Personal Social Networks, Technology Skills, and Workers' Digital Resilience

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With the recent, sweeping transition to remote work arrangements, due to the COVID-19 pandemic, workplace peer-support mechanisms have grown strained, fostering concerns about professional isolation, the long-run implications for worker performance, and workers' digital resilience more generally. In this study, we consider that potential remote workers may substitute workplace peer support with support from personal social networks, outside of the organization. Drawing on a novel, large and granular dataset that incorporates worker earnings, employment relationships, demographics, family-connections, educational backgrounds and employers' remote work practices, for 400,000 Portuguese workers, we estimate that partner technology expertise has significant spillover benefits for a worker's wages following a shift to remote-work. Specifically, we estimate that the wage return from spousal technology skills was approximately 75% of the wage return from own technology skills. We demonstrate the robustness of our findings to alternative explanations and measures, and we discuss the implications of our findings for firms, remote workers and society.

Key words: Remote Work, Work from Home (WFH), Work from Anywhere (WFA), Tele-work, Telecommuting, Difference-in-Differences, Digital Resilience

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1. Introduction

The introduction of new digital technologies in the workplace often necessitates shifts in the processes and procedures that workers follow in carrying out their day-to-day responsibilities (Greenwood et al. 2019). These new technologies may thus impose significant costs on a worker (Robey et al. 2002), and its adoption may vary with the worker's prior technology training and experience (Jasperson et al. 2005). Rapid and frequent technological change now characterize the modern workplace (Autor 2015, Stone et al. 2015), and employee retraining is an increasingly difficult and costly proposition for both employers (and workers) to bear. To lessen that burden, firms often supplement formal training initiatives with various peer-support mechanisms, e.g., communities of practice (COPs), mentoring and buddy systems. Indeed, by some estimates, nearly three-quarters of Fortune 500 firms now offer peer support programs.[1]

With the recent transition to telework arrangements, as a result of the COVID-19 pandemic, workplace peer-support mechanisms have grown strained, raising concerns about professional isolation and worker performance. In this study, we consider a natural alternative that employees' may draw upon for support: their personal social connections, outside of the workplace. Although a small body of prior research has examined the phenomenon of home technology help, wherein one tech savvy household member influences and aids other household members' adoption of computing technologies (Poole et al. 2009, Kiesler et al. 2000), our work is the first (to our knowledge) that seeks to draw a connection between the availability of technology peer support outside of the workplace and employee performance following the transition to telework. More formally, we address the following question: ***To what extent does access to household members with relevant technology-expertise enable the digital resilience of employees under teleworking arrangements?***

We address this question leveraging a unique, granular dataset on 400,000 Portuguese workers from Statistics Portugal (the Portuguese national statistics authority) to implement a difference-in-differences design. We provide evidence that spousal technology expertise has a significant, positive spillover benefit for workers' wages following a mandated shift to telework (otherwise known as a work-from-home, WFH arrangement). Among workers whose employers mandated WFH arrangements with the onset of the COVID-19 pandemic, we estimate that the wage return from spousal technology skills was approximately 75% of the wage return from own own-technology skills over the subsequent three months. We also report a number of secondary analyses that support a causal interpretation and which rule out alternative explanations.

Our work makes a number of contributions to the literature. While prior work has documented the value of personal social networks for job search and attainment (Zang 2003, Garg and Telang 2018),

[1] Huffington Post - Four Key Benefits of Workplace Mentoring Initiatives.

as well as the value of social networks (within the workplace) for worker performance (Bandiera and Rasul 2006), our work is novel in terms of the mechanism it addresses. Whereas these past works have considered that social networks may enable job discovery, influence job attainment, or help maintain worker motivation, our work highlights the value of human-capital workers may access via their personal social networks. Our work also contributes more specifically to the IS literature, identifying and documenting the importance of personal social networks for the digital resilience of individual employees under telework arrangements, and workplace technological change more generally.

The ability of workers to flourish under remote working is only likely to increase in importance as time goes on, for at least two reasons. First, the gig economy, which necessitates something of a location-independent nomadic life, continues to expand (Burtch et al. 2018, Sutherland and Jarrahi 2017). Second, our climate and environment are under stress. Firms are increasingly likely to seek to reduce employee travel by instituting remote work programs. At the same time, extreme shifts in local climate may give rise to more frequent natural disasters or reduced air quality, which in turn may produce scenarios that necessitate temporary remote work. Both trends suggest that workers may broadly fare better when able to access viable substitutes for workplace peer interaction.

2. Literature Review

2.1. Drivers of Success in Telework

As a result of the COVID-19 pandemic, and the associated need for social distancing to mitigate viral spread, workers have experienced sudden shifts in their daily routines, transitioning toward technology-mediated communication and virtual collaboration. These transitions have necessitated that individuals adapt and incorporate new technologies into their daily work activities (Hodder 2020). Although prior work has observed that WFH arrangements can have beneficial productivity effects in certain work settings (Bloom et al. 2015), the pandemic has shown that the impact on worker performance is varied, depending on a variety of factors. For example, recent work has highlighted that some jobs, primarily knowledge-work, are naturally better suited to WFH arrangements (Bartik et al. 2020). Some knowledge workers have exhibited productivity gains under WFH (Yang et al. 2020), particularly when they have some prior experience with telecommuting. Workers' collective performance has also tended to be greater when their employer has previously facilitated such experience, e.g., investing in telecommuting infrastructure (Bai et al. 2020).

Although many workers' jobs are structurally well-suited to telecommuting, and many employers have invested heavily in preparing their operating environment for remote working arrangements, aspects of an employee's personal life can also contribute to their performance and career outcomes under tele-working arrangements. Indeed, this has been evidenced in research addressing the recent forced shift toward tele-work and remote education, which has observed that individual productivity

has varied widely. For example, children in households that benefit from higher-quality internet have fared better at school (Chiou and Tucker 2020), while females have generally fared worse than males at work (Myers et al. 2020, Cui et al. 2020). The latter finding may be attributable to a number of factors, an obvious candidate being that women tend to shoulder a greater share of childcare responsibilities in the household. As a result, the confluence of forced tele-work and an absence of third-party childcare options has resulted in reduced bandwidth for female employees to complete their work activities.

More generally, past work has documented that marginalized employee groups tend to suffer disadvantages in the workplace (Kane and Wu 2020). Marginalized employees typical hold a position on the fringes of the organization's social network, implying reduced information access, as well as reduced visibility to co-workers and superiors (Barsness et al. 2005). Because of their fringe position in the network, marginalized employees stand to benefit most from formalized opportunities for peer interaction. Unfortunately, under tele-work arrangements, the opportunities for workplace peer interactions are significantly reduced and peer support mechanisms become relatively inaccessible (Kraut 1989). Notably, the notion that tele-work may lead to professional isolation is not particularly new (Cooper and Kurland 2002, Golden et al. 2008), but the recent trend toward WFH during the COVID-19 pandemic has drawn media attention back to this issue, and its long-term implications for worker performance.[2,3] This is crucial to consider because, as we review next, a great deal of prior work has highlighted the importance of peer-support mechanisms in the workplace for employees' success in the face of technological shifts. We next consider that variation in workers' access to peer support, via their personal social networks, may affect their digital resilience and performance under tele-work.

2.2. Personal Networks and Technology Support

Firms facilitate employee development in a variety of ways, which often extend beyond formal training. Most notably, firms also rely on a variety of peer-support mechanisms, such as COPs, a concept that has seen extensive consideration in past literature, specifically as a means to facilitating technology integration within the workplace (Hawley and Barnard 2005, Hislop 2003). COPs are just one peer-support mechanism, however. Other peer-support mechanisms include coaching, buddy systems and mentoring (Thach 2002). Across all of these initiatives, context is an important determinant of realized benefits. Learners and peer educators require sustained access to one another, as well as sufficient slack time and resources, to engage in mentoring (on the peer educator's side), and to

[2] Bank of England – Is Home Working Good for You?

[3] Forbes – Beware: Professional Isolation Is More Than Loneliness

experiment flexibly, practice, and reflect on performance (on the learner side) (Broad and Newstrom 1992, Chiaburu and Tekleab 2005, Lim and Morris 2006).

The recent shift to digitally-enabled tele-work arrangements has reduced employees' ability to draw on traditional mechanisms of peer-support in the workplace, across the board. This is problematic, as prior work has documented that this aspect of tele-work leads to reduced workplace performance (Golden et al. 2008). Moreover, as noted previously, these effects may be more pronounced among marginalized groups of workers (Kane and Wu 2020). However, working from home creates other opportunities for peer support, by enabling the potential for workers to obtain assistance from other members of their household. A small body of prior research has examined the phenomenon of home technology help, wherein one tech savvy household member influences and aids other household members' adoption of computing technologies (Poole et al. 2009, Kiesler et al. 2000).

