and -12.9%

[Table 14 about here]

5.4 Inspecting the mechanism

We inspect the model mechanism by investigating the impulse responses of the model and conducting counterfactual analysis.

5.4.1 Impulse responses

We simulate the impulse responses of the baseline model. We run our model for 500 simulations each with 250 periods and then kick labor and demand shocks to the low level and the uncertainty to its high level in period 201 and then let the model to continue to run as before. Hence, we are simulating the response to a one period impulse and its gradual decay. To capture the cross-sectional heterogeneity, we simulate the model for high, medium and low ICT human capital groups.

We see in Figure 9 that the general responses across all groups are that output, labor and firm value decrease while the remote work likelihood increase upon the impact of these shocks. Furthermore, there is large heterogeneity in responses across ICT human capital group. High ICT human group sees much smaller decreases in output, labor and firm value and bigger increase in remote work likelihood than both medium and low ICT human capital groups, whereas the low ICT human group has the largest decreases in output, labor and firm value, but almost no response in their remote work policy. More importantly, we see that output drop in the flexible task is significantly smaller than in-person task for all ICT human capital groups, however the low ICT human capital group experiences the largest drops in both two tasks, which explains its biggest drop in both asset prices and quantities across all groups.

[Figure 9 about here]

5.4.2 Counterfactual analysis

To understand the model mechanism in generating the heterogeneous effects on ICT human capital groups, we investigate the six different model specifications by changing one key channel at a time. Table 15 reports the result. First, turning off the remote work option and turning off risk prices for all shocks increase the average drops in revenue, labor and firm value; these two changes also lead to much smaller cross-sectional differences between high and low ICT human capital groups. This is intuitive. Removing the remote work option reduces the operating flexibility of all firms hence affecting the cash flows, making firms more homogeneous even if there is difference in the ICT human capital share; turning of risk prices removes the discount rate effect, which also reduces the heterogeneous response of firms. Second, increasing the elasticity of substitution between ICT human capital and physical capital reduces both the average drops and the cross-sectional spread; this happens between physical capital and ICT human capital more substitutable, making firms less affectd by shocks. Increasing the elasticity of substitution between in-person and flexible tasks affects the average drops and the cross-sectional spread differently. By making two tasks more substitutable, the remote work option's effect in mitigating pandemic shocks is reduced, hence we see increases in the average drops in output, labor and firm value, but smaller cross-sectional differences. Lastly, turning off either labor shock or demand shock leads to much smaller decreases in average drops and the cross sectional spreads, implying both shocks are quantitatively important to capture the responses during the pandemic.

[Table 15 about here]

6 Conclusion

The Covid-19 pandemic has significantly impacted the global economy and financial markets. We study the impact of the Covid-19 pandemic on asset prices and firm policies from the angle of labor supply disruptions. We show that ICT human capital is a first-order effect in driving the variations of stock returns and firm fundamentals.

Empirically, we utilize the industry-job composition and job-attributes information to construct a measure that captures the industry-level ICT human capital. We find that ICT human capital explains a large portion of variations in the ex-ante measures of WFH used in the literature. Moreover, firms in high ICT human capital industries significantly outperform firms in low ICT human capital industries in stock returns during the pandemic, and it is the main driving force behind the positive relationship between WFH and asset returns. In addition, we document that the positive ICT human capital-return relation extends to bonds and G7 countries and is affected by the pandemic severity in individual countries. Finally, we find that despite the fact that the effect of the pandemic has waned, the WFH practice has remained persistent, especially among industries that have a higher ICT human capital.

Theoretically, we develop a dynamic model economy wherein firms have multiple tasks. The central insight is that ICT human capital is the key driving force of firm value and firm policy fluctuations. In the model, the industry heterogeneity in ICT human capital is driven by two factors: : 1) the fraction of the flexible job task in producing the output, and 2) the ICT human capital share in flexible tasks across industries. We show that the model generates a sizable spread in the drop of the firm value between industries with heterogeneous ICT human capital, consistent with the data. Intuitively, the higher the fraction of the flexible task, the more flexible the industry is in smoothing the response to negative shocks. Hence, the higher ICT human capital industry suffers less in firm value drop because its output (cashflow) is less affected by the negative shocks.

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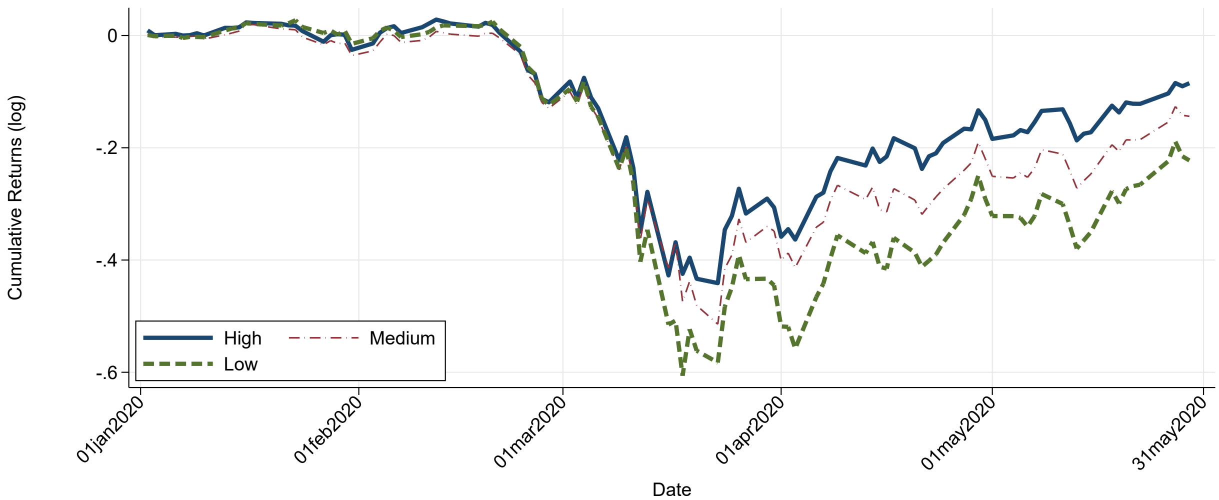
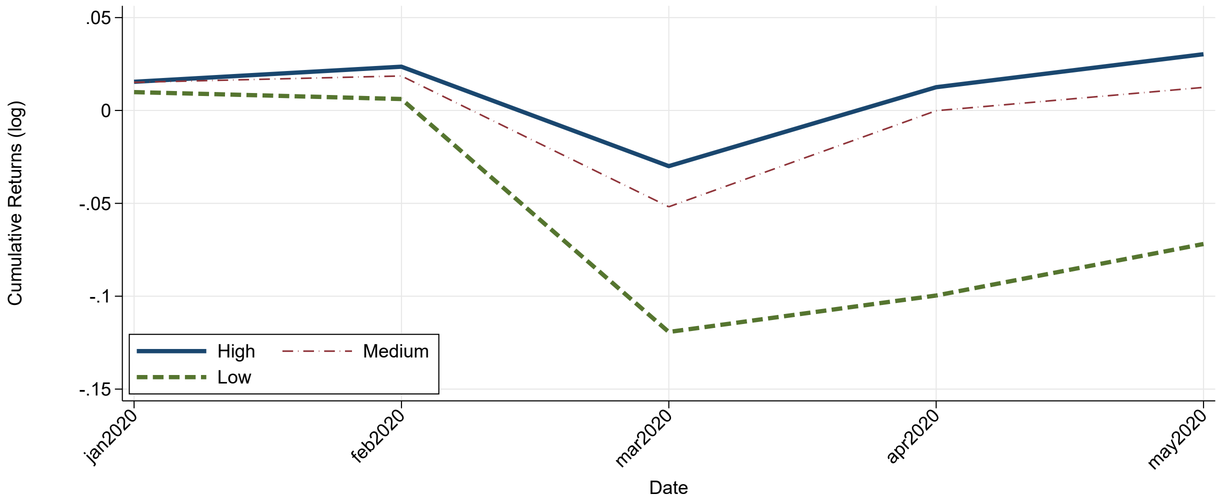
Figure 1: Cumulative stock returns across ICT human capital groups: during pandemic



