Three Essays in Labor Economics

by

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Abstract

I focus on the task content of work and its effects on labor market outcomes. In Chapter 1, I estimate the impact of an individual's occupational tasks on decisions to claim disability insurance. I show that changes in the intensity of worker tasks across and within occupations are essential in understanding decisions to apply for disability. I find that workers in occupations that are higher in routine tasks are more likely to apply for SSDI. On the other hand, workers in occupations that require more non-routine tasks, both cognitive and non-cognitive, are less likely to shift out of the workforce and onto disability insurance. Of the workers who apply for SSDI, those in more routine intensive occupations have higher award rates due to work-related health impairments. Taken together with changes to the requirements of work, the Social Security Administration might expect disability claiming rates to be lower in the future. In Chapter Two, I investigate how the task content of work changed from the early-2000s to the late-2010s for different age-race/ethnicity-gender groups. I find that White men transition into occupations that are more intensive in non-routine cognitive tasks early in their careers, whereas Hispanic and Black men work physically demanding jobs over their entire working lives. Increases in routine manual tasks increase for all workers 55-67 years old except Asian men and women. Chapter 3 examines the effects of the emergency switch to remote instruction because of COVID-19 on the research productivity of NBER-affiliated and IZA-affiliated professors. I find that remote instruction caused a temporary increase in the number of working papers produced by researchers. Further, the number of weeks of remote instruction did not influence the overall number of papers produced. Using the number of weeks until the first case COVID-19 case as an instrument for the number of weeks remote, I find similar results, corroborating previous findings.

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List of Abbreviations

SSA – Social Security Administration
SSDI – Social Security Disability Insurance
HRS – Health and Retirement Study
ACS – American Community Survey
O*NET – Occupation Information Network
NBER – National Bureau of Economic Research
IZA – Institute of Labor Economics

Chapter 1

The Effects of Occupational Task Intensity on Disability Benefit Claiming in the U.S.

1.1 Introduction

One in four workers will be over the age of 55 by 2026 (Collins and Casey 2017). Due to the size of the baby boom birth cohort and the expected depletion of the Old-Age, Survivors Insurance, and Disability Insurance (OASIDI) trust funds in the mid-2030s, policymakers will likely make substantial changes to these entitlement programs (Shoven, Slavov, and Watson 2021; Board of Trustees 2021). Approximately 12 percent of the Social Security trust fund is devoted to Social Security Disability Insurance (SSDI) beneficiaries, the majority of whom are impaired workers. Of the nine million disability beneficiaries, nearly 71 percent are workers aged 50-65, under the full retirement age (Board of Trustees 2021). The Social Security Administration has reported that the industries in which beneficiaries were last employed have altered over time (SSA 2019). Yet the literature on disability lacks substantial evidence as to how changes to work affect claiming decisions.

It is well documented that the requirements of work today have significantly changed from those of the past (Atalay et al. 2020; Ross 2017, 2021; Spitz-Oener 2006; Autor, Levy, and Murnane 2003). Changes to work occurred over the same period that disability awards peaked in 2010 and gradually fell thereafter.[1] I document how changing work characteristics impact decisions to claim SSDI. In addition, I show that the degree of tasks required within an occupation is the cause of health impairments that improve award rates for applicants.

This article uses data from the Occupation Information Network (O*NET) and the Health and Retirement Study (HRS).[2] First, I construct a panel data set of occupational characteristics from the O*NET for the 2004-2016 period. Linking the panel data of occupations to bi-annual waves of the HRS using a crosswalk between Occupational Census Codes and the O*NET Standard Occupation Codes. By measuring the task intensity of how abstract, routine, or non-routine manual an occupation is, I estimate the likelihood of applying for SSDI given worker task

[1] See Figure 1

[2] The RAND HRS Longitudinal File is an easy-to-use dataset based on the HRS core data. This file was developed at RAND with funding from the National Institute on Aging and the Social Security Administration.

content in previous employment. Furthermore, for the pool of applicants, I test whether being awarded disability benefits is impacted by work task content. As a last piece of analysis, I examine if the mechanism that worker tasks affect SSDI uptake is through work-caused health impairments.

My analysis focuses on task intensity differences across occupations and intensity changes within a specific occupation. Results suggest that changes in abstract task content across and within occupations are associated with a decrease in SSDI application. In contrast, differences in routine task content across occupations has no relationship to claiming decisions. Changes within an occupation of routine task content have a considerable effect on disability-claiming decisions. Specifically, a one standard deviation increase in the intensity of routine task content within an occupation increases the probability of applying for benefits by 0.75 percentage points, about 44% of the mean (1.67%). The size of one standard deviation in routine work intensity is equivalent to the difference in routine tasks required of Medical Assistants and Childcare Workers, the former being larger. By including individual fixed effects, I present robust correlations between SSDI applications and worker tasks. The use of models with individual fixed effects presents consistent results. Additionally, I estimate a Two-Stage Least Squares (2SLS) specification using a shift-share style instrument developed by Ross (2021). The 2SLS specification addresses concerns that occupational survey data is potentially endogenous from incumbent workers in the O*NET survey underestimating the degree of change in the tasks of their occupation. My 2SLS results are relatively consistent with the OLS models. My results show that as occupations become more abstract intensive, there is a lower probability of applying for disability benefits. Whereas workers in occupations high in routine task content, such as manufacturing, have higher claiming rates.

To test whether task content affects award rates, I estimate the probability of becoming a beneficiary using the sample of those who apply. Application of benefits is a relatively low-cost decision, but with about 70 percent of applicants being rejected, they face a significant barrier to receiving an award (Lu 2021). I find that workers in occupations that have become increasingly more routine (abstract or non-routine manual) have increased (decreased) odds of receiving SSDI. A causal mechanism of worker tasks that could impact award rates is their effect on health. Nearly 40 percent of disability denials are due to not providing medical evidence that supports a claimant’s inability to work (Lu 2021). For workers in increasingly more routine occupations to have higher rates of awards, they should also report greater levels of work-limiting disabilities.

Previous studies have shown that work characteristics across occupations explain little differences in health outcomes (Robone et al. 2011; Fletcher et al. 2011; Schmitz 2016). I provide new empirical evidence of how worker tasks are related to health using more robust correlations and by taking advantage of the variation of task content within an occupation. I find there is a positive relationship between arthritis and routine intensive occupations, as well as abstract tasks and back problems, two of the most common health disabilities (Lu 2021). Examining the differences in health impairments of the sample that are awarded and denied benefits, on average those who are awarded benefits have higher routine task content and rates of arthritis. To analyze if task content causes disabilities, I estimate a set of regressions for how task content impacts the likelihood of a disabled worker reporting an impairment caused by the nature of their work. For worker tasks to be the causal mechanism driving application and higher award rates, routine tasks should also have a positive relationship to work-caused disabilities. I find results consistent with previous findings. Disabled workers in occupations growing in routine task content have higher probabilities of having a disability due to their occupation.

This paper documents a clear relationship between changes in worker task content and health disabilities. I caution against taking these results as the only causal pathway that task content may induce disability claiming. Selection of occupations by disabled workers may be another way occupational tasks impact decisions related to SSDI application. Disabled workers may self-select into occupations that are becoming more intensive in abstract tasks increasing longevity in the workforce. These jobs may be better at accommodating workers reducing the probability of disability insurance application. Workers who have the possibility to be in routine occupations where the pace is an important prerequisite may simply choose disability instead. This is to say that the nature of work may not only be triggering disabilities, but occupations high in different task content may offer better outcomes for disabled workers.

Of the SSDI applicants, those who worked jobs with higher levels of routine work are more likely to receive benefits. Abstract or cognitive intensive occupations increase the odds of working into the next period by 15%, which could reduce the stress on entitlement programs. Because of rapid technological changes to the nature of work, the number of disability applicants and the magnitude of awards given in the future will likely depend on more than demographic trends. As shown by Atalay et al. (2020), the distribution of work tasks from post-WWII to 2000 shifted from routine to more abstract tasks. If work continues to trend to be more abstract and less routine intensive, Social Security Administration might expect SSDI application rates to decline.

1.2 Institutional Background

Autor and Duggan (2006) first presented their concerns about the growth of disability rolls over the 2000s after the number of beneficiaries had doubled since 1984, encompassing a little over 4 percent of non-elderly adults.[3] As Figure 1 shows, Autor and Duggan correctly indicate that of SSDI rolls would continue their positive trend if left unchecked. However, following the Great Recession the number of new and current awardees have declined over the 2010s. Maestas, Mullen, and Strand's (2018) analysis shows that the Great Recession caused nearly 8.9 percent of SSDI entrants in the years following. Other literature has found clear evidence that disability rolls fluctuate along with economic cycles (Liebman 2014; Cutler, Maera, and Richards 2012; Black, Daniel, and Sanders 2002; Autor and Duggan 2003; Charles, Li, and Stephens 2018). SSA (Social Security Administration) themselves claim that it has yet to quantify how much the recovery after the Great Recession accounts for the decline in the incidence rate of SSDI (SSA 2019). A large literature exists outside of business cycles to explaining the impact of other factors effecting trends in SSDI uptake. For example, some literature has shown that changes in the Full Retirement Age (FRA) cause individuals to spend more time on disability as the penalty for early retirement grows (Duggan, Singleton, and Song 2007; Coe and Haverstick 2010). Other papers have suggested that changes to the availability of Medicare, Medicaid, and other health insurance have allowed individuals to receive treatment for health concerns. As SSDI has provisions for Medicare, expansions through the Affordable Care Act reduces the need to be on disability to receive affordable health care (Maestas, Mullen, and Strand 2014; Chatterji and Li 2017). The literature on disability, while fairly substantive, lacks any evidence of how the nature of work impacts the decision to apply for benefits or the effect on award rates.