Although some work in economics speaks to the important role of personal social networks for individuals' adoption and use of home computing technology (Goolsbee and Klenow 2002, Bandiera and Rasul 2006), scholars in human-computer interaction (HCI) have dedicated perhaps the greatest attention to these phenomena. As Poole et al. (2009) have observed, "relying on social networks for computer help has become common in many homes." However, studies have documented evidence of home technology support and peer influence in technology learning since the mid-1990s. The earliest such study, the HomeNet project (Kiesler et al. 2000, Franzke and McClard 1996), explored help-seeking and provision behavior in relation to residential computing issues. Early studies documented that teenagers, in particular, were most likely to seek support from within their personal social network. Over time, however, as technology proliferated, home technology support shifted away from being solely the domain of teenagers, such that home technology support is now often delivered and received by adults (Chetty et al. 2007, Grinter et al. 2005).

While the original studies in this domain focused on the provision of support from other members of the same household, subsequent work has documented that the phenomenon extends further, with technology support often being provided and received within extended personal social networks, including individuals who reside outside of the recipient's home (Poole et al. 2009). Further, while early work focused largely on support in relation to home computing networks, subsequent work has shown that similar peer support mechanisms arise in other technology domains, such as cyber-security (Redmiles et al. 2016a,b) and online investing (Konana and Balasubramanian 2005),

3. Data and Methods

We divide this section into three parts. In the first subsection, we provide a brief overview of a linear model of social interactions that we use to test our research hypotheses. In the second subsection, we present our dataset and its descriptive statistics. We then discuss our econometric specification and identification strategy in the third subsection.

3.1. A Simple Model of Social Interactions

Our objective is to estimate to what extent family members' technology-expertise yields spillover benefits for a worker's performance and earnings when the worker contends with new workplace technologies. We consider this dynamic in the context of a linear model of social interactions.

We assume there is a population of N persons whose behavior maximizes a utility function, $U()$, which depends on an individual's own effort and characteristics, as well as on the effort and characteristics of other persons in the population. $U()$ is defined by the following equation (1):

$$U(w_i, w_{-i}) = \gamma x_i w_i + z_i w_i + \delta \sum_j c_{ij} x_j w_i + \phi \sum_j a_{ij} w_j w_i - \frac{1}{2} w_i^2 \tag{1}$$

Equation (1) captures the strategic complements utility function for peer effects. This is a classical model that appears in a number of prominent papers in the literature on social interactions, such as Sacerdote (2001) and Calvó-Armengol et al. (2009). Here, x_i is a publicly observed characteristic of person i; z_i is a private type known only to i, independent of x_i; w_i is the level of effort that i deploys to maximize her utility; a_{ij} and c_{ij} are elements of $N \times N$ adjacency matrices, A and C. The elements of A and C determine whether person i is connected to person j in the population and also the strength of the connection. In this specification, $\delta \sum_j c_{ij} x_j$ captures the direct influence of others' characteristics on the choices of person i. In the literature, this is referred to as the contextual effect (Manski 1993, 2000, Durlauf and Ioannides 2010, Blume et al. 2015). The endogenous peer effect is determined by $\phi \sum_j a_{ij} w_j w_i$. This parameterization allows for the effort of others to yield a positive spillover to a connected individual, yielding an increase in the marginal product of each party's effort. Finally, ϕ determines the marginal rate of substitution between the private and the social components of utility, and $-\frac{1}{2} w_i^2$ captures the cost of effort.

All persons in the population choose their effort levels simultaneously to maximize their expected utility, conditional on their type and the public types of others (Blume et al. 2015). The first-order conditions of the expected utility maximization problem ($\frac{\partial E[U(w_i, w_{-i})|x]}{\partial w_i} = 0$) generate a system of N equations similar to 2:

$$w_i = \alpha + \gamma x_i + \delta \sum_j c_{ij} x_j + \phi \sum_j a_{ij} E[w_j|x] + \epsilon_i \tag{2}$$

We are particularly interested in measuring coefficient δ, which is associated with the technology expertise of the family members of each individual, i. We thus estimate the reduced form Equation (2), treating wage compensation as a proxy for individual effort.

We implement a difference-in-differences design that contrasts an individual's wage compensation in 2019 with their wage compensation in 2020 in the calendar months before and after the COVID-19 pandemic while controlling for individual fixed effects and family fixed effects.

We describe the data sources that enable the estimation of our empirical model in the next section.

3.2. Data and Measures

We obtained data from Statistics Portugal (the Portuguese national statistics authority). The dataset includes anonymized records pertaining to a population of four hundred thousand persons who filed income taxes as Portuguese residents in 2017 and who were also employed by firms that answered the 2020 IREE[4] survey (INE 2020).

The survey was launched during the initial phase of the COVID-19 crisis in Portugal, as a collaboration between Statistics Portugal and the Bank of Portugal. The goal of the survey was to quickly identify the impact of pandemic containment measures on business activity. The containment measures in question were a series of policy responses that were implemented to limit the spread of COVID-19 in Portugal, beginning on March 18, 2020, when the government declared a state of emergency. Specifically, the government issued a stay at home order, restricted movement between municipalities, closed airports to civil transportation and imposed border controls. The state of emergency ended on May 2^{nd}, after which Portugal began a phased reopening of its economy. In March and April 2020, several firms asked their employees to work from home, and the majority of such arrangements persisted even as the economy started to re-open.

The IREE survey contains firm-level questions that identify the companies that adopted work from home arrangements during the pandemic months. The questionnaire started in the first week of April, and it repeated weekly in April. The questionnaire moved to a fortnightly frequency with the end of the State of Emergency in May. It was suspended in August after the relief of the primary containment measures impacting firms' business activity.

For each person in the sample, we have an anonymized identifier for their employer, and we know if the firm they work for adopted a WFH arrangement, from March 2020 onward. We also observe each person's monthly salary, from January through May in each of 2019 and 2020. Additionally, we have information on each individual's age, gender, 2018 income bracket, the number of dependents each individual declared to the tax authority in 2018, their level of education and their job definition according to the international standard classification of occupations (ISCO-08).

Beyond individual-level data, we also have an anonymized family identifier that allows us to link individuals who appeared together on a tax filing. About ten percent of the individuals in our sample can be linked together as partners based on 2018 tax filings, and this linkage is what enables us to measure the spillover effects of digital expertise of family members on an individual's labor market outcomes.

Finally, we obtained nominal monthly consumption expenditures for each person following the same approach as in Eichenbaum et al. (2020). Note that we draw on the expenditure data primarily in Appendix A, to validate our measures of individual and peer computing skills.

[4] The English translation of the survey title is roughly 'Rapid and Exceptional Business Survey,' reflecting the fact that the survey was deployed quickly in response to changes in business activity around the COVID-19 pandemic.

We map the ISCO-08 occupation codes to their equivalent O*NET occupation classification. O*NET is a database from the US Department of Labor that contains detailed information on 974 occupations (Department of Labor 2020), which notably summarizes an occupation's key features using a standardized set of measures that have been collected via worker surveys. The results of these questionnaires summarize (for each occupation code) the specific aspects of the skills, working environment and typical tasks required of individuals that hold such a position at a firm. Accordingly, we can use occupation codes to identify individuals whose jobs necessitate substantial computer technology use.

To integrate O*NET's data, we link its classification of occupations to the Standard Occupational Classification (SOC) system of the US Bureau of Labor Statistics. We then match the 6-digit SOC codes from the Bureau of Labor Statistics to the 4-digit International Standard Classification of Occupations (ISCO-08). Because many O*NET occupations match a single ISCO-08 4-digit code, we follow Frey and Osborne (2017)'s procedure to resolve multiple (ambiguous) matches: we aggregate the duplicate occupations by calculating averages of the continuous variables that characterize jobs, and we calculate the mode for categorical variables. Of particular interest to our study is the classification of computer skills that characterize different occupations.[5]

Table 1 reports the average, standard deviation, and interquartile range of our dataset's main variables. The table provides descriptive statistics for the complete sample and the sub-sample of couples we use in our spillover analyses. The table highlights that 20 percent of our dataset's observations pertain to individuals working for firms that adopted high levels of WFH arrangements following the onset of the COVID-19 pandemic. This statistic applies to the broader sample, as well as to the subsample of couples that inform our peer effects analysis.

Panels (A) and (B) of Figure 1 depict the average wage of workers over time, across firms that adopt low- and high- levels of remote work, i.e., firms having less versus greater than or equal to 50% of their employees operating in a WFH arrangement. Panels (C) and (D) in the same figure depict the median wage of workers over time across firms that adopt low- and high-levels of remote work. The dashed vertical line marks what we denote as the Post (After) period; that is, the year months in 2020 during which COVID-19 drove policy responses, most notably stay-at-home orders.