This figure plots the (log of) cumulative stock return for three groups sorted within sector based on ICT human capital. The cumulative stock returns for industry i is calculated using the daily value-weighted return of that industry during the period between January 1, 2020 and May 31, 2020. The High group includes industries that rank among the top 20%, the Low group includes industries that rank among the bottom 20%, the rest industries are included in the Medium group. Industries (sectors) are defined at the 4-digit (2-digit) NAICS level.

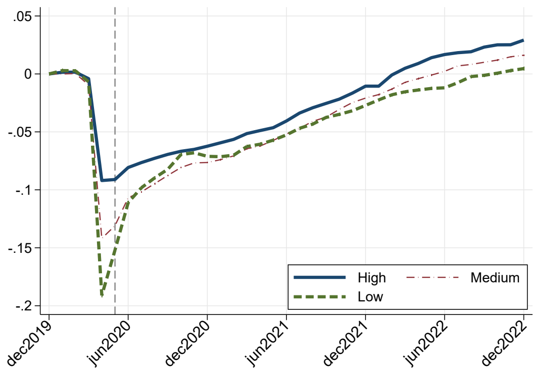
Figure 2: Cumulative bond returns across ICT human capital: during pandemic



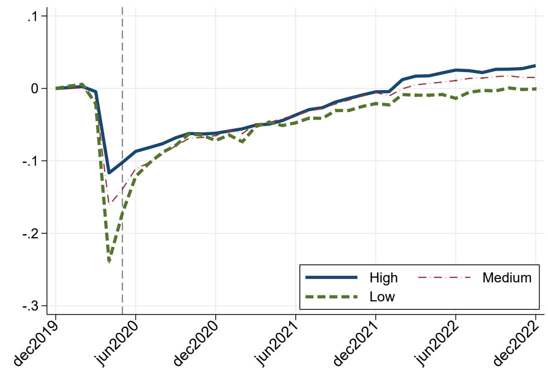
This figure plots the (log of) cumulative bond returns for three groups sorted within sector based on ICT human capital. The cumulative bond returns for industry i is calculated using the monthly value-weighted return of that industry during the period between January 2020 and May 2020. For each group, we assign industries sorted using stock returns so that the results for stock and bond returns are comparable. Industries (sectors) are defined at the 4-digit (2-digit) NAICS level.