[3] Beginning in 1976 disability rolls significantly fall until 1984 (Autor and Duggan 2003). This is due to the tightening of medical eligibility and state boards interpreting the SSA eligibility standards. The fraction of applicants awarded benefits fell from 45 percent in 1976 to 32 percent in 1980. Congress continued to tighten applicants in 1980, by requiring more frequent beneficiary health reassessments. This led to a significant political backlash in 1984, with congress giving a broader definition of disability, giving less weight to diagnostic or medical factors, and more on the ability to function at work or in work.

Over the same length of time that there were dramatic changes to the number of disability beneficiaries, the nature of work has also changed. Atalay et al. (2020), using job ad data, finds that the tasks of workers have shifted away from doing routine intensive functions to those that are more cognitive. Through a panel of occupations, they find that while the tasks of occupations overall have shifted, the largest contributor of the change to work is due to changes within an occupation. A substantial amount of literature has focused on the overall changes in the demands of occupations in the labor market. Their findings consistently find that workers are shifting out of routine intensive work due to technological changes (Autor, Katz, and Kearney 2008; Acemoglu and Autor 2011; Autor and Dorn 2013; Deming 2017). Recent literature by Ross (2017, 2021) and Hershbein and Kahn (2018) focus on changes within an occupation, providing new insight on how changes to worker task content affects labor market outcomes. Their work has found that workers who are required to do more routine tasks have significantly worse outcomes than those in highly abstract jobs.

My work examines how changes in worker tasks affect the transition into SSDI. The application and reception of SSDI through worker tasks could occur through two mechanisms. The first is the relationship between work and health, this is because the most common barrier to receiving disability insurance is providing medical evidence of a work-limiting disability.[4] The literature on job demands and health is well documented, finding inconsistent results for the contemporaneous relationship between physically demanding work and health measures (Robone et al. 2011; Fletcher et al. 2011; Schmitz, 2016). Other literature on work and health has used cross-sectional data to show that lifetime job requirements play a crucial role in physical health later in life (Case and Deaton 2005; Nicholas, Done, and Baum 2020). There is a gap in the literature on how the variation of tasks within an occupation impacts health outcomes. If worker tasks cause disabilities that prevent work, this may explain why workers both apply for and have higher rates of receiving SSDI.

[4] SSA determines disability through five questions qualifying questions: "Are you working?", "Is your condition "severe"?", "Is your condition found in the list of disabling conditions?", "Can you do the work you did previously?", and "Can you do any other type of work?". The questions put forth are in attempts to determine how an individual's impairment might prevent them from working. An applicant may have an impairment, but SSA determines based on your age, education, and skills to obtain other gainful employment they can reject benefits. Lastly, an individual must work and contribute to Social Security for a set number of years before receiving SSDI. See: https://www.ssa.gov/help/iClaim_medicalEvidence.html;

The second mechanism is workers' ability to select into occupations that give them better opportunities for sustained labor participation. Workers having an awareness of their work capabilities may view certain occupations as being more favorable to their abilities. This relationship could be that disabled workers view occupations high in certain task content as being more accommodating to them. Accommodations at work could be provided or supplemented through the use of technology. As shown by Autor et al. (2006) and Ross (2021), abstract tasks are complemented by technology. Workers may find that as an occupation becomes more abstract intensive, technology integration may offset their health impairment. Routine occupations, such as tire builders, may find that routine tasks such as operating a machine are difficult to modify for all workers. The complementary nature of technology and abstract tasks may prevent the need to apply for disability insurance to supplement their income if they cannot work.

1.3 Data

I primarily use two data sets, the Occupational Information Network's administrative data on occupational information and survey data from the Health and Retirement Study. Combining these two data sets allows me to analyze the contemporaneous changes in work requirements on decisions to apply for SSDI.

I use occupational data from the Work Activities, Work Context, and Abilities modules of the O*NET database. O*NET collects information on occupations through two steps: creating a random sample of businesses that employ workers in selected occupations and choosing a random sample of workers in those occupations within a company. Those incumbent workers are surveyed on their occupations through one of three randomly assigned questionnaires. Occupational analysts use this information to update the values of work characteristics for an occupation's given identifier or Standard Occupation Code (SOC). Due to the changing taxonomy of the survey, the occupations within a SOC will split off or combine with other SOCs to create newly assigned identifiers. These changes make it impossible to follow certain occupations in a SOC from the start of the O*NET data to the present. To address changes in the taxonomy, I follow Ross (2017, 2021) to create a panel of Standard Occupation Codes from 2004 to 2019. As a result, occupations are in consistent SOCs over my sample period.

Table 1 presents the O*NET survey questions that Acemoglu and Autor (2011) and Autor and Handel (2013) used to create measures for how abstract, routine, or non-routine manual task intensive an occupation is. Creating the abstract task intensity uses the survey questions about incumbent workers' ability to analyze data, think creatively, interpret information for others, establish and maintain personal relationships, guide/direct/motivate others, and coach/develop others. The routine task intensity is made from questions about the importance of repeating the same task, of being exact or accurate, to what degree the work is unstructured versus structured, the time spent controlling machines or processes, what amount of time is spent making repetitive motions, and how much the pace of work is determined by the speed of the equipment. Lastly, the questions for the non-routine manual task intensity are those having to do with operating vehicles, mechanized devices or equipment, spending time using hands to handle, control, or feel objects, tools, or controls, and about a worker's manual dexterity and spatial orientation abilities. Using the computation provided by Ross (2021), I combine responses for each occupation into their respective abstract, routine, and non-routine manual task intensity.[5]

Individual-level data come from the Health and Retirement Study (HRS). The HRS is sponsored by the National Institute on Aging (grant number NIA U01AG009740) and is conducted by the University of Michigan. The data set is a nationally representative group of individuals over the age of 50. As previously discussed, most beneficiaries of disability insurance are 50-65 years old, making the older population of the HRS an important analysis group. It is a biannual longitudinal survey of about 20,000 individuals from 1992 to 2018, with initial cohorts born between 1931 to 1941. They were 51 to 61 years old when first surveyed. The high mortality rates in the HRS leads to high levels of attrition. To keep the sample size stable, new younger cohorts enter every six years. Interviews are conducted of both individuals and their spouses up until their death. The original design of the study was to follow older workers into retirement; therefore, it asks for detailed information about work and decisions to transition out of the workforce. Providing a robust set of information on understanding workers' transitions to disability.

[5] Ross (2021) provides a discussion of the construction of the tasks and measures using the O*NET occupation data. With the method developed by Blinder (2007) and Firpo, Fortin, and Lemieux (2011), the scales for level and importance are Cobb-Douglas weighted for tasks from the Work Activities or Abilities modules. Tasks that are from the Work Context module use the context scale. With a loading factor from the first component of a principal component analysis, tasks are weighted and added together to create their respective scales. I differ my construction in one important way, rather than using 2004 occupational employment weights as Ross (2021) does, I weight my values with yearly labor shares from the American Community Survey.

Figures 2, 3, and 4 provide the distribution of each task intensity across all occupations observed in the HRS during a given year.[6] In each figure, I plot the distribution in 2004, 2010, and 2016. The measure for abstract intensity can be found in Figure 2. The blue line represents 2004, the red line 2010, and the green line 2016. The distribution shifted leftward in 2010, but by 2016 drastically shifted right, suggesting that overall work has become more intensive in abstract tasks. As depicted in Figures 3 and 4, occupations became more intensive in routine and non-routine manual tasks as the distribution shifted slightly further to the right by 2016, albeit not to the same degree that the abstract task intensity does. They were largely unchanged from their intensity in 2004. The overall change in all occupations is expected to be only slightly different over time. As shown by Atalay et al. (2020) nearly all changes in task intensities will occur within an occupation and differences between occupations are practically unimportant. Therefore, in Figures 5, 6, and 7 I plot the changes of task intensity within an occupation over time. These figures plot the difference for each occupation in task intensity from their 2004 level compared to 2016. Each shows significant variation over time in how intensive an occupation is in each task.

I link the two data sets using the HRS Occupation Census Code (OCC) and the O*NET Standard Occupation Code (SOC) through administrative crosswalks to estimate the relationship between occupational tasks. The panel of occupations began in 2004, earlier years (1998-2002) of the O*NET were populated from data supplied by occupational analysts, which used refined existing data from the Dictionary of Occupational Titles (DOT). The DOT data was created by occupation analysts, whereas the O*NET information is sourced through incumbent workers. By using the two in tandem, there is concern about measurement error from unintended variation.[7] Occupational data is linked to the HRS only through 2016 because they have not yet been updated to the 2018 7-digit occupational codes.[8] Since the HRS is biannual, my sample spans twelve years

[6] Not all occupations in the O*NET data have an individual in the HRS employed in them. When creating distributions for each task I limit to occupations in which at least one individual in the HRS is employed in during that given year. If the only individual in an occupation leaves that job, then that occupation is not in the distribution in that year. Values are standardized and then plotted.