Three facts emerge from this plot. Before COVID-19, salaries were growing, and COVID-19 interrupted that trend. Average and median wages were lower in 2020 after the COVID-19 crisis than in the same months of 2019 (i.e., from March onward). Average wages are substantially higher than median wages, which highlights the long tail of the salary distribution. Finally, firms that adopted high levels of remote work during the COVID-19 crisis paid higher wages than firms with lower

[5] The relevant O*NET questionnaire items are presented in Appendix A. There, we also validate our measure of computing skill by examining its relationship with individuals' educational backgrounds.

tele-work adoption. We consider these empirical facts in our econometric analysis, which we detail in the next section.

Table 1 Descriptive statistics over the complete dataset

Variable	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
Sample with everyone (405,120 persons)					
Wage Gross (Euros/month)	1,820.5	2,945.5	903.7	1,273.5	2,013.0
Expenses (Euros/month)	618.6	1,687.8	202.1	379.5	647.6
Age	44.2	9.9	37.0	44.0	52.0
Male	0.6	0.5	0.0	1.0	1.0
Family Size	1.5	0.8	1.0	1.0	2.0
Dependents	0.8	0.9	0.0	1.0	1.0
Computing Skills	0.5	0.2	0.4	0.4	0.5
In Sample Partner	0.2	0.4	0.0	0.0	0.0
Primary Education	0.1	0.3	0.0	0.0	0.0
Some High-School	0.4	0.5	0.0	0.0	1.0
High-School	0.3	0.5	0.0	0.0	1.0
University	0.2	0.4	0.0	0.0	0.0
Low skilled blue collar	0.2	0.4	0.0	0.0	0.0
Low skilled white collar	0.3	0.5	0.0	0.0	1.0
Professionals and technicians	0.3	0.4	0.0	0.0	1.0
High skilled blue collar	0.1	0.3	0.0	0.0	0.0
Managers	0.1	0.2	0.0	0.0	0.0
Firm Telework High	0.2	0.4	0.0	0.0	0.0
Sample of Couples (39,764 persons)					
Wage (Euros/month)	1,833.1	2,517.9	908.8	1,288.5	2,032.9
Expenses (Euros/month)	643.2	1,871.4	217.8	399.5	671.8
Age	44.5	8.4	38.0	44.0	50.0
Male	0.5	0.5	0.0	1.0	1.0
Family Size	1.8	0.8	1.0	2.0	2.0
Dependents	1.1	0.8	1.0	1.0	2.0
Computing Skills	0.5	0.2	0.4	0.4	0.5
Primary Education	0.1	0.2	0.0	0.0	0.0
Some High-School	0.4	0.5	0.0	0.0	1.0
High-School	0.3	0.5	0.0	0.0	1.0
University	0.2	0.4	0.0	0.0	0.0
Low skilled blue collar	0.2	0.4	0.0	0.0	0.0
Low skilled white collar	0.3	0.5	0.0	0.0	1.0
High skilled blue collar	0.1	0.3	0.0	0.0	0.0
Professionals and technicians	0.3	0.4	0.0	0.0	1.0
Managers	0.1	0.2	0.0	0.0	0.0
Firm Telework High	0.2	0.4	0.0	0.0	0.0

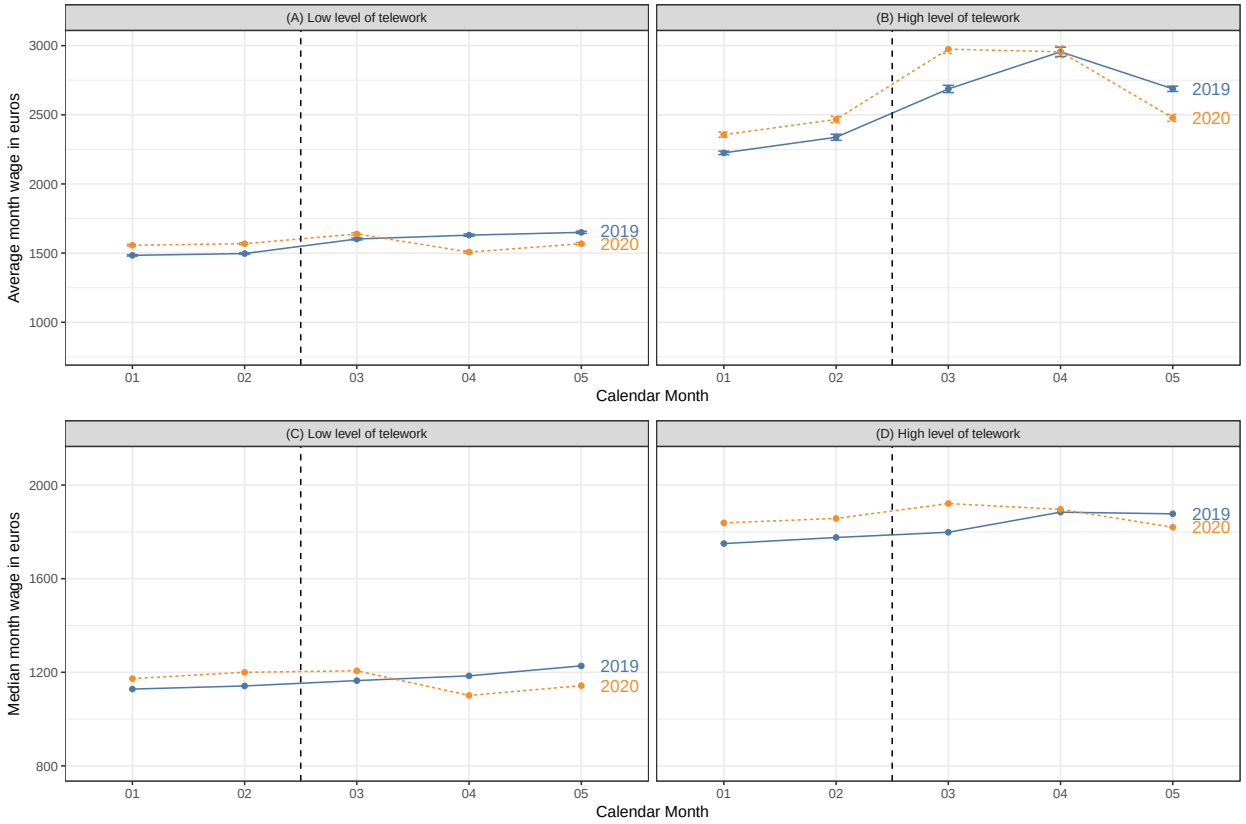


Figure 1 **Wage statistics over time across firms that adopt low- or high- levels of remote work.**

3.3. Identification Strategy

Our analyses employ the same identification strategy used by (Eichenbaum et al. 2020), implementing a differences-in-differences estimator to capture the effects of interest. We rely on observations from the year 2019 to serve as our baseline, and we assume that, absent COVID-19, the seasonal effects for wages from January through May of 2020 (λ_m) would have been equivalent (note that we report an empirical tests of parallel pre-trends in Appendix C).

Our first specification is detailed in Equation (3):

$$
\begin{aligned}
log(wages_{it}) = \\
&\gamma_0 After_t + \\
&\gamma_1 After_t \times \mathbf{1}\{ComputerSkill_i \geq 0.5\} + \\
&\gamma_2 After_t \times \mathbf{1}\{FirmTelework_i \geq 0.5\} + \\
&\gamma_3 After_t \times \mathbf{1}\{FirmTelework_i \geq 0.5\} \times \mathbf{1}\{ComputerSkill_i \geq 0.5\} + \\
&\Lambda_{2020}\mathbf{1}\{Year_t = 2020\} + \sum_{m=Feb}^{May} \lambda_m \mathbf{1}\{Month_t = m\} + \boldsymbol{\theta_i} + \boldsymbol{\Psi_{it}} + \epsilon_{it}
\end{aligned}
\tag{3}
$$

Subscripts i and t denote person i and calendar month t, and $After_t$ is a dummy variable equal to one from March through May and zero otherwise. The γ parameters capture the average change in wages after the onset of the COVID-19 pandemic, for people working in jobs necessitating different levels of computing skill and in firms that adopted WFH arrangements to varying degrees.

The coefficients Λ_y capture the growth trend in wages between 2019 and 2020, shared by all individuals. Coefficients λ_m capture the seasonality in wages for the months included in the sample (January through May). $\boldsymbol{\Psi_{it}}$ is a vector of interaction terms that allow seasonal effects to vary with individual characteristics. We allow our wage trends to change by age, gender, education and family composition. The coefficients $\boldsymbol{\theta_i}$ denote time-invariant individual fixed effects. Finally, ϵ_{it} is the idiosyncratic error term. Equation (3) initially ignores the peer effects dimension that we are interested in studying; this specification merely serves as a benchmark, capturing how wages changed in our overall sample of workers.