Figure 3: Cumulative employment/hours growth across ICT human capital groups

(a) Cumulative employment

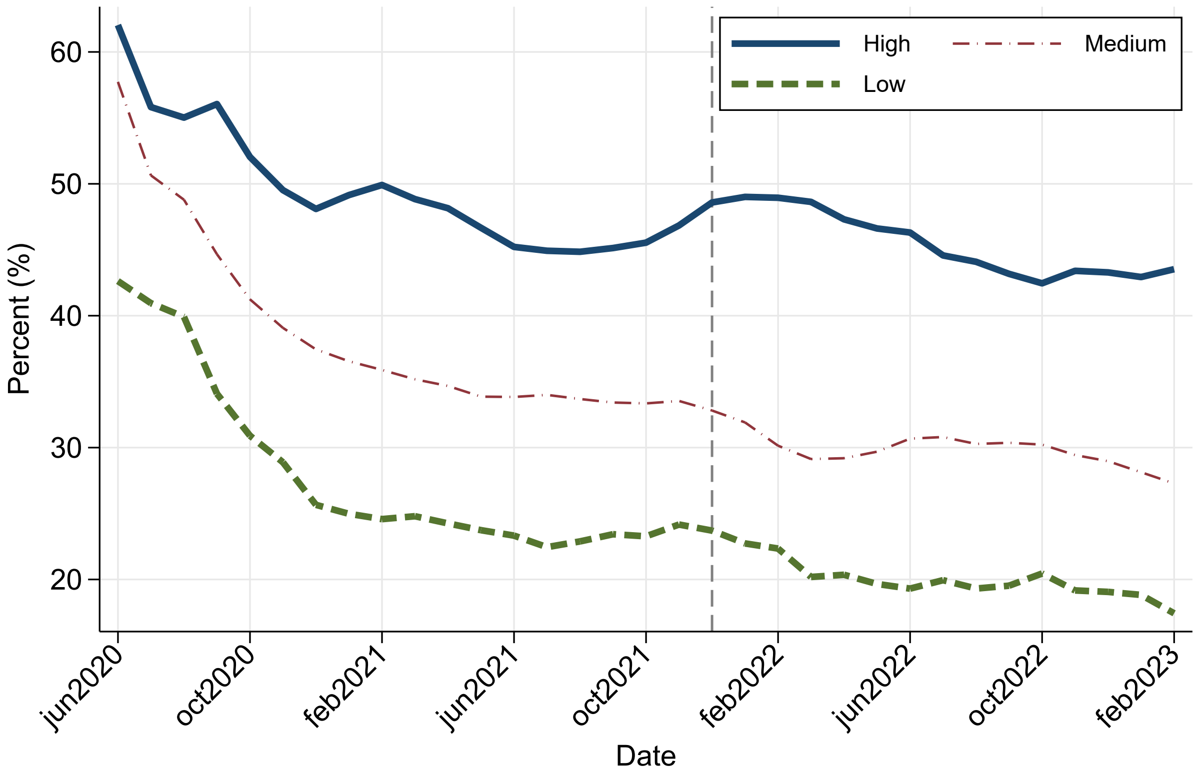


(b) Cumulative working hour growth



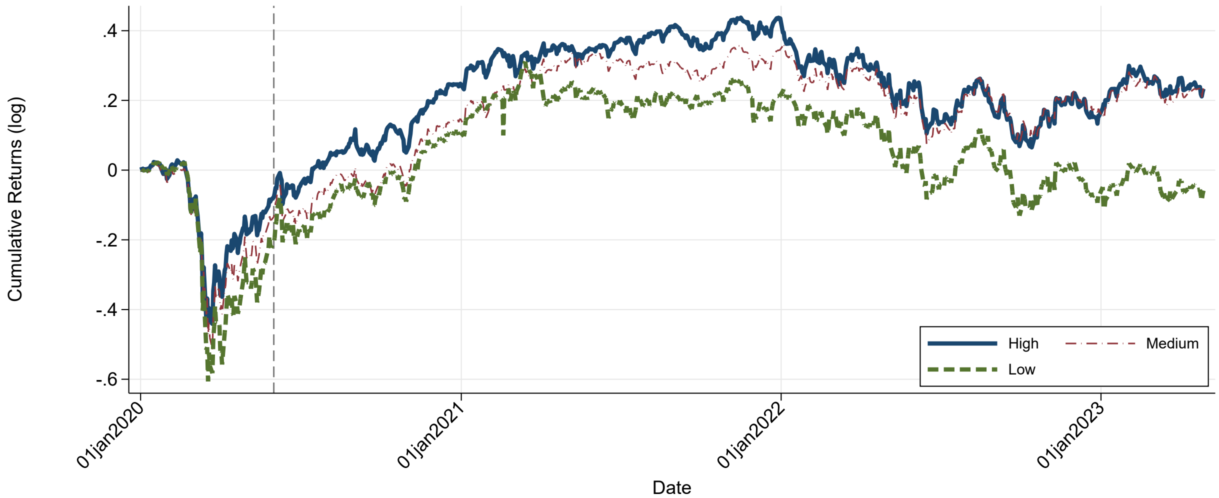
This figure plots the cumulative growth rate of employment (panel (a)) and working hours (panel (b)) relative to Dec 2019 level for three groups sorted within sector based on ICT human capital. The High group includes industries that rank among the top 20%, the Low group includes industries that rank among the bottom 20%, the rest industries are included in the Medium group. Employment and working hour data is obtained from Current Employment Statistics (CES). Industries (sectors) are defined at the 4-digit (2-digit) NAICS level.

Figure 4: Percentage of paid full days worked from home across ICT human capital groups



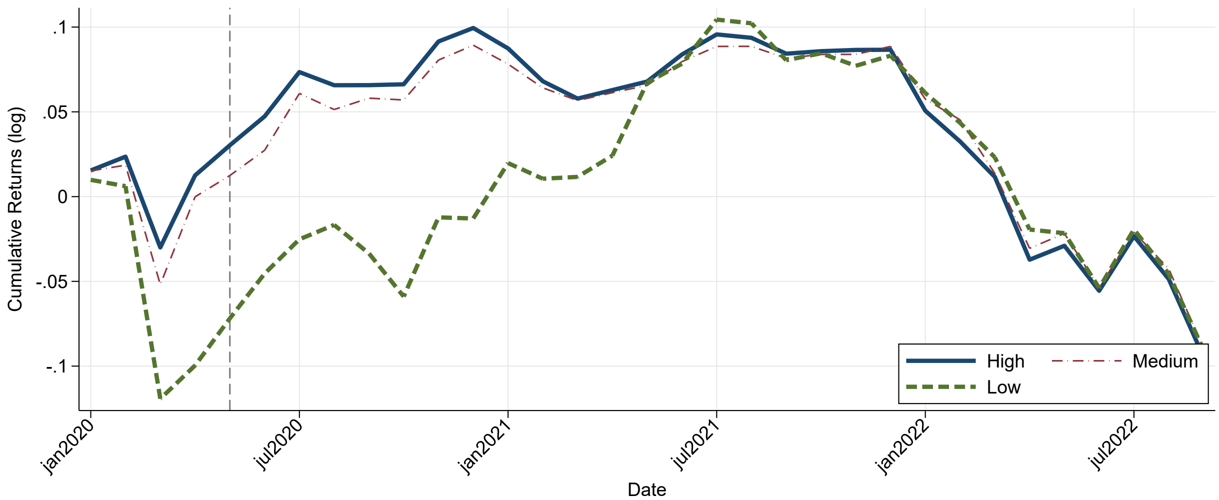
This figure plots the ongoing WFH measure (the percentage of paid full days worked from home) over the period from May 2020 to April 2023 for three groups sorted based ICT human capital. Both WFH and ICTHumanCapital are measured at state-sector level. The High group includes state-sectors that rank among the top 20%, the Low group includes state-sectors that rank among the bottom 20%, the rest state-sectors are included in the Medium group. Data on the percentage of full days worked from home is obtained from SWAA survey (Barrero, Bloom, and Davis (2021). https://wfhresearch.com/data/). We take a 4-month moving average of the WFH values measured in the current and previous three months. For example, the value of 42.6% for the low ICT human capital group corresponding to June 2020 on the x-axis is the average of WFH values of May, June (skipped in the survey), July and August 2020. Sectors are defined at the 2-digit NAICS level.