[7] The Bureau of Labor Statistics (BLS) created the O*NET datasets as a replacement for the DOT. In its transitionary samples, from 1998 to 2002, occupational analysts supplied data using sources such as the DOT. BLS creates task values in the O*NET data thereafter through worker surveys. See: https://www.onetcenter.org/dl_files/appendix_d.pdf

[8] The occupational data for the O*NET and HRS are linked through a series of crosswalks. Both data sets are walked up to the 2019 Standard Occupation Codes (SOC), which is the most recent taxonomy of the O*NET survey data. Following Ross (2021) I have already created a panel of occupations with 2019 SOC taxonomy. Occupations in the HRS are titled using Occupation Census Codes (OCC), for occupations before 2012, these are 2002 OCC, and after using 2010 OCC. I use the Bureau of Labor Statistics crosswalks between OCCs and SOCs to cross both

from 2004 to 2016, or 7 surveys. The analysis sample only includes individuals below their full retirement age because once the full retirement age is reached, individuals are automatically switched from SSDI to SSI. Workers are capable of aging out of SSDI, and their inclusion would attenuate estimates (SSA 2021).[9]

The Health and Retirement Study provides rich demographic information. The study was initially designed to understand how aging impacts health, employment, and wealth, tracking the status of these outcomes over the survey. I use demographic information that may be correlated with a worker's decision to apply for SSDI. Specifically, I use the variables gender, age, reported race\ethnicity, years of education, and the number of years a worker has been in their respective occupation to estimate the effect of worker tasks on SSDI application. Because the study aims to follow workers into old age, the survey asks questions about if an individual applies for SSDI if they win their award. Importantly, they ask when an individual makes this transition, allowing for the estimation of how task intensities of their most recent occupation affect SSDI uptake. Individuals also are survived on if they have a disability that limits work, what health condition causes their impairment, and if that health condition is due to the nature of their work. I report all estimates with analytical weights because of the HRS oversampling Blacks and Hispanics.

I present summary statistics from the Health and Retirement Study in Table 2. The sample contains 6,322 unique individuals. I restrict the estimation sample in a few crucial ways, firstly only those who report employment as I analyze the transition from work to disability. As previously discussed, I also only include individuals under the full retirement age. In addition, if they do not answer all demographic, education, and job tenure-related questions, they are left out of the sample. Of my sample, they are on average observed over 3.98 waves for 22,054 observations. On average, they are about 56 years old. About 53% report being female, and 67% are married. They are predominately White, resembling the national average. The sample is slightly more Black than the national average due to oversampling. The highest degree earned in the panel is larger than normal but occurs because these individuals are more skilled, exiting the labor market less often. On average, they have been in their occupation for over 12 years. Conditional on being employed in the current period, the proportion of individuals that apply to

respective sets of OCCs to their respective SOC. Then I walk these codes up to their 2019 version as done for the O*NET panel. This allows me to link the two data sets.

[9] See also: https://faq.ssa.gov/en-us/Topic/article/KA-01861;

SSDI is 1.67%. Since applying for SSDI is usually a terminal decision, there is a relatively low number of people that transition.

1.4 Empirical Analysis

1.4.1 Applying and Receiving Social Security Disability

My analysis proceeds in two parts. First, using the combined panel of the O*NET and HRS, I estimate the effect of occupational tasks on the likelihood of a worker applying to SSDI conditional on being employed in the previous period. That is, using the task intensities of occupation o in time t, I ask the question, "What is the probability of a worker sending an application to SSDI in time $t + 1$?". Secondly, using a shift-share-style instrument proposed by Ross (2021), I estimate each model again using a 2SLS strategy. The instrument builds on Autor and Dorn (2013), in which the substitutability (complementary) of technology and routine intensive tasks should exogenously predict lower (higher) levels of routine (abstract and non-routine manual) within an occupation as technology becomes accessible over time. To evaluate the effect of a worker's occupational task intensity on shifting out of the workforce to a disability, I estimate the following:

$$\text{(1)} \qquad [Disability\ Application_{t+1,i} \mid Employment_{t,i}] = a_{t,o} + r_{t,o} + m_{t,o} + X_{t,i} + t_t + s_s + e_{tios}$$

The outcome variable of interest is equal to one if individual i working in occupation o in state s at time t is applying for disability insurance in period $t + 1$ conditional on being employed in the period t and under full-retirement age at the time of applying. The variables $a_{t,o}$, $r_{t,o}$, $m_{t,o}$ contain the coefficients of interest for the abstract, routine, and non-routine manual task measures, respectively. $X_{t,i}$ is a vector of personal characteristics such as gender, age, marital status, race, the highest level of educational attainment achieved, as well as job tenure. In my regressions, I include a set of year fixed effects to control for any possible time trends in SSDI take-up and state fixed effects to isolate unobserved state-level differences.

In an additional set of regressions, I include indicators for each occupation. As previously discussed, variation in task intensity is an essential contributor to how occupations have changed over time (Atalay et al., 2020). Understanding how changes within an occupation affect the decision to shift into disability has not yet been studied. By including occupational fixed effects, estimates show how task intensities within an occupation compare from one year to the next. My estimates have weak exogeneity because of a lack of causal method raising concerns about individual-level unobservables biasing results. For example, high-ability individuals may select into occupations they know are highly intensive in abstract tasks as they tend to be more lucrative (Autor and Handel 2013). To address possible individual-level bias, I include individual fixed effects to handle any time-invariant characteristics that demographics fail to control for.

Table 3 presents results from Equation (1). Moving from left to right across the table, an increasingly restrictive set of controls are introduced. Coefficients for the task intensities abstract, routine, and non-routine manual when controlling for worker demographic characteristics, state, and time-fixed effects are found in column (1). Estimates in column (1) use variation in tasks across occupations. Increases in abstract task content is associated with lower liklihoods of worker disability application. The coefficients for routine and non-routine manual tasks are not statistically different from zero. Column (2) includes occupation fixed effects, meaning that variation in task intensities come from differences year to year within an occupation. An increase in the routine task content in an occupation significantly increases worker SSDI claiming rates. A one standard deviation increase in the intensity of routine tasks leads to a 0.75 percentage point increase in the likelihood of applying for disability, about 44% of the mean (1.67%). Contrarily, as the number of abstract tasks done within an occupation grows workers claim disability at a lower rate. Results are robust to the inclusion of individual fixed effects in column (3). There is no relation between non-routine manual and SSDI claiming in all three specifications.

As described by Ross (2021), endogeneity could arise due to surveying the incumbent workers in the O*NET. The construction of the O*NET data relies on interviewing incumbent workers, because of their time within a job they may underrepresent the change in occupational characteristics over time. Underestimating the change may cause the variation in task intensity of the occupation to be biased. Like Autor and Dorn (2013), Ross (2021) uses the exogenous adaptation of technology to instrument for changes in task intensities.[10] Based on the work by Autor, Levy, and Murnane (2003), demonstrating the substitutability of technology for routine

[10] Autor and Dorn (2013) use the adoption of Personal Computers to predict changes in the demand for routine labor. They develop a shift-share instrument for the number of computers in a commuting zone attempting to predict employment in routine or abstract-intensive occupations. Autor and Dorn (2013) use their instrument to predict current employment in routine intensive occupations relying on the extensive change in tasks due to changes in technology. Ross (2021) on the other hand predicts intensive margin task changes in an occupation are affected by substitutability.

tasks, the adoption of technology should have greater effects on occupations that are high in routine intensive tasks. On the other hand, occupations that are relatively high in non-routine tasks, cognitive and non-cognitive, will be affected less because of the complementariness nature of technology.

To take advantage of the exogenous changes provided by the elasticity of the substitution of technology I follow Ross (2021) in constructing a shift-share style instrument. However, rather than using the translated 1991 DOT data as Ross (2021) does, I instead use the 2004 occupation data for the following instrument

$$(2) \qquad Task\ Instrument_{t,o,k} = \left(Task\ Intesity_{t=2004,o,k} - Task\ Intesnity_{k}\right) * ln\ (Tech_{t})$$

I take the mean value of task intensity k in 2004 for occupation o and subtract the mean value of that task intensity over all occupations, left with the difference in the task intensity for each occupation in 2004 from the mean over the entire sample period. I create a task measure for yearly technology adoption within a year from O*NET survey questions. To create a tech adoption measure, I use the O*NET survey questions about how much workers interact with computers and what degree of automation is in the occupation.[11] Taking the log of the average amount of technology intensity over all occupations within each year, I multiply it by the difference for abstract, routine, and non-routine manual task intensities. The intuition behind the instrument suggests that occupations that are higher in routine intensity should be more sensitive to technology adoption. This is to say, if an occupation is high in routine task content in 2004, technology growth should affect the task content of that occupation more than one that is low in routine tasks. Workers in occupations that are in low intensive abstract and non-routine manual type tasks will also have their work altered at a higher rate because of technological development.