Our second specification, detailed in Equation (4), seeks to recover the structural parameters of interest from the linear peer effects model presented in Section 3.1.

$$
\begin{aligned}
log(wages_{it}) = \\
&\gamma_0 After_t + \\
&\gamma_1 After_t \times \mathbf{1}\{ComputerSkill_i \geq 0.5\} + \\
&\gamma_2 After_t \times \mathbf{1}\{FirmTelework_i \geq 0.5\} + \\
&\gamma_3 After_t \times \mathbf{1}\{FirmTelework_i \geq 0.5\} \times \mathbf{1}\{ComputerSkill_i \geq 0.5\} + \\
&\delta_1 After_t \times \mathbf{1}\{PartnerComputerSkill_i \geq 0.5\} + \\
&\delta_2 After_t \times \mathbf{1}\{FirmTelework_i \geq 0.5\} \times \mathbf{1}\{PartnerComputerSkill_i \geq 0.5\} + \\
&\Lambda_{2020}\mathbf{1}\{Year_t = 2020\} + \sum_{m=Feb}^{May} \lambda_m \mathbf{1}\{Month_t = m\} + \boldsymbol{\theta_i} + \boldsymbol{\Psi_{it}} + \boldsymbol{\kappa_{it}} + \epsilon_{it}
\end{aligned}
\tag{4}
$$

Here, the coefficients are interpreted as before, except that we additionally include $\boldsymbol{\kappa_{it}}$, a vector of interaction terms that allows seasonal effects to vary with each person's partner characteristics. The main coefficient of interest in this regression is δ_2, which reflects the effect of a partner's technology skills on a focal worker's earnings, among workers whose employers implemented high (vs. low) levels of WFH arrangements, following the onset of the COVID-19 pandemic. A positive, significant coefficient would indicate the contribution of individual workers' personal networks to their digital resilience; that is, the benefit to a worker from being able to tap the technology skills that reside in their personal social network.

4. Results

We estimate and analyze the results of our econometric specifications in this section. We begin by analyzing the impact of individual computing skills on a worker's own wage resilience during the pandemic months, depending on employers' shift (or not) toward WFH arrangements. Subsequently, we expand our specification to consider the additional effects of partners' computing skills.

Table 2 presents parameter estimates corresponding to equation 3. All specifications include month, year, and person fixed effects. Columns (1) to (4) build up the impact of teleworking and computing skills on wage resilience. We present columns (5) to (8) for robustness. Across the latter four estimations, we incorporate a series of additional controls, accounting for family composition, worker gender, education level, and age. In all columns, we report standard errors clustered by the focal worker, as suggested in Bertrand et al. (2004).

Three key results emerge from Table 2. First, the COVID-19 shock reduced the wage income of persons in our sample by 8.6 percent on average during the epidemic months, as compared to our counterfactual prediction based on the wage data for the year 2019. Second, workers whose employers adopted telework experienced a weaker decline in earnings, relative to firms that did not. Finally, among workers whose employers adopted high levels of remote work, those with high computing skills again experienced a weaker decline in earnings, i.e., they were relatively more protected compared to other workers in our sample. We note that the resilience of wage income for those with high computing skills is both statistically and economically significant.

Table 3 presents parameter estimates that correspond to Equation 4. This table focuses on the subpopulation of workers for whom a family identifier was available, linking them to a second worker, on the basis of a joint income tax filing in the year 2018. In this sub-sample, we analyze the wage resilience of those with high computing skills, in tandem with the spillover effect of partner computing skills.

Column (1) presents our main results, and we include Columns (2) to (5) to assess robustness. The regressions reported in each column include month, year, person, and family fixed effects. The family fixed effects (i.e., dyad dummies) control for latent homophily at the level of the couple, which might otherwise confound the wage spillover effects from partner computing skills. In this case, we report standard errors clustered by couple.

As in Table 2, we observe that workers whose employers instituted WFH arrangements, and who also high computing skills, experienced a lesser wage decrease following the onset of the pandemic. Of particular note, however, is that we also observe a positive spillover on a focal worker's wages from his or her partner's computing skills.

Finally, Table 4 recovers dynamics associated with the main effects of interest (i.e., computing skills and the partner spillover effect) over the initial months of the pandemic. For the sake of

Table 2 Changes in gross wage compensation during the pandemic months for all worker in the sample

	Dependent variable:							
	$log(wage_{it})$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$After$	−0.086***	−0.097***	−0.102***	−0.097***	−0.098***	−0.099***	−0.092***	−0.085***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)
$After \times TeleworkFirm_{\geq 50}$		0.046***	0.041***	0.017***	0.017***	0.017***	0.012***	0.012***
		(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$After \times TeleworkFirm_{\geq 50}$				0.069***	0.069***	0.069***	0.068***	0.068***
$\times ComputingSkills_{\geq 50}$				(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$After \times ComputingSkills_{\geq 50}$			0.024***	0.002+	0.002+	0.002+	−0.005***	−0.004**
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$After \times Dependents$					0.002*	0.002*	0.002*	0.004***
					(0.001)	(0.001)	(0.001)	(0.001)
$After \times Male$						0.0002	0.003**	0.003**
						(0.001)	(0.001)	(0.001)
$After \times Educ_{SomeHighSchool}$							−0.012***	−0.013***
							(0.002)	(0.002)
$After \times Educ_{HighSchool}$							−0.014***	−0.016***
							(0.002)	(0.002)
$After \times Educ_{University}$							0.017***	0.015***
							(0.002)	(0.002)
$After \times Age_{[30;40[}$								−0.003
								(0.002)
$After \times Age_{[40;50[}$								−0.008***
								(0.002)
$After \times Age_{[50;60[}$								−0.009***
								(0.002)
$After \times Age_{\geq 60}$								−0.007*
								(0.003)
Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Person	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,789,825	3,789,825	3,789,825	3,789,825	3,789,825	3,789,825	3,789,825	3,789,825
F-Stat	4188.472	3684.194	3259.267	2990.456	2692.699	2448.518	1945.327	1515.410
Adjusted R^2	0.745	0.745	0.745	0.745	0.745	0.745	0.745	0.745
R^2 (Within)	0.007	0.007	0.007	0.008	0.008	0.008	0.008	0.008

Note: + p<0.1; * p<0.05; ** p<0.01; *** p<0.001
Cluster robust standard errors in ();
Errors clustered by person

parsimony, we omit interaction terms between the post-period dummy variable, $After$, and the dummies for $TeleworkFirm_{\geq 50}$, $ComputingSkills_{\geq 50}$ and $PartnerComputingSkills_{\geq 50}$, as well as the remaining controls that we presented in Table 3. [6] This set of results highlights that the impact of personal computing skills and the partner computing skill spillover were not statistically significant initially, in March, yet they became significant after that point. This dynamic is expected, because Portuguese firms largely moved towards WFH arrangements only at the end of March. The effects became strongest in April 2020, when the lockdown measures became more stringent, and more firms engaged in WFH arrangements. The effects persist into May, despite that the economy gradually began to reopen, because a majority of WFH firms retained those arrangements.

[6] The complete regression output of table 4 is available upon request.

Table 3 Changes in gross wage compensation during the pandemic months for all couples in our sample

	Dependent variable:				
	$log(wage_{it})$				
	(1)	(2)	(3)	(4)	(5)
$After$	-0.089^{***}	-0.087^{***}	-0.086^{***}	-0.081^{***}	-0.048^{*}
	(0.003)	(0.004)	(0.005)	(0.008)	(0.019)
$After \times TeleworkFirm_{\geq 50}$	0.004	0.004	0.004	-0.007	-0.006
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
$After \times TeleworkFirm_{\geq 50} \times ComputingSkills_{\geq 50}$	0.053^{***}	0.053^{***}	0.053^{***}	0.050^{***}	0.051^{***}
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
$After \times TeleworkFirm_{\geq 50}$	0.041^{***}	0.041^{***}	0.041^{***}	0.038^{**}	0.038^{**}
$\times PartnerComputingSkills_{\geq 50}$	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
$After \times TeleworkFirm_{\geq 50} \times ComputingSkills_{\geq 50}$	0.002	0.002	0.002	0.007	0.006
$\times PartnerComputingSkills_{\geq 50}$	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
$After \times ComputingSkills_{\geq 50}$	0.00002	0.00003	0.0004	-0.008	-0.006
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$After \times ComputingSkills_{\geq 50}$	-0.008	-0.008	-0.008	-0.012	-0.013
$\times PartnerComputingSkills_{\geq 50}$	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
$After \times PartnerComputingSkills_{\geq 50}$	-0.007	-0.007	-0.007	-0.013^{*}	-0.011^{*}
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
$After \times Dependents$		-0.002	-0.002	-0.004	-0.003
		(0.004)	(0.004)	(0.004)	(0.005)
$After \times Male$			-0.002	0.001	0.002
			(0.003)	(0.003)	(0.003)
$After \times Educ_{SomeHigh-School}$				-0.005	-0.007
				(0.006)	(0.006)
$After \times Educ_{High-School}$				0.001	-0.002
				(0.007)	(0.007)
$After \times Educ_{University}$				0.037^{***}	0.033^{***}
				(0.008)	(0.008)
$After \times PartnerEduc_{SomeHigh-School}$				-0.008	-0.010
				(0.007)	(0.007)
$After \times PartnerEduc_{High-School}$				-0.007	-0.011
				(0.007)	(0.007)
$After \times PartnerEduc_{University}$				-0.0003	-0.004
				(0.008)	(0.009)
$After \times Age_{[30;40[}$					-0.019
					(0.017)
$After \times Age_{[40;50[}$					-0.034^{*}
					(0.017)
$After \times Age_{[50;60[}$					-0.036^{*}
					(0.017)
$After \times Age_{\geq 60}$					-0.029
					(0.018)
Month	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Person	Yes	Yes	Yes	Yes	Yes
Dyad	Yes	Yes	Yes	Yes	Yes
Observations	357,976	357,976	357,976	357,976	357,976
F-Stat	171.179	159.690	149.200	109.246	92.572
Adjusted R^2	0.744	0.744	0.744	0.744	0.744
R^2 (within)	0.008	0.008	0.008	0.008	0.008