Figure 5: Cumulative stock returns across ICT human capital: post pandemic



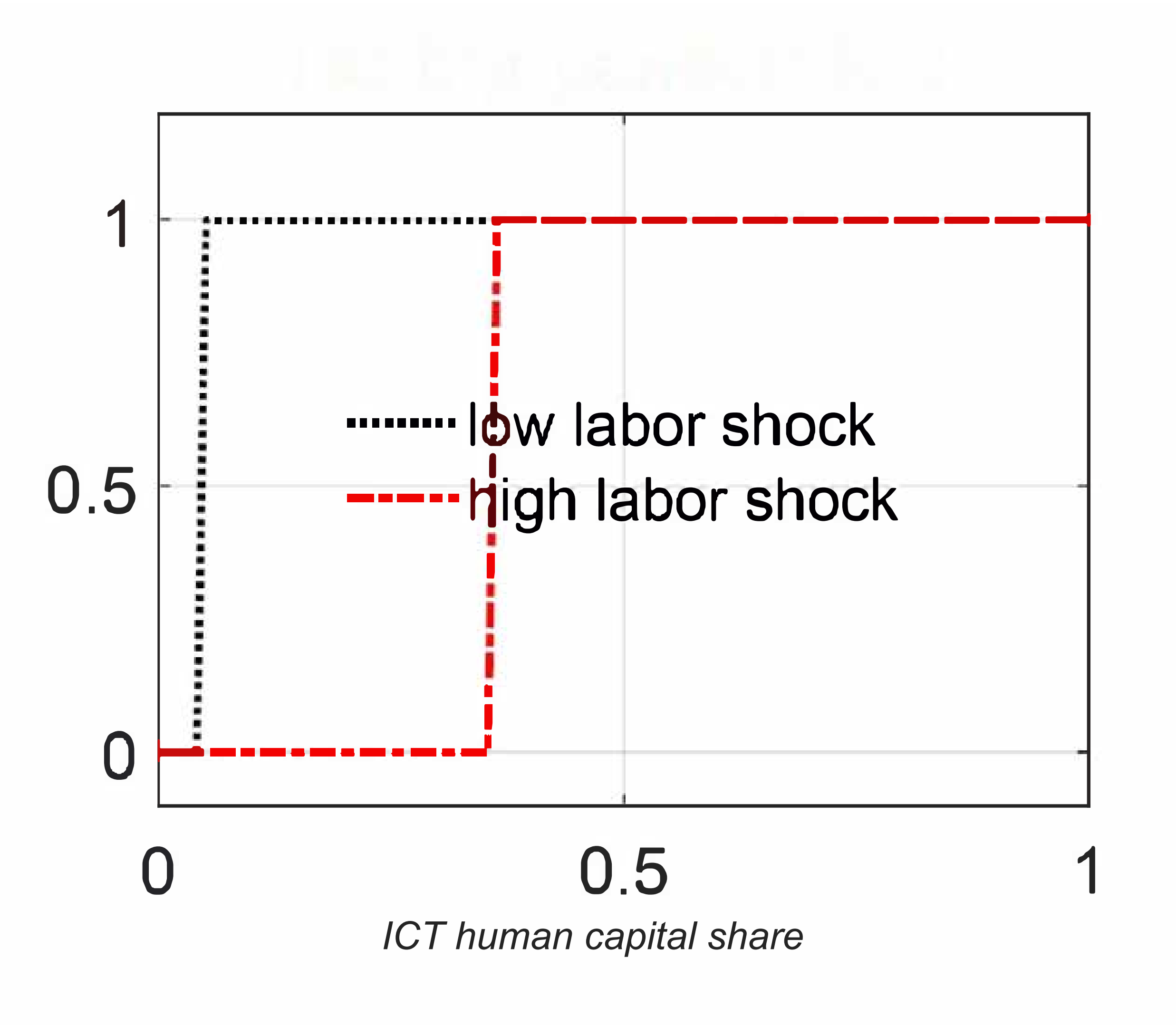
This figure plots the (log of) cumulative stock return for three groups sorted within sector based on ICT human capital. The cumulative stock returns for industry i is calculated using the daily value-weighted return of that industry during the period between January 1, 2020 and April 30, 2023. The High group includes industries that rank among the top 20%, the Low group includes industries that rank among the bottom 20%, the rest industries are included in the Medium group. Industries (sectors) are defined at the 4-digit (2-digit) NAICS level.

Figure 6: Cumulative bond returns across ICT human capital: post pandemic



This figure plots the (log of) cumulative bond returns for three groups sorted within sector based on ICT human capital. The cumulative bond returns for industry i is calculated using the monthly value-weighted return of that industry during the period between January 2020 and September 2022 (when our sample ends). For each group, we assign industries sorted using stock returns so that the results for stock and bond returns are comparable. Industries (sectors) are defined at the 4-digit (2-digit) NAICS level.

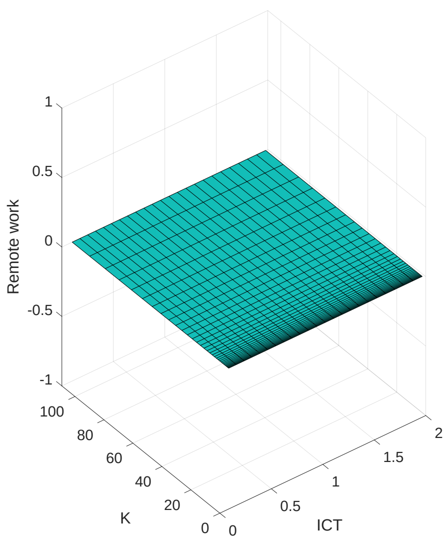
Figure 7: Remote work adoption for low and high labor productivity states



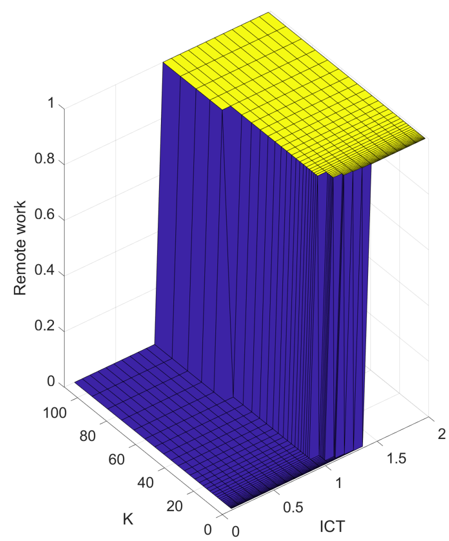
This figure plots the remote work adoption policies associated with low and high labor productivity states. The red dash line is the policy for the high labor productivity state, and the black dash line for the low productivity shock state.