Coefficients for Equation (1) using the 2SLS model can be found in Table 4. Columns (1) – (3) again present each model with gradually more restrictive controls. The F-Statistic excluded IV is above 100 for each model, relieving any weak instrument concerns.[12] Similar to results first presented in Table 3, column (1), which uses demographic, state, and year controls, shows that

[11] How much an occupation interacts with computers and an occupation's degree of automation comes from the Work Activities and Work Activities modules of the O*NET, respectively. The intensity of technology is again created following Blinder (2011) and Ross (2021).

[12] First stage results can be found in Appendix Tables 5,6,7. I satisfy the weak instruments concern by surpassing the F-Statistic threshold of 10 reported by Stock, Wright, and Yogo (2005). As Ross (2021) discusses, because the instrument is to address survey task data, I forgo conducting robustness checks of the shift-share-style instrument.

overall increases in abstract task content causes lower rates of disability claiming by workers. Routine and non-routine manual tasks are both statistically insignificant and imprecise. The specification with occupational fixed effects can be found in column (2). Results differ from those in Table 3, where the estimate for non-routine manual was statistically indistinguishable from zero, Table 4 shows both abstract and non-routine manual cause statistically significant decreases in the probability of SSDI application. Moreover, the changes to routine work intensities have a positive but insignificant effect. Lastly, column (3) contains estimates from the specification that includes individual fixed effects. Unlike column (3) of Table 3, all three task content measures are statistically insignificant for the 2SLS model. Nevertheless, the coefficient for routine tasks still indicates a positive relationship concerning moving into SSDI. It is possible that the use of year-to-year technology changes may not be effective because of the use of highly robust fixed effects, causing imprecision.

In the prior analysis, I presented results for how changes to work tasks affected SSDI claiming decisions. There are relatively low barriers for SSDI application, meaning even those where it is highly rejection is likely may still apply. A significant number of those SSDI applicants end up in rejection. In 2020, only 30.8 percent of applicants received an award (Lu 2021). Providing suitable medical evidence of impairment was the largest reason for denial, at nearly 40 percent. To test if worker tasks affect the award rate, I estimate the probability of receiving SSDI using the sample of applicants given occupation requirements.

The reception of benefits is a terminal outcome for disability applicants. Only some who become beneficiaries then reenter the labor market and rejected applicants will appeal decisions. As application happens in one period, I am unable to use individual-level fixed effects. In Table 5, columns (1) and (2), present coefficients using variation in task content across and within occupations, respectively. Columns (3) and (4) are the corresponding 2SLS models of columns (1) and (2), respectively. Column (1) shows workers in more abstract occupations have a higher probability of being awarded SSDI, but both routine and non-routine manual are insignificant. Column (2) adds occupation dummies, using variation of task content within an occupation. While only significant at 10%, results show that as occupations increase in routine (abstract and non-routine manual) intensive tasks, the chances of being awarded SSDI decreases (increases). Column (4) presents similar but insignificant coefficients, likely due to the sample size.

Interestingly, both the likelihood of application and reception of benefits improves when working in occupations that have become more intensive in routine tasks. Occupations higher in abstract and non-routine manual tasks have lower rates of SSDI application and receipt. Discussed previously, it is unclear how tasks are related to both application and awards. Disabled Workers may be self-selecting into abstract occupations that allow them to extend their labor market participation and lower their need for SSDI. The other mechanism being that task content is causing health impairments that prevent work, leading to labor force exits.

1.4.2 Health Outcomes

This paper, thus far, has provided primarily correlations between occupational tasks and workers' transitions to SSDI. In the previous set of results, I have shown that tasks are related to both the claiming and reception of SSDI. It is unclear whether that mechanism is due to selection by disabled workers or tasks causing health disabilities. In this section, I investigate the relationship between tasks and work-limiting disabilities. Additionally, if those who are disabled had their disability caused by work. Crucially, comparing how task content affects work caused disabilities will provide insight as to how tasks may be related to SSDI up-take.

The HRS asks if an individual has "any impairment or health problem that limits the kind or amount of paid work you can do?". By using the stated health impairment as an outcome, I estimate the relation of disabilities and task content. The size of applicants is too small for analysis on health outcomes, instead, I use the complete sample. Schmitz (2016) has shown, using sample data from the HRS, that differences in overall occupational characteristics have minimal effects on health measures. Instead, I opt for the specification with occupational and individual fixed effects. I chose to use the most restrictive model for two reasons, the first being that the inclusion of fixed effects will alleviate some concerns of bias from unobservables. The second is that the literature has not examined how tasks within an occupation are related to health outcomes.

The HRS has eight health disability groups created using more specific health impairments. For example, Heart, Circulatory, and Blood Conditions include heart problems (such as heart attack), high blood pressure, stroke, blood disorders, and other circulatory problems. Conditions like blood disorders are unlikely to be affected by work tasks and may cause some attenuation.[13]

[13] I provide a full listing of the health impairments that make up each group in Appendix Table 4.

All eight health groups are formed similarly. To address attenuation concerns, I separate the four largest health groupings, Cancers and Tumors, Musculoskeletal System and Connective Tissue, Respiratory System Conditions, and Heart, Circulatory, and Blood Conditions, into their respective parts (Lu 2021). For this reason, I first provide analysis for the eight base health groups and then for more distinctive health impairments.

Estimates for the effect of health outcomes for the major groupings and those that are more specific are in Tables 6 and 7, respectively. As worker tasks change within an occupation, they have relatively no effect on any of the eight comprehensive health groups. Routine task content reduces the rate of Heart, Circulatory, and Blood Conditions, whereas non-routine manual has a positive effect. The more distinctive health conditions in Table 7, also show little evidence of changes to workers' task content affecting work-limiting disabilities. Interestingly, the outcomes for Arthritis and Back Problems have some significant effects. As work becomes more routine intensive, individuals are more likely to have their ability to work limited by arthritis while less likely to have back problems. Additionally, a one unit increase in abstract tasks increases the probability of a worker having back problems by 0.2 percentage points.

My results show that changes in the occupational task content of workers have relatively little effect on health outcomes. Estimates for health outcomes that are hereditary or from old age are small and are not statistically different from zero. While the health outcomes that are affected by work are those related to physical health. Unsurprisingly, arthritis and back problems fall in the musculoskeletal conditions category, the overwhelming health disability that SSDI beneficiaries are awarded for (Lu 2021).

The sample of those who apply for benefits is too small to give precise estimates. To examine how applicants task content affects claiming conditions I compare the unconditional means of those awarded and those rejected. In Table 8, I report the means for all claimant's average task content. Additionally, I include their health conditions for arthritis and back problems and the other eight major health disability categories. Compared to the full sample in Table 2, individuals claiming benefits are in more task intensive occupations. That is, their occupations are higher on average in all three task categories. Those awarded work in more abstract and routine intensive jobs than those who are denied. The likelihood of being SSDI rejection is higher for those in more non-routine manual intensive jobs. Beneficiaries have noticeably more disabilities due to arthritis, cancer, digestive, and respiratory health impairments. Inferring from regressions of task intensity onto health outcomes, higher levels of cancer and respiratory conditions amongst those awarded benefits are not because of differences in task intensities. Whereas the positive relationship between routine tasks and arthritis may explain why those in more routine intensive occupations receive benefits at a higher rate.

Finally, I provide results to confirm the mechanism in which tasks impact disability claiming is because of work causes a disability. Of those who are disabled, the HRS asks if the nature of their work caused their impairment. With the outcome of a disabled worker claiming their disability was caused by work; I analyze the effect of worker tasks. Results in Table 9, use both occupation and individual fixed effects as this is the most robust specification. In addition, I include both OLS and 2SLS models. Estimates for both strategies show that worker tasks have a significant effect on having a work-caused disability. Notably, the relationship between task intensities and a disability caused by work is the same as claiming and receiving SSDI. Occupations that grow in routine task content increase the chance of a worker having a disability caused by the nature of their work. Explaining why workers leave the workforce to apply for SSDI. Workers in an occupation that increases in abstract tasks are less likely to be disabled due to employment. The association of tasks and disabilities suggest that the reason workers claim disability insurance is because the tasks they do in their work cause them to become disabled.

1.5 Robustness and Sensitivity Checks

This section provides results for a few alternative specifications to check the sensitivity and robustness of the main findings.

As my sample period covers the entirety of the Great Recession, there are concerns that this drives my results. Several studies have shown that the Great Recession had a causal positive shock to the number of SSDI applicants (Maestas, Mullen, and Strand 2018; Liebman 2014; Cutler, Maera, and Richards 2012). During the Great Recession, considerable amounts of investment into technology may influenced an occupation's task intensities (Jaimovich and Siu 2012; Hershbein and Kahn 2018).[14] As investments go up, demand for workers in routine work reduces, driving

[14] These papers use cross-sectional data, and therefore only look at the flows in and out of abstract and routine intensive occupations. As their data is cross-sectional, they are only capable of examining what share of workers are in task intensive occupations, not how the tasks of workers have changed.

wages down. Reduced wages could drive workers out of the labor market, into SSDI. I construct a variable for high state-level unemployment to control for possible business cycle impacts like the Great Recession. Specifically, my high unemployment variable is equal to one if on average during the three months leading up to the interview in period $t + 1$ is higher than 7 percent.[15] I use high unemployment as an additional control in estimating eq. (1) again and report results in Table 10. The estimates in Table 10 are nearly identical to those in Table 3. Showing that my results are robust to business cycle concerns.