Note: + p<0.1; * p<0.05; ** p<0.01; *** p<0.001
Cluster robust standard errors in ();
Errors clustered by dyad

5. Robustness

In the appendices, we report the results of several robustness checks. In Appendix A, we consider the validity of our main computing skills measure. We detail our approach to variable construction, which

Table 4 Changes over time in the gross wage compensation during the pandemic months

	Dependent variable:		
	$log(wage_{it})$		
	(1)	(2)	(3)
$After \times Mar$	-0.017^{***}	-0.026^{***}	-0.034^{***}
	(0.004)	(0.005)	(0.010)
$After \times Apr$	-0.147^{***}	-0.143^{***}	-0.136^{***}
	(0.004)	(0.006)	(0.012)
$After \times May$	-0.103^{***}	-0.093^{***}	-0.074^{***}
	(0.004)	(0.006)	(0.012)
$After \times Mar \times TeleworkFirm_{\geq 50} \times ComputingSkills_{\geq 50}$	0.022	0.022	0.020
	(0.017)	(0.017)	(0.017)
$After \times Apr \times TeleworkFirm_{\geq 50} \times ComputingSkills_{\geq 50}$	0.085^{***}	0.085^{***}	0.082^{***}
	(0.016)	(0.016)	(0.016)
$After \times May \times TeleworkFirm_{\geq 50} \times ComputingSkills_{\geq 50}$	0.050^{**}	0.050^{**}	0.049^{**}
	(0.016)	(0.016)	(0.016)
$After \times Mar \times TeleworkFirm_{\geq 50} \times PartnerComputingSkills_{\geq 50}$	0.013	0.012	0.010
	(0.017)	(0.017)	(0.017)
$After \times Apr \times TeleworkFirm_{\geq 50} \times PartnerComputingSkills_{\geq 50}$	0.061^{***}	0.061^{***}	0.056^{**}
	(0.018)	(0.018)	(0.017)
$After \times May \times TeleworkFirm_{\geq 50} \times PartnerComputingSkills_{\geq 50}$	0.049^{**}	0.049^{**}	0.047^{**}
	(0.017)	(0.017)	(0.017)
Person	Yes	Yes	Yes
Dyad	Yes	Yes	Yes
Month	Yes	Yes	Yes
Month × After × Other Main Effects	Yes	Yes	Yes
Month × After × Dependents	No	Yes	Yes
Month × After × Gender	No	No	Yes
Month × After × Education	No	No	Yes
Month × After × Partner Education	No	No	Yes
Observations	357,976	357,976	357,976
F-Stat	123.987	113.243	70.719
Adjusted R^2	0.745	0.745	0.745
R^2 (within)	0.013	0.013	0.013

+ p<0.1; * p<0.05; ** p<0.01; *** p<0.001
Cluster robust standard errors in ();
Errors clustered by dyad

closely follows prior work. Subsequently, we demonstrate that the resulting indicator of computing skill correlates significantly with individuals' educational background. Specifically, we show that our measure correlates highly with individuals' possession of a STEM degree, generally, as well as a BSc, MSc or PhD in Computer Science or Computer Engineering, specifically. Further, in Appendix B, we demonstrate that our main results are robust to the use of this alternative measure of computing skills.

Next, we consider the assumption in our benchmark specification that seasonal effects for January through May are common between 2019 and 2020. In Appendix C, we provide evidence of the empirical plausibility of this assumption, contrasting the trends for the months of January and February, wherein the COVID-19 pandemic had not yet sparked broad concern or policy response. There, we demonstrate that the trends are statistically indistinguishable, providing evidence in support of parallel pre-trends.

In Appendix D, we repeat our spillover analysis employing a matched sample. Specifically, we constructed a matched sample employing coarsened exact matching, or CEM (Iacus et al. 2012). We show that the matching procedure is effective at eliminating imbalance across a variety of measures, and that our main results persist.

In Appendix E, we re-estimate our main models focusing on worker-spouse pairs where the spouse's employer did *not* shift to a WFH arrangement following the pandemic onset. This analysis provides a useful placebo, as we would expect no (or diminished) benefits of spousal technology skills if the spouse is not co-located with the focal employee, at home. In this analysis, we therefore expect to observe a smaller, or statistically insignificant estimate of the wage-returns to partner technology skills. And, this is precisely what we observe.

Additionally, we consider models conditioning on the number of dependents in the household. Demonstrating robustness to a control for dependents enables us to rule out the possibility that the effects we observe derive from household flexibility, wherein technologically capable spouses may be more likely to WFH alongside the focal worker, enabling the pair to split childcare duties (benefiting both individuals' work productivity). As we show, after accounting for the number of dependents, our results persist.

6. Discussion

We have reported what is to our knowledge a first empirical consideration of the effect of personal social networks on individuals workers' digital resilience in the face of technological change in the workplace. More specifically, we provide robust evidence that, when forced into a WFH arrangement, workers' earnings are buttressed by their access to peer technology support from within their household. While a number of prior studies have documented the value of personal social connections for job search (Garg and Telang 2018, Zang 2003) and the returns to socialization within the workplace (Bandiera et al. 2009), our work speaks to a novel aspect of those relationships; the access they afford to job-relevant technology skills and knowledge.

Our findings also suggest possible side-benefits of services that facilitate job-related social interactions outside of the workplace, e.g., co-working spaces. A number of studies have recently documented the benefits of co-working spaces for freelancers, entrepreneurs and tele-workers, in terms of social support and community (Gerdenitsch et al. 2016, Garrett et al. 2017). Our findings point to the related potential that co-working spaces may enable remote workers to form personal social connections, and thereby access job-relevant knowledge and skills that can buttress workplace performance.

The implications of our results are potentially far reaching, and warrant further examination and exploration. While we demonstrate the benefits for individuals engaged in WFH arrangements from maintaining personal connections with others who have job-relevant skills and knowledge, this result

implies a dual. The flip side of this conclusion is that individuals who lack personal social network connections that embed job-relevant skills and knowledge may suffer relative to their more fortunate peers.

A lengthy literature speaks to various sources of digital inequality (DiMaggio et al. 2004, Hargittai and Hinnant 2008, Hsieh et al. 2008, Chiou and Tucker 2020). A broad conclusion in that literature has been that existing social inequalities may be amplified by digital technologies, e.g., because marginalized communities may lack technology access or education. Accordingly, our result suggests a source of social-amplification, such that workplace inequality may be amplified in the face of technological change, if employees who are on the margins at work may also have fewer personal social connections with relevant knowledge to draw upon.

It is also worth considering that these dynamics may differ across marginalized employee groups, depending on the demographic or structural basis of marginalization. For example, although female and new employees are known to occupy systematically less advantageous positions in workplace social structures (Kane and Wu 2020), those individuals may nonetheless have some access to job-relevant skills and knowledge outside of the workplace, within personal social networks. By contrast, this may not be the case among racial minorities.

It is important to consider the generalizability of our findings, beyond the COVID-19 pandemic. Large scale shocks to WFH arrangements, such as the one we consider here, are not unprecedented,[7,8,9] though the present shock is unique in a number of respects, e.g., the imposition of study from home for students, the need for social distancing, etc. That said, our findings are only likely to grow in relevance as time goes on, and the generalizability of our findings for individuals' digital resilience are likely to rise with time. We say this for at least two reasons.

First, beyond a lack of pandemic preparedness (Peiris et al. 2012) (an issue that may admittedly improve following the COVID-19 pandemic), climate and the environment continue to degrade, as greenhouse gas emissions go relatively unchecked. Corporate travelers account for huge portions of global emissions, e.g., just 1% of airline travelers account for 50% of the air travel industry's carbon emissions (Gössling and Humpe 2020). Many firms are thus pursuing programs to reduce employee employee travel, as part of Corporate Social Responsibility efforts. Gallup has reported that Sun Microsystems' Open Work Program reduced carbon dioxide emissions among its employees by 30,000 metric tons, annually, and Xerox's WFH program similarly led to carbon emission reductions on the order of 40,000 metric tons.[10] Firms' efforts aside, climate change will continue to wreak havoc on

[7] Quartz - IBM, remote-work pioneer, is calling thousands of employees back to the office.