Figure 8: Remote work adoption dynamics

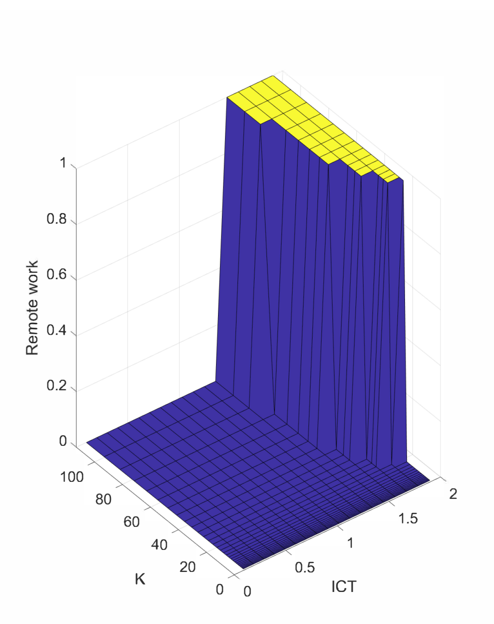
(a) Before pandemic



(b) During pandemic

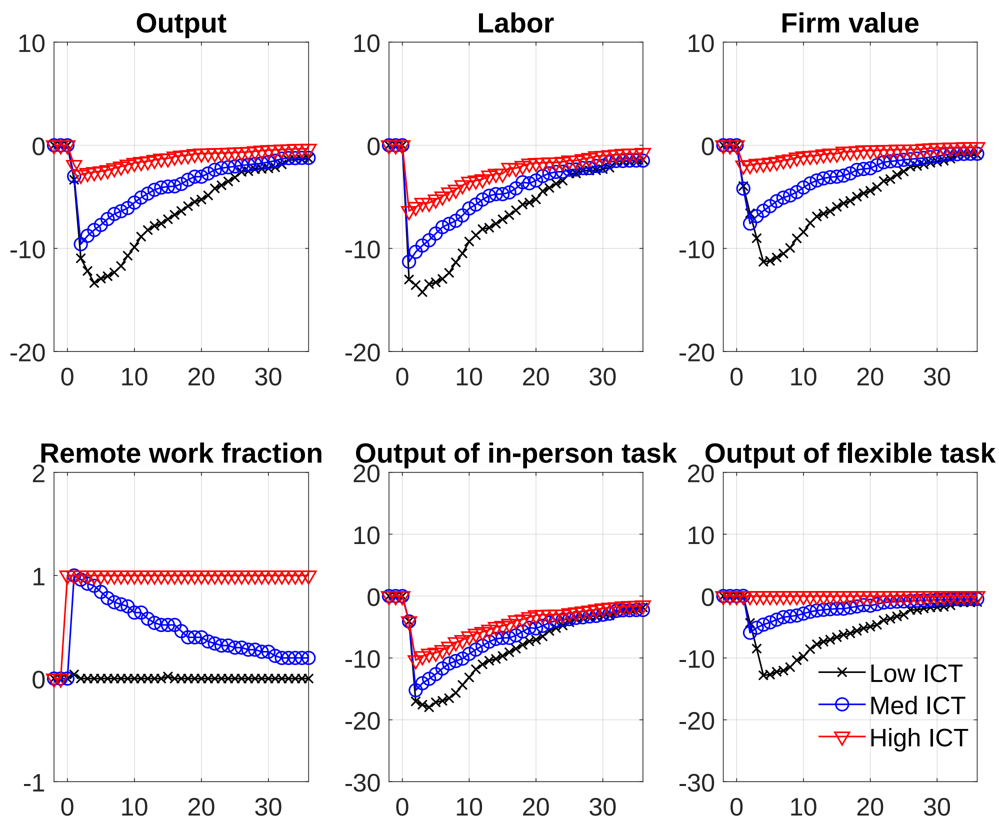


(c) Post pandemic



This figure plots the remote work policies before (panel (a)), during (panel (b)) and after the pandemic (panel (c)). Panel (a) shows that pre-pandemic, benefit of remote work less than switching cost thus the adoption of remote work is low. Panel (b) shows that during the pandemic, productivity gain of remote work outweighs switching cost so we have high adoption especially when ICT human capital is high. Panel (c) shows that post pandemic, productivity gain is lower than during pandemic, and switching cost is also lower than pre-pandemic, so we have medium adoption.

Figure 9: Impulse responses of combined shocks during the pandemic



This figure plots the impulse response functions for output, labor, firm value, remote work fraction, and the output of in-person task and flexible task for firms with different ICT intensities.

Table 1: List of occupations with the highest and lowest ICT score in 2019

This table presents the top and bottom 10 occupations sorted on ICT score in 2019 (from jobs with the highest ICT score to the lowest). ICT score is constructed by adding the standardized scores associated with the following job characteristics from the O*NET: "Interacting with Computers", "Computer and Electronics" knowledge, "Telecommunications" knowledge, "Analyzing Data or Information", and "Programming" skills. The ICT score is scaled to have values between 1 and 10.

Rank	Occupation Code	Occupation Title
1	15-1143	Computer Network Architects
2	15-1111	Computer and Information Research Scientists
3	15-1131	Computer Programmers
4	15-1132	Software Developers, Applications
5	15-1142	Network and Computer Systems Administrators
6	15-1141	Database Administrators
7	25-1021	Computer Science Teachers, Postsecondary
8	19-2012	Physicists
9	15-1152	Computer Network Support Specialists
10	15-1133	Software Developers, Systems Software
	...	
801	51-6041	Shoe and Leather Workers and Repairers
802	47-2043	Floor Sanders and Finishers
803	45-2092	Farmworkers and Laborers, Crop, Nursery, and Greenhouse
804	47-2022	Stonemasons
805	27-2031	Dancers
806	47-3014	Helpers-Painters, Paperhangers, Plasterers, and Stucco Masons
807	53-7111	Mine Shuttle Car Operators
808	47-2082	Tapers
809	45-4021	Fallers
810	41-9012	Models

Table 2: List of industries with the highest and lowest ICT human capital in 2019

This table presents the top and bottom 10 industries sorted on ICT human capital measure in 2019 (from industries with highest ICT human capital to the lowest). We construct the ICT capital measure for each industry using the perpetual inventory method applied to the labor expenditure associated with the ICT occupations in that industry from the OES data. The ICT occupations are defined as the top 10% of all jobs in terms of the sum of scores for the following job characteristics from the O*NET: “Interacting with Computers”, “Computer and Electronics” knowledge, “Telecommunications” knowledge, “Analyzing Data or Information”, and “Programming” skills. Once we have the capitalized labor expenditure for each industry in each year, we scale it by the industry’s total employment in that year to obtain the ICT human capital measure.

Rank	NAICS Code	Industry Title
1	334100	Computer and Peripheral Equipment Manufacturing
2	541500	Computer Systems Design and Related Services
3	511200	Software Publishers
4	518200	Data Processing, Hosting, and Related Services
5	334200	Communications Equipment Manufacturing
6	541700	Scientific Research and Development Services
7	519100	Other Information Services
8	334500	Navigational, Measuring, Electromedical, and Control Instruments Manufacturing
9	515200	Cable and Other Subscription Programming
10	336400	Aerospace Product and Parts Manufacturing
	...	
243	445100	Grocery Stores
244	448200	Shoe Stores
245	453100	Florists
246	448100	Clothing Stores
247	624400	Child Day Care Services
248	485400	School and Employee Bus Transportation
249	445200	Specialty Food Stores
250	445300	Beer, Wine, and Liquor Stores
251	722500	Restaurants and Other Eating Places
252	447100	Gasoline Stations

Table 3: Relationship between ICT human capital and WFH measures

This table presents the results of regressing four WFH measures on ICT human capital (2019). It shows that ICT human capital and WFH measures used in previous literature are highly correlated. WFHDN is defined based on Dingel and Neiman's (2020) occupation-level measure of tele-workability which is obtained by taking the weighted average of the scores associated with 7 "Work Context" and 8 "Generalized Work Activity" job attributes from the O*NET. WFHPS is the industry exposure to Covid, constructed following Papanikolaou and Schmidt (2021) using the American Time Use Survey. WFHATUS is constructed following Mongey, Pilossoph and Weinberg (2020) who also use the ATUS microdata. Industries (sectors) are defined at the 4-digit (2-digit) NAICS level.