Another concern is that task content is only a proxy for income. Low incomes reduce the opportunity cost for workers to apply for SSDI. Previous work by Autor and Handel (2013), show that occupations that are more intensive in abstract tasks have higher wages. In contrast, those in higher levels of routine tasks have lower wages. I introduce a variable for the log of a worker's inflation-adjusted income as a control in eq. (1).

Results from eq. (1) with the addition of inflation-adjusted income can be found in Table 11. The inclusion of income has some effects on my estimates' precision. Notably, all estimates stay the same sign. Column (1) of Table 11 shows all coefficients to be statistically insignificant. Previously, in Table 3, increases in abstract tasks significantly decreased SSDI claiming. Results in Table 11 for columns (2) and (3) are consistent to previous results. Columns (2) and (3) include occupation dummies using variation in tasks within an occupation. Income differences from year to year in an occupation may be less significant than overall occupation differences, therefore not as critical to SSDI decisions. The coefficient for routine task content in both columns (2) and (3) is positive and statistically significant at the 10% level. However, the measure for abstract task content in column (2) is statistically insignificant but of similar magnitude to previous results. Coefficients in column (3), remain significant but slightly smaller and less precise. As previously discussed, there is a significant relationship between task measures and income. The correlation between task measures and income is likely causing imprecision.

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[15] The cutoff of 7 percent is chosen based on the average unemployment of the sample period being below 6% but when high is well above 7 percent.

1.6 Discussion

This paper presents new insights on the relationship between occupational tasks and disability benefit claiming. By using a panel of occupational characteristics from the Occupational Information Network (O*NET) linked to a longitudinal data set of workers from the Health and Retirement Study (HRS), I estimate how changes to task content affect decisions to claim Social Security Disability Insurance (SSDI). In a set of highly robust correlations, I find that being employed in an occupation that increases in routine (abstract) task content causes workers to apply for SSDI at higher (lower) rates. Additionally, to address possible bias from incumbent worker survey data from the O*NET underestimating changes in task content I use a shift-share-style instrument. I show that results are mostly robust to estimation using a 2SLS model. Furthermore, I find a relationship between receiving benefits and worker tasks for a pool of applicants. Like results on claiming benefits, workers that are required to do more routine tasks have higher rates of awards. In contrast, increases in abstract or non-routine manual task content lowers the likelihood of workers receiving benefits.

To be awarded SSDI, applicants must provide some medical evidence of a work preventing disability. I find that increases in routine tasks cause workers to have higher rates of disabilities related to arthritis. Compared to the sample of applicants, those that win awards also have higher rates of arthritis and routine task content. To show that worker tasks are causing higher levels of disability, I estimate the relationship between worker task content and having a disability caused by work. Increases in tasks that are routine give rise to higher rates of work-caused disabilities. Furthermore, abstract worker tasks are associated with lower work associated disabilities. These results suggest that disabilities caused by the nature of work are from workers in occupations that require more routine tasks, which in turn leads to the need to claim SSDI.

In this article, I demonstrate work-caused health impairments are a potential causal mechanism between tasks and disability insurance uptake. Another pathway may be disabled workers sorting into occupations that accommodate their limitations. Future work is required to disentangle if or how much workers can self-select into occupations that allow them to have longer labor force participation. From the perspective of The Social Security Administration, when projecting the future burden of Disability Insurance on the Social Security trust fund, they must consider how work may change. Past trends shown by Atalay et al. (2020) demonstrate how work has become more abstract intensive than the past, if trends continued into the 2000’s, this may be indicative of lower disability benefit claiming.

Table 1: Occupation Intensity Measures

Task	O*NET Module	Survey Questions	Scale
Abstract	Work Activities	Analyzing data/information	IM/LV
	Work Activities	Thinking creatively	IM/LV
	Work Activities	Interpreting information for others	IM/LV
	Work Activities	Establishing and maintaining personal relationships	IM/LV
	Work Context	Guiding, directing, and motivating others	CX
	Work Context	Coaching/developing others	CX
Routine	Work Context	Importance of repeating same tasks	CX
	Work Context	Importance of being exact or accurate	CX
	Work Context	Structured vs. unstructured work (reverse scale)	CX
	Work Activities	Pace determined by speed of equipment	IM/LV
	Work Context	Controlling machines and processes	CX
	Work Context	Spend time making repetitive motions	CX
Non-routine Manual	Work Activities	Operating vehicles, mechanized devices, or equipment	IM/LV
	Work Context	Spend time using hands to handle, control or feel objects, tools or controls	CX
	Abilities	Manual dexterity	IM/LV
	Abilities	Spatial orientation	IM/LV

Questions for the Work Activities and Abilities module use the importance and level scale, while Work Context only uses the context scale. The importance scale asks an incumbent worker how important an activity or ability is in their occupation. The level scale asks how often they do an activity or use an ability. The context scale asks if a certain task is done in the context in which they do work. The importance scale is initially 1-5, the level scale 0-7, and the context scale 1-5 (https://www.onetonline.org/help/online/scales#foot1). For consistency, all are normalized from 0-10.

Table 2: Descriptive Statistics

	Mean	SD
Unique Observations	6,322	
Average Number of Waves	3.4	
Occupations	487	
	Mean	SD
Abstract	14.84	6.41
Routine	11.47	5.74
Non-routine Manual	7.46	4.28
Applying to SSDI	0.02	0.10
Receiving SSDI after Applying	0.33	0.34
Age	57.69	4.84
Female	0.53	0.50
Married	0.67	0.46
White	0.63	0.48
Black	0.18	0.39
Hispanic	0.15	0.36
Other	0.04	0.20
Less than High School	0.10	0.30
High School	0.29	0.45
Some College	0.30	0.46
Bachelors	0.20	0.40
Graduate/Professional	0.12	0.32
Job Tenure	12.23	10.78
Log Income	10.30	1.15
N	22,054	

Note: Observation is an individual wave.

Table 3: OLS Results for the Effect of Task Content on Applying for SSDI

	(1)	(2)	(3)
Abstract	-0.0004**	-0.0006*	-0.0011***
	(0.0002)	(0.0003)	(0.0004)
Routine	0.00002	0.0011*	0.0013**
	(0.0002)	(0.0005)	(0.0006)
Non-routine Manual	-0.0001	-0.0006	-0.0001
	(0.0003)	(0.0006)	(0.0008)
Occupation F.E.	No	Yes	Yes
Individual F.E.	No	No	Yes
N	22,054	22,054	22,054

Note: This table reports results for the dependent variable applying for disability insurance; it takes a value of 1 when individuals state that they are applying for disability insurance in t+1, and 0 otherwise. The sample is those employed in time t, and under full retirement age in t+1. All regressions include state and year dummies and demographic controls such as age, education level, race/ethnicity, sex, marital status, and job tenure. Robust standard errors in parentheses are clustered on individual. * $p<0.1$ ** $p<0.05$ *** $p<0.01$.

Table 4: 2SLS Results for the Effect of Occupational Task Content on Applying for SSDI

	(1)	(2)	(3)
Abstract	-0.0009**	-0.001**	-0.0005
	(0.0004)	(0.0005)	(0.0058)
Routine	-0.0002	0.002*	0.0094
	(0.0007)	(0.001)	(0.0088)
Non-routine Manual	-0.0001	-0.0002	-0.0040
	(0.0004)	(0.0006)	(0.0053)
Occupation F.E.	No	Yes	Yes
Individual F.E.	No	No	Yes
N	22,054	22,054	22,054

Note: This table reports results for the dependent variable applying for disability insurance; it takes a value of 1 when individuals state that they are applying for disability insurance in t+1, and 0 otherwise. The sample is those employed in time t, and under full retirement age in t+1. All regressions include state and year dummies and demographic controls such as age, education level, race/ethnicity, sex, marital status, and job tenure. Robust standard errors in parentheses are clustered on individual. * p<0.1 ** p<0.05 *** p<0.01.

Table 5: The Effect of Task Content on Disability Awards for Applicants

	(1)	(2)	(3)	(4)
	OLS	OLS	2SLS	2SLS
Abstract	0.011*	-0.055*	0.0048	-0.0011
	(0.006)	(0.03)	(0.011)	(0.0296)
Routine	-0.008	0.088*	-0.021	0.032
	(0.01)	(0.05)	(0.013)	(0.125)
Non-routine Manual	0.005	-0.11**	0.017	-0.124
	(0.016)	(0.05)	(0.019)	(0.116)
Occupation F.E.	No	Yes	No	Yes
N	370	370	337	337

Note: This table reports results for the dependent variable receiving SSDI; it takes a value of 1 when the individual's applying for disability state that they are now receiving benefits, and 0 otherwise. The sample is those employed in time t, and under full retirement age in t+1. All regressions include state and year dummies and demographic controls such as age, education level, race/ethnicity, sex, marital status, and job tenure. Robust standard errors in parentheses are clustered on state. * p<0.1 ** p<0.05 *** p<0.01.