[8] Washington Post - As remote work rises at U.S. companies, Trump is calling federal employees back to the office.

[9] CNN Money - Marissa Mayer: Yahoos can no longer work from home.

[10] Is Working Remotely Effective? Gallup Research Says Yes.

the global ecosystem, leading to reduced air-quality, and increased frequency of wild-fires (Stephens et al. 2013), hurricanes (Bender et al. 2010) and other climate-related natural disasters. Accordingly, workers' digital resilience will increasingly depend on their ability to confront scenarios of relocation and telework.

Second, the gig economy continues to expand (Burtch et al. 2018, Greenwood et al. 2017). Recent work has examined how workers in the gig economy (location independent, digital nomads) structure their work practices and environment for success (Sutherland and Jarrahi 2017). Our findings are highly relevant to that phenomenon, in that our work speaks to the possible resilience of individual workers within the digital gig economy. Some recent work has documented gig workers reliance upon online communities for peer social support and learning (Maffie 2020). Our work suggests that a co-located personal network connection may be particularly beneficial. Indeed, as the benefits of peer support mechanisms are known to depend upon sufficiently frequent, dedicated personal interactions, our findings raise the prospect that, in some respects, gig workers may fare better when they engage in gig work as a collective. Notably, this proposition contrasts past work in the area of self-employment and entrepreneurship, which has observed that income security and risk mitigation are necessary conditions for individuals to seek self-employment (Blanchflower and Oswald 1998), often achieved through the maintenance of a diversified income portfolio (Carter et al. 2004), e.g., maintaining a mix of income streams, such as a combination of self-employment and long-term employment with a firm. In short, our work points to a potential trade-off, between the benefits of income stream diversification across household members, and the benefits of peer support in remote work arrangements.

7. Conclusion

Our work is not without limitations. First, it is notable that past work has documented the value of communication-enhancing technologies for the management of professional isolation among tele-workers (Golden et al. 2008). These past findings suggest that the average effects we report here may in fact vary considerably across firms, depending on the nature of the support they provide to tele-workers, as well as the processes and policies firms' institute to encourage sustained interaction among employees. Although we lack the relevant data to explore those sources of heterogeneity, future work might attend to this.

Second, our analyses enable us to rule out a number of alternative explanations for the peer skill-spillover that we observe. Nonetheless, it remains possible that some other factor confounds both firm choices to engage in WFH programs. Our data does not enable us to observe individual activities and interactions between household members or co-workers. Accordingly, future work might look to employ alternative methods, perhaps akin to interview, survey and ethnographic methods employed in earlier HCI studies on the subject of home technology support (e.g., Kiesler et al. 2000, Franzke and McClard 1996).

Limitations aside, our work speaks to an important line of inquiry about whether and when personal social networks affect performance of workers. While prior work speaks to relevant aspects of the interplay between personal and professional life (e.g., the determinants and importance of striking a balance between personal and work life), we believe our work raises greater attention to specific elements of that interplay that are of direct relevance to the IS literature, specifically in regard to virtual teams and telework.

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Appendix A: O*NET Measure of Computing Skills

Our primary measure of computing skill is derived from the O*NET Questionnaires. Among these questionnaires, we draw on survey items from the 'Generalized Work Activities' questionnaire, and the 'Knowledge' questionnaire. More specifically, from the Work Activities questionnaire, we leverage an item capturing the degree to which a job involves interacting with computers. From the Knowledge questionnaire, we leverage two items, capturing the degree to which the job requires (i) knowledge of computers and electronics, and (ii) knowledge of engineering and technology.

For each of these survey items, we draw on two values, Importance and Level, which are reported by job-code. The meaning of these values is articulated in the O*NET help files as follows: *"To make sense of the different rankings, you need to understand the significance of the scale. Some people find it particularly difficult to understand the difference between Importance and Level. As an example, consider skills. While the same skill can be important for a variety of occupations, the amount or level of the skill needed in those occupations can differ dramatically. For example, the skill "speaking" is important for both lawyers and paralegals. However, lawyers (who frequently argue cases before judges and juries) are required to have a higher Level of speaking skill, while paralegals only need an average Level of this skill."*

To construct our label of computing skill, by job code, we follow the approach of Blinder et al. (2009). That is, we assign a Cobb-Douglas weight of two-thirds to importance and one-third to level, and we then sum the corresponding values. To simplify interpretation, we then transform the resulting value, normalizing it to the 0-1 range. Lastly, we dichotomize the resulting variable, such that we work with an indicator of high (> 0.5) versus low computing skill.

Upon constructing this variable, we next explored its face validity as a measure of computing skill (or general technology savvy). Specifically, for each person in our sample, we identify if they have educational degree types heavily associated with STEM disciplines (that is, Science, Technology, Engineering, and Math). We achieve this by hand-coding each of the 150 degree majors maintained by Statistics Portugal according to the STEM degree majors curated by the US Department of Veterans Affairs for the provision of educational benefits, namely the Edith Nourse Rogers STEM Scholarship.[11]. Within STEM degrees, we also single out those linked specifically to computer technologies, namely Computer Science and Computer Engineering. Using these classifications, we label individuals having STEM-related degrees and individuals having IT-related degrees, and we explore the association between these labels and our normalized computing skill index.

Figure 2 presents the analysis and highlights that STEM/IT-related degrees explain a substantial amount of the variation in our normalized computing skill measure consistently with what we would expect.

[11] US Dept. of Veterans Affairs - Edith Nourse Rogers STEM Scholarship Degree Requirements.

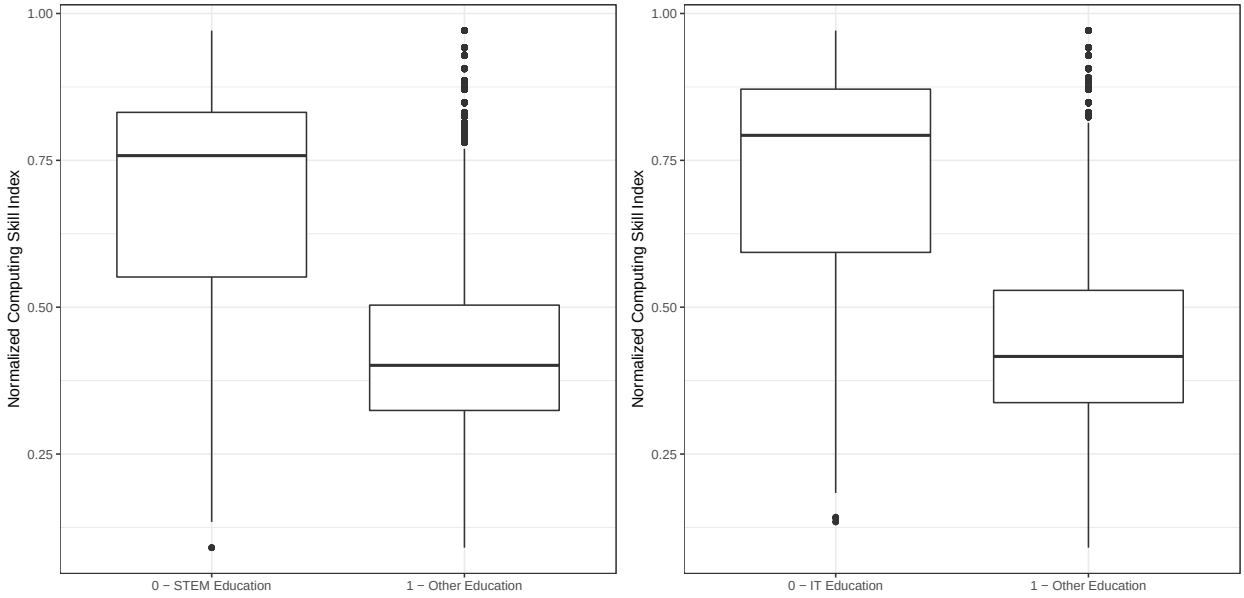


Figure 2 Association between our normalized O*NET-based measure of computing skill with technology-related educational background.

Appendix B: STEM as proxy for computing skill

In the analyses below, we employ our measure of STEM educational background (see Appendix A), in lieu of our normalized O*NET-based measure of computing skill.