***,**,* indicate significance at the 1%, 5% and 10% levels, respectively.

	(1) WFHDN	(2) WFHDN	(3) WFHPS	(4) WFHPS	(5) WFHATUS	(6) WFHATUS
ICTHumanCapital	0.008***	0.005***	0.010***	0.010***	0.001***	0.001***
	(10.16)	(8.45)	(4.75)	(3.73)	(9.47)	(7.08)
FE	-	Sector	-	Sector	-	Sector
N	103	103	86	86	103	103
R2	0.472	0.808	0.483	0.589	0.408	0.840

Table 4: ICT human capital as a main driver of WFH measures' stock return predictability

This table presents the results of regressing industry-level cumulative stock return on ICT human capital and the residual of four WFH measures used in the literature (all measured in 2019). Specifically, it reports the slope coefficients in the regression of the form

$$CumRet_i = b_0 + b_1 \cdot ICTHumanCapital_i + b_2 WFH_i(res) + f_s + \epsilon_i$$

where $CumRet_i$ is the cumulative stock returns for industry i over the period between January 1, 2020 and May 31, 2020, calculated using the daily value-weighted return of each industry over this period. f_s is the sector fixed effect (if included).
The residual term $WFH(res)$ is obtained by regressing WFH measures on ICT human capital:

$$WFH_i = c_0 + c_1 \cdot ICTHumanCapital_i + f_s + WFH_i(res).$$

Industries (sectors) are defined at the 4-digit (2-digit) NAICS level. ***,**,* indicate significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ICTHumanCapital	0.001**	0.003***	0.001**	0.003***	0.001**	0.002***	0.001**	0.003***
	(2.11)	(2.85)	(2.14)	(2.87)	(2.30)	(3.68)	(2.10)	(3.08)
WFHDN(res)			0.046	0.222				
			(0.42)	(1.44)				
WFHPS(res)					0.188***	0.201***		
					(3.97)	(3.93)		
WFHATUS(res)							0.044	-1.881**
							(0.08)	(-2.12)
FE	-	Sector	-	Sector	-	Sector	-	Sector
N	105	105	105	105	89	89	105	105

Table 5: ICT human capital as a main driver of WFH measures' bond return predictability

This table presents the results of regressing industry-level cumulative bond return on ICT human capital and the residual of four WFH measures used in the literature (all measured in 2019). Specifically, it reports the slope coefficients in the regression of the form

$$CumRet_i = b_0 + b_1 \cdot ICTHumanCapital_i + b_2 WFH_i(res) + f_s + \epsilon_i$$

where $CumRet_i$ is the cumulative bond returns for industry i over the period between January 2020 and May 2020, calculated using the monthly value-weighted return of each industry over this period. f_s is the sector fixed effect (if included).
The residual term $WFH_i(res)$ is obtained by regressing cumulative bond returns on ICT human capital:

$$WFH_i = c_0 + c_1 \cdot ICTHumanCapital_i + f_s + WFH_i(res)$$

Industries (sectors) are defined at the 4-digit (2-digit) NAICS level. ***,**,* indicate significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ICTHumanCapital	0.000**	0.002**	0.000**	0.002**	0.000*	0.001***	0.000**	0.002**
	(2.40)	(2.02)	(2.31)	(2.06)	(1.79)	(3.39)	(2.07)	(2.08)
WFHDN(res)			-0.049	0.176*				
			(-0.72)	(1.81)				
WFHPS(res)					0.016	0.018	-0.774	
					(0.96)	(0.87)	(-1.00)	
WFHATUS(res)								-0.516
								(-0.50)
FE	-	Sector	-	Sector	-	Sector	-	Sector
N	58	58	58	58	50	50	58	58

Table 6: ICT human capital as a main driver of WFH measures' stock return predictability in G-7

This table presents the results of regressing industry-level cumulative stock return on ICT human capital and the residual of four WFH measures used in the literature (all measured in 2019). Specifically, it reports the slope coefficients in the regression of the form

$$CumRet_i = b_0 + b_1 \cdot ICTHumanCapital_i + b_2 WFH(res) + f_s + f_{cs} + \epsilon_i$$

where $CumRet_i$ is the cumulative stock returns for industry i in country c over the period between January 1, 2020 and May 31, 2020, calculated using the daily value-weighted return of each industry over this period. The countries in this regression include Canada, Germany, France, United Kingdom, Italy and Japan. For each industry, ICTHumanCapital is the ICT human capital calculated for the US industry with the same 4-digit NAICS. f_s is the sector fixed effect (if included) and f_{cs} is the country-sector fixed effect (if included).
The residual term $WFH_i(res)$ is obtained by regressing cumulative stock returns on ICT human capital:

$$WFH_i = c_0 + c_1 \cdot ICTHumanCapital_i + f_s + f_{cs} + WFH_i(res)$$

Panel A presents the results for all countries. Panel B presents the results for each country. Industries (sectors) are defined at the 4-digit (2-digit) NAICS level. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively.

(a) Panel A: All countries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ICTHumanCapital	0.002***	0.002***	0.002***	0.002***	0.001**	0.002***	0.002***	0.002***
	(3.29)	(3.67)	(3.31)	(3.66)	(2.46)	(3.05)	(3.30)	(3.80)
WFHDN(res)			0.050	0.099				
			(0.89)	(0.90)				
WFHPS(res)					0.066*	0.032		
					(1.73)	(0.74)		
WFHATUS(res)							0.125	-1.310***
							(0.47)	(-2.65)
FE	-	Country-Sector	-	Country-Sector	-	Country-Sector	-	Country-Sector
N	400	398	400	398	354	348	400	398

(b) Panel B: Country Details

	(1) Canada	(2) Germany	(3) France	(4) UK	(5) Italy	(6) Japan	(7) Canada	(8) Germany	(9) France	(10) UK	(11) Italy	(12) Japan	(13) Canada	(14) Germany	(15) France	(16) UK	(17) Italy	(1 Ja
THumanCapital	0.002	0.002	0.003**	0.002	0.006***	0.001	0.001	0.002	0.003**	0.002	0.006***	0.001	0.002	0.002	0.003**	0.002	0.006***	0.0
	(1.37)	(1.31)	(2.31)	(1.13)	(7.50)	(1.04)	(0.60)	(1.49)	(2.24)	(1.04)	(9.88)	(0.63)	(1.33)	(1.38)	(2.32)	(1.16)	(7.52)	(1.
FHDN	0.369	-0.080	0.208	-0.008	0.397	0.093												
	(1.21)	(-0.24)	(0.67)	(-0.02)	(0.71)	(0.78)												
FHPS							-0.008	0.136	-0.022	0.102	0.250	-0.007						
							(-0.10)	(1.38)	(-0.20)	(0.95)	(1.39)	(-0.14)						
FHATUS													-2.315	-0.956	-0.125	-0.882	0.610	-1.40
													(-1.38)	(-0.57)	(-0.10)	(-0.50)	(0.17)	(-2.
E	Sector	Sector	Sector	Sector	Sector	Sector	Sector	Sector	Sector	Sector	Sector	Sector	Sector	Sector	Sector	Sector	Sector	Sec
	59	43	47	64	26	159	53	37	44	57	19	138	59	43	47	64	26	15

Table 7: Pandemic Severity and the Return-ICT Human Capital Sensitivity across Countries

This table reports the slope coefficients for the regression of the form

$$b_{ICT,c} = b_0 + b_1 Intensity_c + \epsilon_i \tag{26}$$

where $Intensity_c$ is the severity of Covid-19 in country c, measured as the logarithm of the death rate (infection rate) per hundred thousand population. $b_{ICT,c}$ is the coefficient obtained from the following regression

$$CumRet_{i,c} = b_0 + b_{ICT,c} \cdot ICTHumanCapital_i + f_s + \epsilon_i \tag{27}$$

where $CumRet_{i,c}$ is the cumulative returns (times 100) for industry i in country c over the period between January 1, 2020 and May 31, 2020, calculated using the daily value-weighted return of the industry portfolio over this period. fs is the sector fixed effect (if included). Industries (sectors) are defined at the 4-digit (2-digit) NAICS level. Only industries with at least 3 public-traded firms are included, and countries with fewer than 15 industries are excluded from the sample.