Table 6: OLS Results for Effect of Task Content on Health Outcomes

	(1)	(2)	(3)	(4)
	Cancers	Musculoskeletal	Heart	Respiratory
Abstract	0.0001	0.0033	0.0001	-0.0005
	(0.0003)	(0.0014)	(0.0001)	(0.0004)
Routine	0.0001	-0.0020	-0.0003*	0.0007
	(0.0005)	(0.0023)	(0.0002)	(0.0006)
Non-routine Manual	-0.0009	-0.0013	0.0003*	-0.0018
	(0.0003)	(0.0026)	(0.0002)	(0.0012)
N	22,054	22,054	22,054	22,054

	(5)	(6)	(7)	(8)
	Digestive	Neurological	Emotional	Endocrine
Abstract	0.0000	-0.0002	-0.0001	0.0003
	(0.0003)	(0.0002)	(0.0002)	(0.0005)
Routine	-0.0001	0.0006	0.0001	-0.0004
	(0.0004)	(0.0004)	(0.0004)	(0.0010)
Non-routine Manual	0.0002	-0.0011	-0.0001	0.0005
	(0.0005)	(0.0002)	(0.0005)	(0.0009)
N	22,054	22,054	22,054	22,054

Note: This table reports results for the health disability outcomes, it takes a value of 1 when individuals state that they have a given work-limiting health disability. in t+1, and 0 otherwise. The sample is those employed in time t, and under full retirement age in t+1. All regressions include individual, occupation, state, year fixed effects and demographic controls that are not fixed such as age, marital status, and job tenure. Robust standard errors in parentheses are clustered on individual. 2SLS results are found in Appendix Table 6. * p<0.1 ** p<0.05 *** p<0.01.

Table 7: The Effect of Task Content on Finer Health Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Cancer	Tumors	Skin Conditions	Arthritis	Back Problems	Other Musculoskeletal	Heart Problems
Abstract	0.0001	0.000	0.0002	-0.001	0.002**	-0.001	0.0003
	(0.0003)	(0.003)	(0.0001)	(0.001)	(0.001)	(0.001)	(0.0003)
Routine	-0.0000	0.0001	0.000	0.002*	-0.0034**	0.002	-0.0005
	(0.001)	(0.0002)	(0.0002)	(0.001)	(0.0014)	(0.002)	(0.0006)
Non-routine Manual	-0.001	-0.0003	-0.0001	-0.003*	0.003	-0.0013	0.0019**
	(0.001)	(0.0002)	(0.0002)	(0.014)	(0.002)	(0.002)	(0.0009)
N	22,054	22,054	22,054	22,054	22,054	22,054	22,054

	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Blood Disorder	Hypertension	Stroke	Allergies	Asthma	Bronchitis	Emphysema
Abstract	-0.0001	0.0003	-0.0000	-0.0000	-0.0000	0.0001	-0.0003
	(0.0001)	(0.0002)	(0.0000)	(0.0000)	(0.0003)	(0.0001)	(0.0003)
Routine	0.0001	-0.0002	-0.0000	0.0000	0.0002	0.0000	0.0005
	(0.0002)	(0.0004)	(0.0002)	(0.004)	(0.0003)	(0.0000)	(0.0005)
Non-routine Manual	0.0001	-0.0001	-0.0000	-0.0001	-0.0013	-0.0000	-0.0004
	(0.0002)	(0.0004)	(0.0003)	(0.0001)	(0.001)	(0.0001)	(0.0003)
N	22,054	22,054	22,054	22,054	22,054	22,054	22,054

Note: This table reports results for the health disability outcomes, it takes a value of 1 when individuals state that they have a given work-limiting health disability in t+1, and 0 otherwise. The sample is those employed in time t, and under full retirement age in t+1. All regressions include individual, occupation, state, year fixed effects and demographic controls that are not fixed such as age, marital status, and job tenure. Robust standard errors in parentheses are clustered on individual. 2SLS estimates found, and in Appendix Table 7. * p<0.1 ** p<0.05 *** p<0.01.

Table 8: Health Disabilities of SSDI Applicants

	All Applicants		Received Benefits		Rejected Benefits	
	Mean	SD	Mean	SD	Mean	SD
Abstract	12.96	5.70	13.98	5.84	12.45	5.56
Routine	12.58	6.25	12.77	6.37	12.48	6.20
Non-routine Manual	8.69	4.36	8.61	4.42	8.73	4.34
Arthritis	0.09	0.28	0.10	0.30	0.08	0.27
Back Problems	0.24	0.43	0.20	0.40	0.26	0.44
Cancers and Tumors; Skin Conditions	0.06	0.23	0.11	0.31	0.03	0.18
Musculoskeletal System and Connective Tissue	0.48	0.50	0.49	0.50	0.47	0.50
Heart, Circulatory and Blood Conditions	0.01	0.07	0.01	0.09	0.00	0.06
Respiratory System	0.09	0.28	0.12	0.33	0.07	0.25
Digestive System	0.06	0.23	0.10	0.30	0.04	0.19
Neurological and Sensory	0.03	0.16	0.04	0.20	0.02	0.14
Emotional and Psychological	0.04	0.18	0.02	0.13	0.04	0.21
Endocrine, Metabolic, and Nutritional	0.04	0.20	0.05	0.22	0.04	0.20
Work Caused Health Impairment	0.61	0.49	0.83	0.38	0.52	0.50
N	370		123		247	

Note: Observation is an individual wave which has applied for SSDI.

Table 9: The Effect of Task Content on Having Work Caused Disability

	(1)	(2)
	OLS	2SLS
Abstract	-0.020**	-0.006*
	(0.009)	(0.003)
Routine	0.027*	0.001*
	(0.016)	(0.0007)
Non-routine Manual	-0.019	-0.013
	(0.020)	(0.009)
N	1,341	1,341

Note: This table reports results for the dependent variable having a health disability due to the nature of work; it takes a value of 1 when individuals applying for disability state that their health disability is due to the nature of their work, and 0 otherwise. The sample is those employed in time t, and under full retirement age in t+1. All regressions include individual, occupation, state, year fixed effects and demographic controls that are not fixed such as age, marital status, and job tenure. Robust standard errors in parentheses are clustered on state. * $p<0.1$ ** $p<0.05$ *** $p<0.01$. A full set of coefficients can be found in the appendix.

Table 10: The Effect of Task Content on Applying for SSDI with Unemployment Controls

	(1)	(2)	(3)
Abstract	-0.0004**	-0.0006*	-0.0011***
	(0.0002)	(0.0004)	(0.0004)
Routine	0.00002	0.0011*	0.0013**
	(0.0003)	(0.0007)	(0.0006)
Non-routine Manual	-0.0001	-0.0006	-0.0001
	(0.0003)	(0.0006)	(0.0008)
High Unemployment	-0.001	0.0004	-0.0017
	(0.0025)	(0.0025)	(0.0024)
Occupation F.E.	No	Yes	Yes
Individual F.E.	No	No	Yes
N	22,054	22,054	22,054

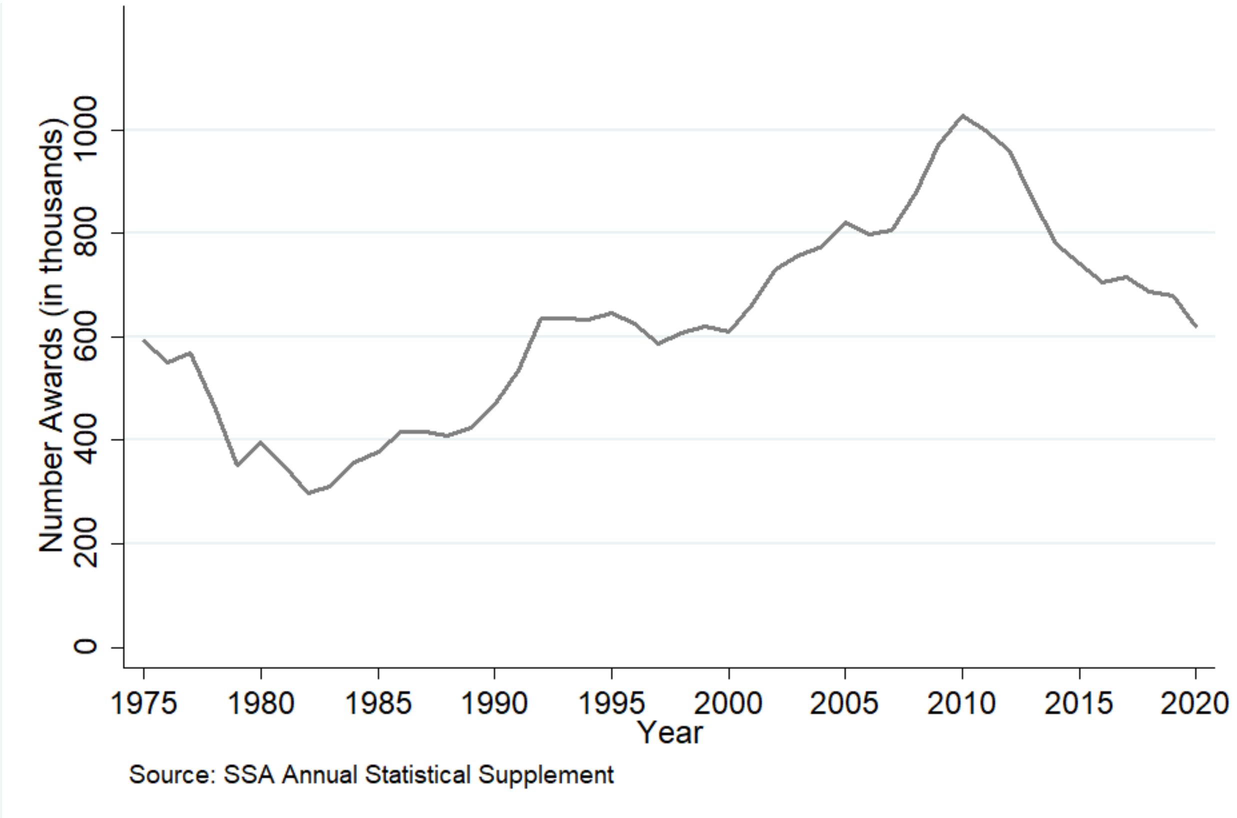
Note: This table reports results for the dependent variable applying for disability insurance; it takes a value of 1 when individuals state that they are applying for disability insurance in t+1, and 0 otherwise. The sample is those employed in time t, and under full retirement age in t+1. The control for high unemployment is equal to 1 if unemployment in the three months before the interview in the next period the state the individual lives in has unemployment above 7%, and 0 otherwise. All regressions include state and year dummies and demographic controls such as age, education level, race/ethnicity, sex, marital status, and job tenure. Robust standard errors in parentheses are clustered on individual. * p<0.1 ** p<0.05 *** p<0.01.