Table 5

	Dependent variable:				
	$\log(\text{wage}_{it})$				
	(1)	(2)	(3)	(4)	(5)
$After$	-0.094^{***}	-0.091^{***}	-0.088^{***}	-0.084^{***}	-0.056^{*}
	(0.003)	(0.005)	(0.006)	(0.009)	(0.022)
$After \times TeleworkFirm_{\geq 50}$	0.026^{**}	0.026^{**}	0.026^{**}	0.003	0.003
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
$After \times TeleworkFirm_{\geq 50} \times STEM$	0.092^{***}	0.092^{***}	0.093^{***}	0.113^{***}	0.115^{***}
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
$After \times TeleworkFirm_{\geq 50} \times PartnerSTEM$	0.074^{**}	0.073^{**}	0.073^{**}	0.087^{***}	0.088^{***}
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
$After \times TeleworkFirm_{\geq 50} \times STEM \times PartnerSTEM$	-0.093^{*}	-0.093^{*}	-0.093^{*}	-0.104^{**}	-0.106^{**}
	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)
$After \times STEM$	0.006	0.006	0.007	-0.034^{**}	-0.034^{**}
	(0.011)	(0.011)	(0.011)	(0.013)	(0.013)
$After \times STEM \times PartnerSTEM$	-0.003	-0.003	-0.003	0.024	0.024
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
$After \times PartnerSTEM$	0.003	0.003	0.002	-0.029^{+}	-0.028^{+}
	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)
$After \times Dependents$		-0.004	-0.004	-0.006	-0.004
		(0.006)	(0.006)	(0.006)	(0.006)
$After \times Male$			-0.007^{+}	-0.005	-0.003
			(0.004)	(0.004)	(0.004)
$After \times Educ_{SomeHigh-School}$				-0.006	-0.008
				(0.007)	(0.007)
$After \times Educ_{High-School}$				0.005	-0.001
				(0.011)	(0.011)
$After \times Educ_{University}$				0.038^{***}	0.035^{***}
				(0.011)	(0.011)
$After \times PartnerEduc_{SomeHigh-School}$				-0.007	-0.010
				(0.007)	(0.007)
$After \times PartnerEduc_{High-School}$				-0.003	-0.008
				(0.011)	(0.011)
$After \times PartnerEduc_{University}$				0.004	0.001
				(0.011)	(0.011)
$After \times Age_{[30;40[}$					-0.005
					(0.021)
$After \times Age_{[40;50[}$					-0.033
					(0.021)
$After \times Age_{[50;60[}$					-0.029
					(0.021)
$After \times Age_{\geq 60}$					-0.027
					(0.023)
Month	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Dyad	Yes	Yes	Yes	Yes	Yes
Person	Yes	Yes	Yes	Yes	Yes
Observations	198,770	198,770	198,770	198,770	198,770
F-Stat	101.338	94.325	88.138	64.624	55.121
R^2	0.796	0.796	0.796	0.796	0.796
R^2 (within)	0.009	0.009	0.009	0.009	0.009

Note: + p<0.1; * p<0.05; ** p<0.01; *** p<0.001
Cluster robust standard errors in ();
Errors clustered by dyad

Appendix C: Common Trend Test

Our regression specifications assume that, in the absence of the epidemic, the seasonal variation in wages paid from January through May 2020 would be the same as the seasonal effects in 2019. To assess the empirical plausibility of this assumption, we estimated the following specification using data for the months of January and February in the years 2019 and 2020. Note that this analysis also provides an empirical evaluation of the parallel trends assumption, required to draw causal inferences based on our difference-in-differences estimation.

$$Wage_{it} = \phi_0 \mathbf{1}\{Year_t = 2020\} + \phi_1 \mathbf{1}\{Month_t = Feb\} + \phi_2 \mathbf{1}\{Month_t = Feb\} \times \mathbf{1}\{Year_t = 2020\} + \boldsymbol{\theta_i} + \epsilon_{it} \quad (5)$$

The ϕ_2 coefficient measures the difference in the average salary trend from January to February for the years 2019 and 2020. Under the null hypothesis that the trend is identical, ϕ_2 should be zero. Table 6 provides estimates of ϕ_2 for the complete sample and for the sub-sample of couples, with and without person fixed effects. We are unable to reject the joint null hypothesis that ϕ_2 is zero, providing support for our identifying assumption.

Table 6 Common salary trend from January to February in the years 2019 and 2020

	Dependent variable:			
	$wage_{it}$			
	All		Couples	
	(1)	(2)	(3)	(4)
$1\{Year = 2020\} \times 1\{Month = Feb\}$	2.844	4.766	14.361	20.392
	(5.359)	(5.239)	(20.215)	(19.792)
$1\{Month = Feb\}$	33.789***	28.656***	32.496+	24.140
	(4.281)	(3.953)	(19.023)	(19.432)
$1\{Year = 2020\}$	79.352***	79.210***	54.634**	63.901***
	(3.687)	(3.793)	(18.025)	(18.601)
Constant	1,667.806***		1,731.876***	
	(3.886)		(19.238)	
Person	No	Yes	No	Yes
Observations	1,526,162	1,526,162	144,507	144,507
F-Stat	264.207	341.589	19.674	31.368
R^2	0.0003	0.639	0.0002	0.536
R^2 (within)		0.0009		0.0005
Note:				+ p<0.1; * p<0.05; ** p<0.01; *** p<0.001
				Errors clustered by person in ()

Appendix D: Coarsened Exact Matching

We repeat our spillover analysis on a matched sample. Specifically, we construct a matched sample employing coarsened exact matching, or CEM (Iacus et al. 2012). We match persons working for firms with high levels of WFH arrangements to persons working for firms with low levels of WFH arrangements. We use data in January 2019 (before COVID-19) to construct the matched sample. Figure 3 depicts covariate (im)balance before and after the application of matching adjustment, while Table 8 reports the spillover regression using the matched sample. This estimation yields results very similar to those reported in the main body of the paper.

Table 7 K-to-K coarsened exact matching outcome

	$TeleworkFirm_{<50}$	$TeleworkFirm_{\geq 50}$
All	29,258	8,342
Matched	3,872	3,872
Unmacthed	25,386	4,470

Table 8 Changes in gross wage compensation during the pandemic months in a coarsened exact matching k-to-k sample

	Dependent variable:		
	$log(wage_{it})$		
	(1)	(2)	(3)
$After$	-0.083^{***}	-0.064	-0.239^{**}
	(0.008)	(0.070)	(0.090)
$After \times TeleworkFirm_{\geq 50}$	-0.029^{*}	-0.029^{*}	-0.028^{*}
	(0.012)	(0.012)	(0.011)
$After \times TeleworkFirm_{\geq 50} \times ComputingSkills_{\geq 50}$	0.089^{***}	0.088^{***}	0.083^{***}
	(0.019)	(0.019)	(0.018)
$After \times TeleworkFirm_{\geq 50} \times PartnerComputingSkills_{\geq 50}$	0.057^{**}	0.057^{**}	0.057^{**}
	(0.021)	(0.021)	(0.020)
$After \times TeleworkFirm_{\geq 50} \times ComputingSkills_{\geq 50}$	-0.047	-0.046	-0.051^{+}
$\times PartnerComputingSkills_{\geq 50}$	(0.030)	(0.029)	(0.028)
$After \times ComputingSkills_{\geq 50}$	-0.004	-0.028^{*}	-0.025^{*}
	(0.012)	(0.013)	(0.012)
$After \times ComputingSkills_{\geq 50} \times PartnerComputingSkills_{\geq 50}$	0.011	0.012	0.012
	(0.020)	(0.020)	(0.019)
$After \times PartnerComputingSkills_{\geq 50}$	0.001	-0.017	-0.022
	(0.013)	(0.014)	(0.014)
$After \times Dependents$		-0.006	-0.005
		(0.014)	(0.013)
$After \times Male$		0.010	0.018^{*}
		(0.007)	(0.008)
$After \times Educ_{SomeHigh-School}$		-0.042	-0.048^{+}
		(0.030)	(0.028)
$After \times Educ_{High-School}$		-0.032	-0.042
		(0.030)	(0.029)
$After \times Educ_{University}$		0.013	-0.003
		(0.032)	(0.031)
$After \times PartnerEduc_{SomeHigh-School}$		-0.022	-0.028
		(0.025)	(0.025)
$After \times PartnerEduc_{High-School}$		-0.009	-0.019
		(0.026)	(0.026)
$After \times PartnerEduc_{University}$		0.001	-0.024
		(0.028)	(0.029)
$After \times Age_{[30;40[}$		0.024	0.016
		(0.061)	(0.058)
$After \times Age_{[40;50[}$		0.016	0.004
		(0.061)	(0.058)
$After \times Age_{[50;60[}$		0.020	0.002
		(0.061)	(0.058)
$After \times Age_{\geq 60}$		0.064	0.046
		(0.063)	(0.061)
$After \times log(PartnerWage_{it})$			0.030^{**}
			(0.010)
$log(PartnerWage_{it})$			0.125^{***}
			(0.009)
Month	Yes	Yes	Yes
Year	Yes	Yes	Yes
Person	Yes	Yes	Yes
Observations	70,257	70,257	70,257
F-Stat	52.352	28.969	35.978
R^2	0.712	0.712	0.717
Adjusted R^2	0.676	0.677	0.682
R^2 (Within)	0.013	0.014	0.030

Note: + p<0.1; * p<0.05; ** p<0.01; *** p<0.001
Cluster robust standard errors in ();
Errors clustered by dyad