***,**,* indicate significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Intensity (Infection)	0.023*	0.049*		
	(1.75)	(1.95)		
Intensity (Death)			0.025**	0.043**
			(2.62)	(2.23)
Intercept	0.291**	0.521**	0.389***	0.622**
	(2.56)	(2.42)	(3.43)	(2.72)
Within Sector	No	Yes	No	Yes
N	23	23	23	23

Table 8: ICT human capital and labor policies

This table presents the results of regressing cumulative growth of employment, working hour and weekly earning growth on ICT human capital. Specifically, it reports the slope coefficients in the regression of the form

$$Y_i = b_0 + b_1 \cdot ICTHumanCapital_i + f_s + \epsilon_i$$

where Y_i is the cumulative growth of employment, working hour and weekly earning for industry i over the period between January 2020 and May 2020, calculated using 4-digit NAICS industry level employment, working hour and weekly earning data from Current Employment Statistics (CES). f_s is the sector fixed effect (if included).

Sectors are defined at the 2-digit NAICS level. ***,**,* indicate significance at the 1%, 5% and 10% levels, respectively.

	Growth in employment		Growth in hours worked		Growth in weekly earning	
	(1)	(2)	(3)	(4)	(5)	(6)
ICTHumanCapital	0.0023***	0.0015***	0.0026***	0.0022***	-0.0009***	0.0001
	(4.58)	(4.19)	(4.39)	(3.46)	(-2.61)	(0.38)
FE	-	Sector	-	Sector	-	Sector
N	185	185	152	152	152	152

Table 9: Difference-in-Differences Regression Results for Firm Returns on the COVID-19 Shock

This table reports results for the following DID regression

$$log(Return)_{ijct} = b_0 + b_1 Treat_{ct} * ICTHumanCapital_{jt} + b_2 Treat_{ct} + f_i + f_t + \epsilon_{it} \tag{28}$$

where $Return_{ijct}$ is the daily stock return (gross) of firm i from industry j headquartered in county c . $Treat_{ct}$ equals 1 if a county c has been hit by Covid-19 at time t, 0 otherwise. $log(Return)$ is 100 times the logarithm of $Return_{ijct}$. The sample starts from January 1, 2020 and ends on May 31, 2020. Treatment day is defined as the date when the first case of COVID-19 is reported in the county where the firm is headquartered in. Firm headquarter locations are obtained from Compustat. Information on the COVID-19 cases is obtained from the *New York Times*. f_i is the firm fixed effect and f_t is the date fixed effect. ***,**,* indicate significance at the 1%, 5% and 10% levels, respectively.

	(1) logReturn	(2) logReturn
Treat	-0.135**	-0.248***
	(-2.12)	(-2.80)
Treat*ICTHumanCapital		0.004**
		(2.25)
Firm FE	Y	Y
Date FE	Y	Y
N	101155	101155

Table 10: ICT human capital explains stock returns after controlling for the internet quality

This table presents the results of regressing industry-level cumulative stock return on ICT human capital and the residual of four WFH measures used in the literature (all measured in 2019). Specifically, it reports the slope coefficients in the regression of the form

$$CumRet_i = b_0 + b_1 \cdot ICTHumanCapital_i + b_2 WFH_i(res) + InternetQuality_s + \epsilon_i$$

where $CumRet_i$ is the cumulative returns for industry i over the period between January 1, 2020 and May 31, 2020. Panel A reports the stock results where $CumRet_i$ is calculated using the daily value-weighted return of each industry over this period. Panel B reports the results where $CumRet_i$ is calculated using the monthly value-weighted bond return of each industry over this period. Panel C reports the results for G-7 countries (excluding the U.S.) where $CumRet_i$ is calculated using the daily value-weighted return of each industry over this period. The countries in this regression include Canada, Germany, France, United Kingdom, Italy and Japan. The internet quality is measured based on responses to the SWAA survey question "fraction of time that internet works" (Barrero, Bloom, and Davis, 2021). We aggregate respondents' answers to sector level, and take the annual average across all months. Because this measure is at the sector level, it will be omitted in regressions with sector fixed effects. Therefore, in this table we only present the results with no fixed effects.

The residual term $WFH(res)$ is obtained by regressing cumulative stock returns on ICT human capital:

$$WFH_i = c_0 + c_1 \cdot ICTHumanCapital_i + WFH_i(res).$$

Industries (sectors) are defined at the 4-digit (2-digit) NAICS level. ***,**,* indicate significance at the 1%, 5% and 10% levels, respectively.

	Panel A: U.S. Stock			Panel B: U.S. Bond			Panel C: G-7 Stock		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ICTHumanCapital	0.001*	0.001**	0.001*	0.001*	0.000**	0.001*	0.001***	0.001**	0.001***
	(1.72)	(2.54)	(1.76)	(1.72)	(2.53)	(1.96)	(2.86)	(2.19)	(2.59)
InternetQuality	0.173	-0.426	0.216	-1.583	-0.297	-1.206	0.306	0.034	0.499
	(0.17)	(-0.56)	(0.20)	(-1.26)	(-1.05)	(-1.43)	(0.57)	(0.06)	(0.82)
WFHDN (res)	-0.011			0.017			0.040		
	(-0.09)			(0.35)			(0.68)		
WFHPS (res)		0.187***			0.020			0.084*	
		(3.83)			(1.11)			(1.80)	
WFHATUS (res)			-0.081			-0.304			-0.036
			(-0.12)			(-0.54)			(-0.12)
Within Sector	No	No	No	No	No	No	No	No	No
N	100	84	100	56	48	56	380	334	380

Table 11: ICT human capital and ongoing WFH practices

This table presents the results of regressing a work-from-home measure on ICT human capital. Specifically, it reports the slope coefficients in the regression of the form

$$WFHBBD_{it} = b_0 + b_1 \cdot ICTHumanCapital_{it} + f_s + f_{st} + f_t + \epsilon_i$$

where $WFHBBD_{it}$ is the percentage of paid full days worked from home for each month over the period from May 2020 to April 2023. Both WFHBBD and ICTHumanCapital are measured at state-sector level. Data on the percentage of full days worked from home is obtained from the SWAA survey (Barrero, Bloom, and Davis (2021). https://wfhresearch.com/data/). ICTHumanCapital is at annual frequency. f_s is the 1-digit NAICS industry fixed effect (if included),f_{st} is the state fixed effect (if included), f_s is the time (month) fixed effect (if included). Panel B tests whether the relation between ICTHumanCapital is stronger post pandemic. The cutoff time for pre- and post-pandemic is January 2022. *Post* is a dummy variable that equals 1 from January 2022 to April 2023, 0 between 2020 and 2021.

Sectors are defined at the 2-digit NAICS level. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively.