Table 11: The Effect of Task Content on Applying for SSDI with Income Controls

	(1)	(2)	(3)
Abstract	-0.0002	-0.0004	-0.0007*
	(0.0002)	(0.0004)	(0.0004)
Routine	0.0002	0.0011*	0.0013*
	(0.0003)	(0.0007)	(0.0007)
Non-routine Manual	-0.0004	-0.0011*	-0.002*
	(0.0003)	(0.0006)	(0.0009)
Income	-0.003	-0.0013	0.0011
	(0.0011)	(0.001)	(0.0015)
Occupation F.E.	No	Yes	Yes
Individual F.E.	No	No	Yes
N	22,054	22,054	22,054

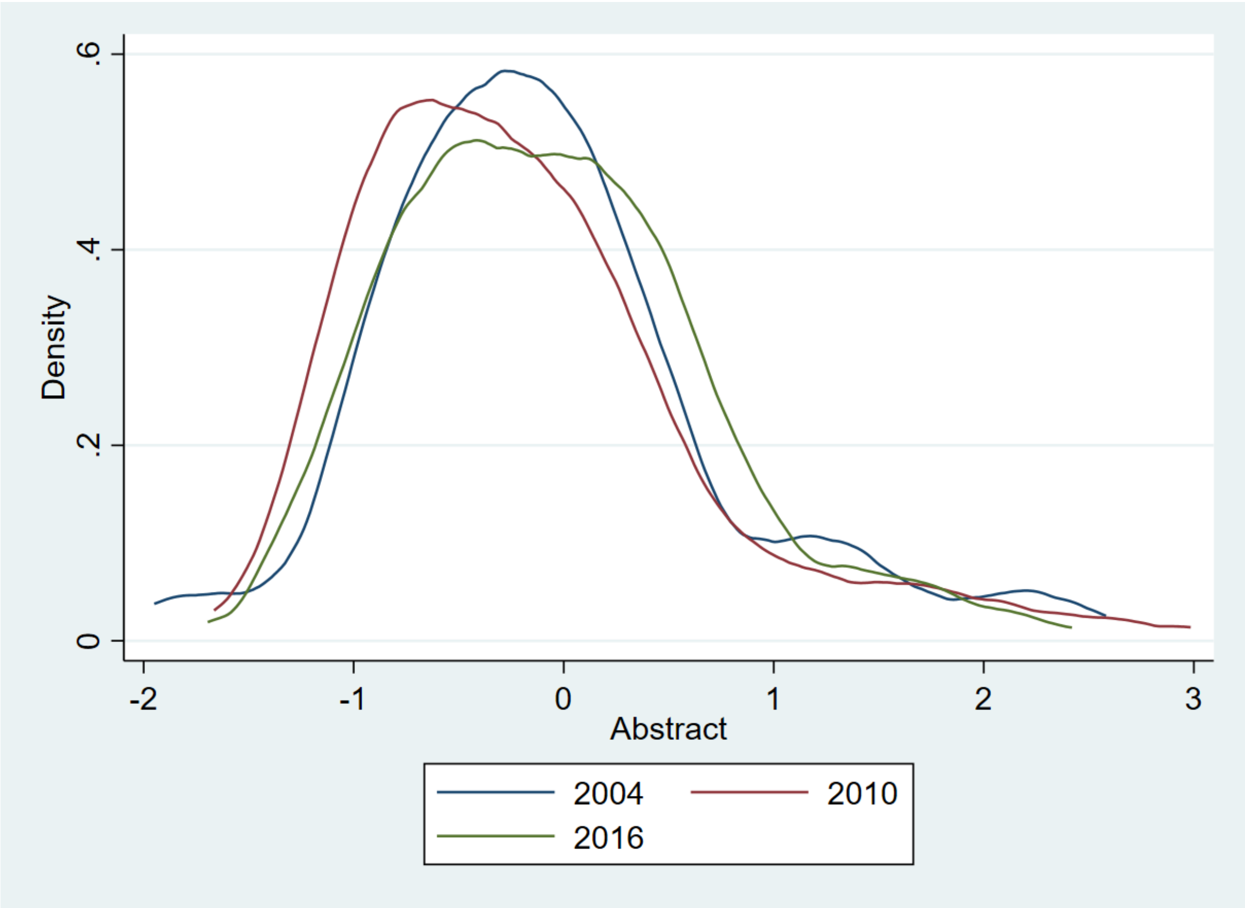
Note: This table reports results for the dependent variable applying for disability insurance; it takes a value of 1 when individuals state that they are applying for disability insurance in t+1, and 0 otherwise. The sample is those employed in time t, and under full retirement age in t+1. The control for Income is a continuous variable for inflation-adjusted income. All regressions include state and year dummies and demographic controls such as age, education level, race/ethnicity, sex, marital status, and job tenure. Robust standard errors in parentheses are clustered on individual. * p<0.1 ** p<0.05 *** p<0.01.

Figure 1: Number of New Awards to Disabled Workers



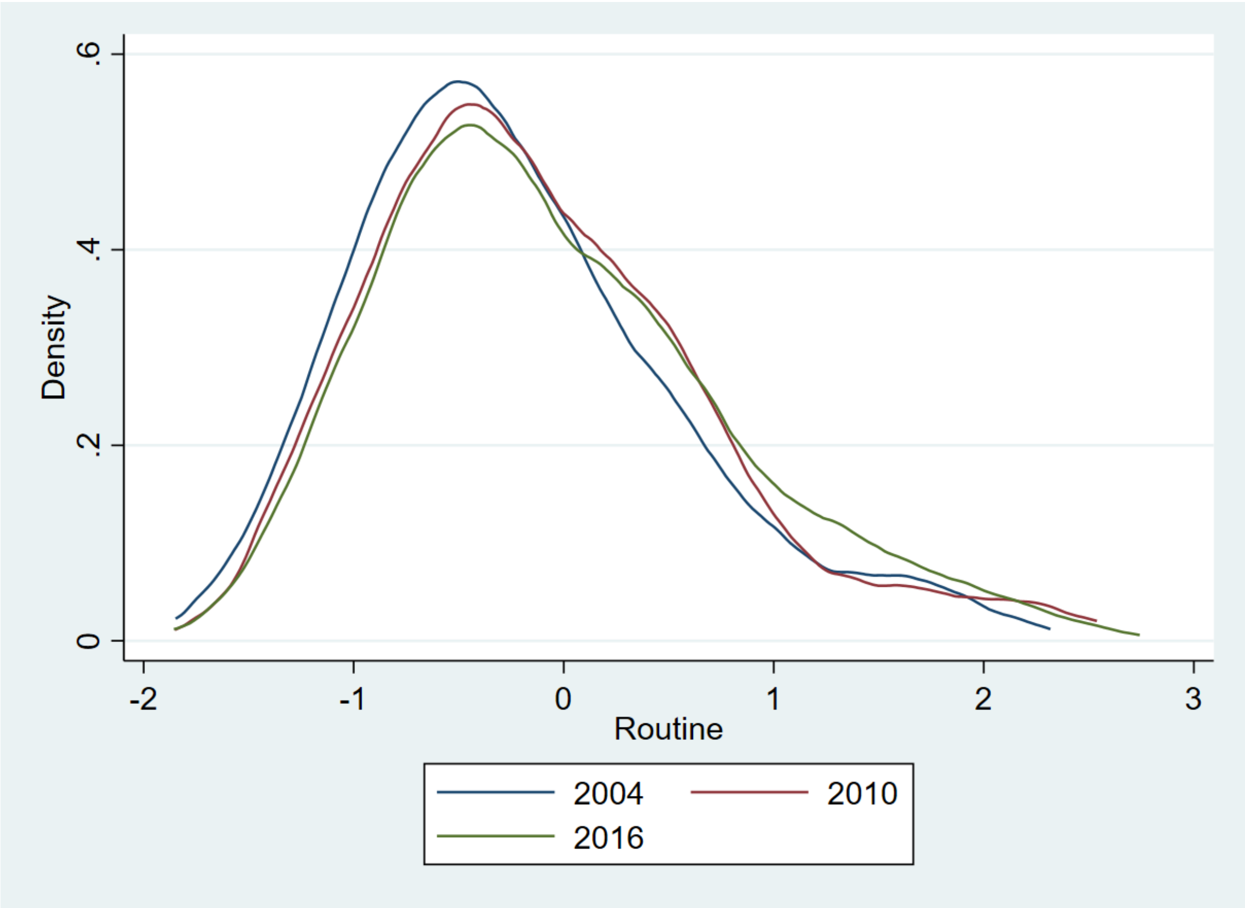
Note: The above graph shows the number of new awards given each year to workers who claim disability.