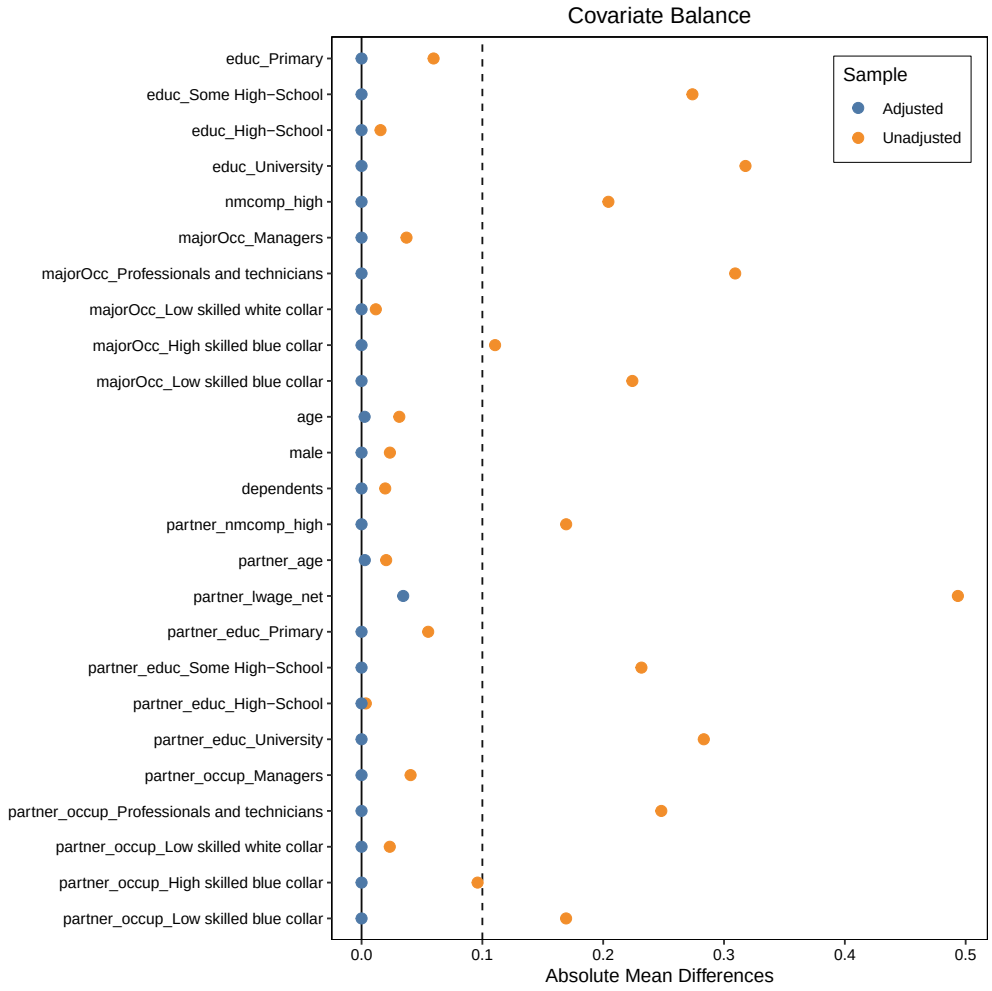


Figure 3 Absolute mean differences in observables before and after coarsened exact matching

Appendix E: Additional Specifications

In Table 9, we consider two models, conditioning on the number of dependents in the household, interacted with partners' level of teleworking. The two regressions demonstrate robustness to a control for dependents that enables us to rule out the possibility that the effects we observe derive from household flexibility, wherein technologically capable spouses may be more likely to WFH alongside the focal worker, enabling the pair to split childcare duties. As we show, after accounting for the existence of dependents, our results persist.

Table 9 Changes in gross wage compensation during the pandemic months for all worker in the sample controlling for the teleworking status of partners and whether the couple has dependents

	Dependent variable:	
	$log(wage_{it})$	
	(1)	(2)
$After$	-0.046^{*}	-0.045^{*}
	(0.019)	(0.019)
$After \times TeleworkFirm_{\geq 50}$	-0.007	-0.007
	(0.008)	(0.008)
$After \times TeleworkFirm_{\geq 50} \times ComputingSkills_{\geq 50}$	0.050^{***}	0.050^{***}
	(0.012)	(0.012)
$After \times TeleworkFirm_{\geq 50} \times PartnerComputingSkills_{\geq 50}$	0.037^{**}	0.036^{**}
	(0.012)	(0.013)
$After \times TeleworkFirm_{\geq 50} \times ComputingSkills_{\geq 50} \times PartnerComputingSkills_{\geq 50}$	0.006	0.006
	(0.019)	(0.019)
$After \times ComputingSkills_{\geq 50} \times PartnerComputingSkills_{\geq 50}$	-0.013	-0.013
	(0.010)	(0.010)
$After \times PartnerComputingSkills_{\geq 50}$	-0.011^{*}	-0.013
	(0.006)	(0.010)
$After \times PartnerTeleworkFirm_{\geq 50}$	-0.011	-0.009
	(0.010)	(0.013)
$After \times ComputingSkills_{\geq 50}$	-0.006	-0.006
	(0.005)	(0.005)
$After \times Dependents$	-0.007	-0.007
	(0.005)	(0.006)
$After \times PartnerTeleworkFirm_{\geq 50} \times Dependents$	0.019^{+}	0.015
	(0.011)	(0.015)
$After \times PartnerComputingSkills_{\geq 50} \times Dependents$		0.002
		(0.011)
$After \times PartnerComputingSkills_{\geq 50} \times PartnerTeleworkFirm_{\geq 50}$		-0.003
		(0.020)
$After \times PartnerComputingSkills_{\geq 50} \times PartnerTeleworkFirm_{\geq 50} \times Dependents$		0.007
		(0.021)
Month	Yes	Yes
Year	Yes	Yes
Person	Yes	Yes
Dyad	Yes	Yes
After × Dependents	Yes	Yes
After × Age	Yes	Yes
After × Gender	Yes	Yes
After × Education	Yes	Yes
After × Partner Education	Yes	Yes
Observations	357,976	357,976
F-Stat	85.735	77.202
Adjusted R^2	0.744	0.744
R^2 (Within)	0.008	0.008

+ p<0.1; * p<0.05; ** p<0.01; *** p<0.001
Cluster robust standard errors in ();
Errors clustered by dyad

In Table 10 we re-estimate our main models focusing on worker-spouse pairs where the spouse's employer did *not* shift to a WFH arrangement with the pandemic onset. This analysis provides a useful placebo. We expect no (or diminished) benefits of spousal technology skills if the spouse does not co-locate with the focal employee at home. In line with our expectations, we observe a statistically insignificant estimate of the wage-returns to partner technology skills for partners working in firms with less than 50% of the workforce in WFH arrangements. However, the spillover effects persist in the sample of persons whose partners employers maintained high WFH arrangements, despite the reduced statistical power of the smaller split sample.

Table 10 Changes in gross wage compensation during the pandemic months splitting households with partner working for low- high- WFH arragement firms

	Dependent variable:	
	$log(wage_{it})$	
	$ParterTeleworkFirm_{<50}$	$PartnerTeleworkFirm_{\geq 50}$
	(1)	(2)
$After$	-0.043^{*}	-0.141^{*}
	(0.020)	(0.056)
$After \times TeleworkFirm_{\geq 50}$	-0.013	0.004
	(0.010)	(0.014)
$After \times TeleworkFirm_{\geq 50} \times ComputingSkills_{\geq 50}$	0.059^{***}	0.029
	(0.016)	(0.021)
$After \times TeleworkFirm_{\geq 50} \times PartnerComputingSkills_{\geq 50}$	0.028	0.036^{+}
	(0.018)	(0.021)
$After \times TeleworkFirm_{\geq 50} \times ComputingSkills_{\geq 50}$	0.014	0.022
$\times PartnerComputingSkills_{\geq 50}$	(0.027)	(0.033)
$After \times ComputingSkills_{\geq 50}$	-0.008	0.009
	(0.006)	(0.016)
$After \times ComputingSkills_{\geq 50} \times PartnerComputingSkills_{\geq 50}$	-0.009	-0.034
	(0.011)	(0.025)
$After \times PartnerComputingSkills_{\geq 50}$	-0.011^{+}	-0.009
	(0.006)	(0.015)
Month	Yes	Yes
Year	Yes	Yes
Person	Yes	Yes
Dyad	Yes	Yes
After × Dependents	Yes	Yes
After × Age	Yes	Yes
After × Gender	Yes	Yes
After × Education	Yes	Yes
After × Partner Education	Yes	Yes
Observations	278,558	79,418
F-Stat	69.105	34.745
R^2	0.753	0.771
R^2 (within)	0.007	0.016
Note:	+ p<0.1; * p<0.05; ** p<0.01; *** p<0.001	
	Errors clustered by dyad in ()	