(a) Panel A: Pooled regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ICTHumanCapital	0.497***	0.229***	0.199***	0.479***	0.464***	0.178***	0.152***
	(17.98)	(7.84)	(7.04)	(17.62)	(17.43)	(6.09)	(5.30)
FE	-	Naics1d	Naics1d Date	State	State Date	State Naics1d	State Naics1d Date
N	17269	17269	17269	17269	17269	17269	17269

(b) Panel B: Pre and post January 2022

	(1)	(2)	(3)	(4)	(5)	(6)	(8)
ICTHumanCapital	0.396***	0.138***	0.139***	0.382***	0.385***	0.092***	0.097***
	(15.25)	(4.93)	(5.04)	(15.05)	(15.28)	(3.27)	(3.46)
Post	-9.314***	-9.327***		-9.115***		-9.091***	
	(-15.22)	(-15.45)		(-14.87)		(-15.07)	
Post*ICTHumanCapital	0.211***	0.171***	0.167***	0.206***	0.203***	0.160***	0.157***
	(6.32)	(5.13)	(5.01)	(6.21)	(6.09)	(4.85)	(4.74)
FE	-	Naics1d	Naics1d Date	State	State Date	State Naics1d	State Naics1d Date
N	17269	17269	17269	17269	17269	17269	17269

Table 12: Parameter Values for Calibration

This table presents the parameters used in calibrating the model. Panel A presents the common parameters for all ICT human capital groups, panel B presents parameters varying before and post pandemic, panel C presents the parameters during the pandemic, and panel D presents the parameters that are different across the groups.

Symbol	**Value**	**Parameter**
A: Common parameters		
β	0.999	Subjective discount factor
δ_K	0.004	Physical capital depreciation rate
δ_l	0.007	Labor exit rate
δ_n	0.008	ICT human capital depreciation rate
ξ	-0.500	Controls elasticity of substituion between physical capital and ICT human capital
ρ	0.400	Controls elasticity of substituion between in-person and flexible tasks
ε	4.000	Controls demand elasticity
W	1.000	Normalized wage rate
B: Parameters before and post pandemic		
ζ_b	0.004	Productivity gain of WFH before and after pandemic
ρ_S	0.983	Persistence of aggregate labor productivity
σ_S	0.003	Conditional volatility of aggregate labor productivity
ρ_X	0.983	Persistence of aggregate demand shock
σ_X	0.003	Conditional volatility of aggregate demand shock
f	0.02/.015	Adoption cost of WFH before/after pandemic
C: Parameters during pandemic		
ζ_d	0.007	Productivity of WFH during pandemic
S_H	1.000	Normal state of aggregate labor productivity
S_L	0.950	Pandemic state of aggregate labor productivity
X_H	1.000	Normal state of aggregate demand
X_L	0.940	Pandemic state of aggregate demand
σ_H	0.200	Pandemic state of conditional aggreagte volatility
σ_L	0.050	Normal state of conditional aggreagte volatility
π^{σ}_{LH}	0.026	Probability from low to high uncertainty state
π^{σ}_{HH}	0.943	Probability of staying high uncertainty state
$\pi^{SX}_{HH}(\sigma_L)$	0.999	Probability of labor and demand shocks staying in normal state conditional on low uncertainty
$\pi^{SX}_{LL}(\sigma_L)$	0.750	Probability of labor and demand shocks staying in pandemic state conditional on low uncertainty
$\pi^{SX}_{HH}(\sigma_H)$	0.999	Probability of labor and demand shocks staying in normal state conditional on high uncertainty
$\pi^{SX}_{LL}(\sigma_H)$	0.987	Probability of labor and demand shocks staying in pandemic state conditional on high uncertainty
f	0.020	Adoption cost of WFH before pandemic
D: Parameter heterogeneous across groups		
Share of ICT human in flexible task		
μ	0.002	Low ICT group
μ	0.020	Mid ICT group
μ	0.500	High ICT group
Share of in-person task in output		
φ	0.930	Low ICT group
φ	0.900	Mid ICT group
φ	0.800	High ICT group

Table 13: Target Moments of Three ICT Human Capital Groups

This table presents the target moments of three ICT human capital groups. Panel A presents the data moments and panel B the model implied moments. The three portfolios are sorted by ICT human capital. ICT/assets is ICT human capital to total assets (physical capital in the model) ratio and ICT/Revenue is ICT human capital to firms' revenue.

Portoflio	**ICT/assets**	**ICT/Revenue**
	A: Data	
Low	0.005	0.497
Mid	0.059	2.822
High	0.702	28.885
	B: Model	
Low	0.010	0.500
Mid	0.050	3.120
High	0.680	30.600

Table 14: Comparison of Data and Model Moments

This table presents selected quantity and asset pricing moments in the data and model, including the firms' revenue growth (dRevenue), employment growth (dEmployment) and stock returns. "L", "H" and "L-H" refer to the low and high ICT human capital portfolios, and "L-H" stands for the spread between the low and high groups. "Avg" stands for the average of all five ICT human capital portfolios.

	dRevenue	**dEmployment**	**Return**
		A: Data	
Low	-12.526	-10.932	-18.280
High	-4.215	-4.050	-7.460
Avg	-8.195	-7.517	-12.858
L-H	8.664	8.312	10.821
		B: Model	
Low	-13.793	-13.917	-13.986
High	-3.048	-6.112	-3.312
Avg	-9.263	-10.774	-9.910
L-H	10.744	7.805	10.674

Table 15: Comparison of Data and Model Moments

This table presents the counterfacutal analysis of the model. These model specifications include A) data, B) baseline model calibration, C) no work-from-home opion, D) zero prices of risk for aggregate labor and demand shocks, E) a high elasticity of substitution between physical capital and ICT human capital, F) a high elasticity of subsitution between in-person task and flexible task, F) aggregate labor shock only and G) aggregate demand shock only. The moments include firms' revenue growth (dRevenue), employment growth (dEmployment) and stock returns. "L-H" stands for the spread between the low and high groups. "Avg" stands for the average of all five ICT human capital portfolios.

	dRevenue	**dEmployment**	**Return**		**dRevenue**	**dEmployment**	**Return**
A: Data							
Avg	-8.20	-7.52	-12.86	L-H	8.66	8.31	10.82
B: Baseline model							
Avg	-9.26	-10.77	-9.91	L-H	10.74	7.80	10.67
C: No WFH							
Avg	-11.51	-12.68	-12.10	L-H	1.22	1.52	-1.26
D: Zero price of risk							
Avg	-13.07	-14.02	-14.20	L-H	5.26	4.66	1.29
E: High elasticity between K and N							
Avg	-3.77	-9.41	-3.14	L-H	4.41	6.34	2.97
F: High elasticity between tasks							
Avg	-12.45	-13.38	-13.85	L-H	9.34	6.78	9.88
G: Labor shock only							
Avg	-4.91	-5.75	-5.24	L-H	4.82	4.37	1.89
H: Demand shock only							
Avg	-4.01	-4.09	-5.61	L-H	0.28	0.52	0.42