Figure 2: Distribution of the Abstract Task Measure



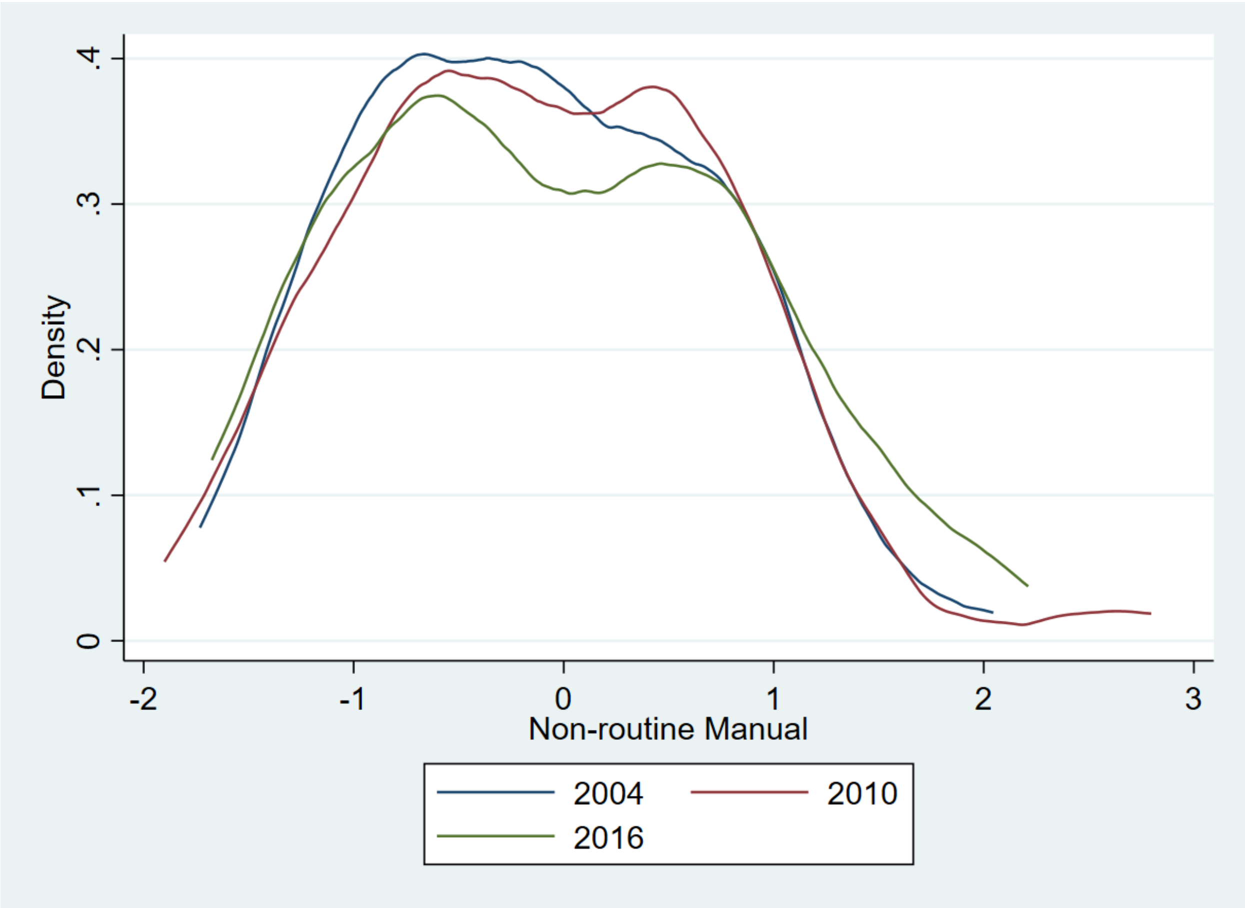
Note: The above graph shows the distribution of tasks for an occupation that at least one individual in the Health and Retirement Study survey is currently employed in. The task measure is standardized and then plotted over the years 2004, 2010, and 2016.

Figure 3: Distribution of the Routine Task Measure



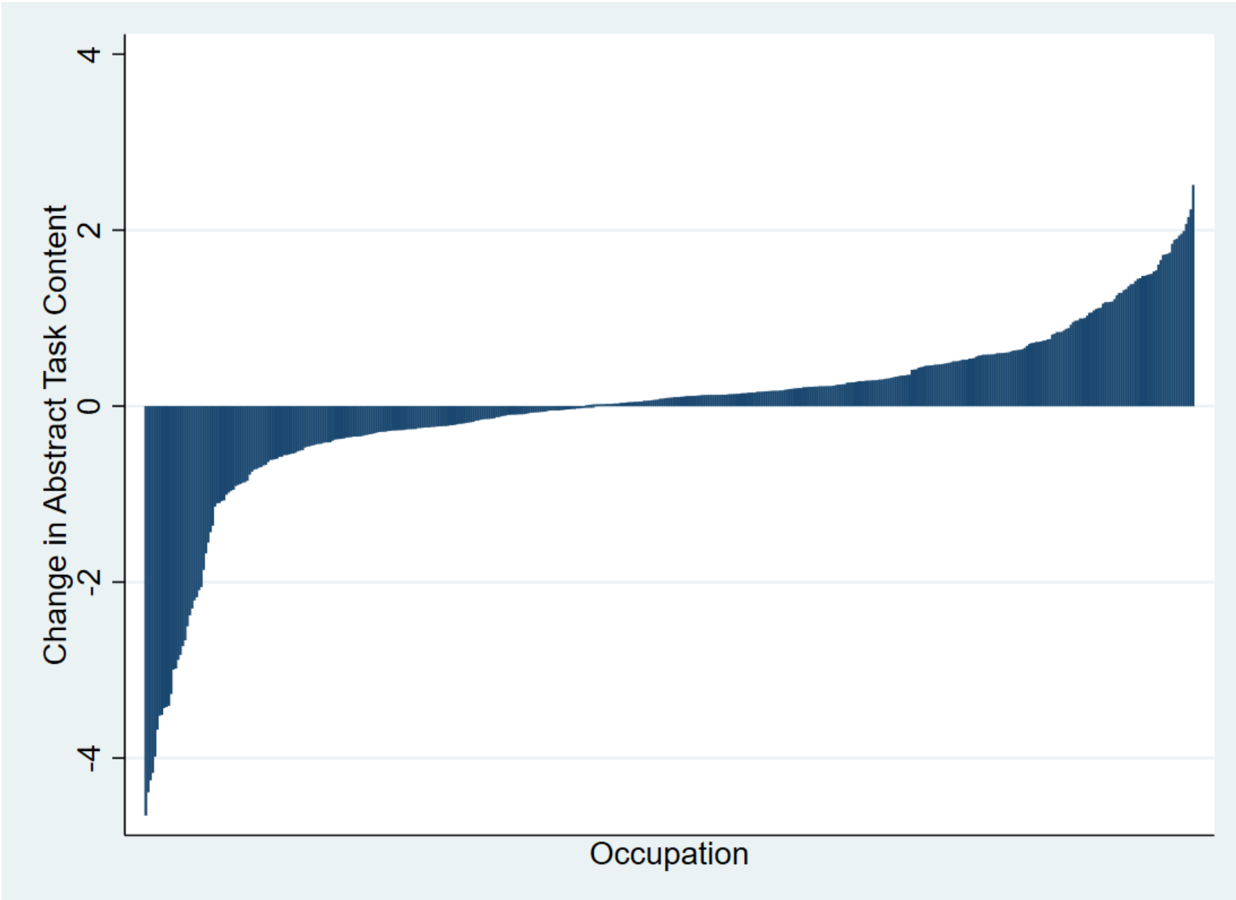
Note: The above graph shows the distribution of tasks for an occupation that at least one individual in the Health and Retirement Study survey is currently employed in. The task measure is standardized and then plotted over the years 2004, 2010, and 2016.

Figure 4: Distribution of the Non-routine Manual Task Measure



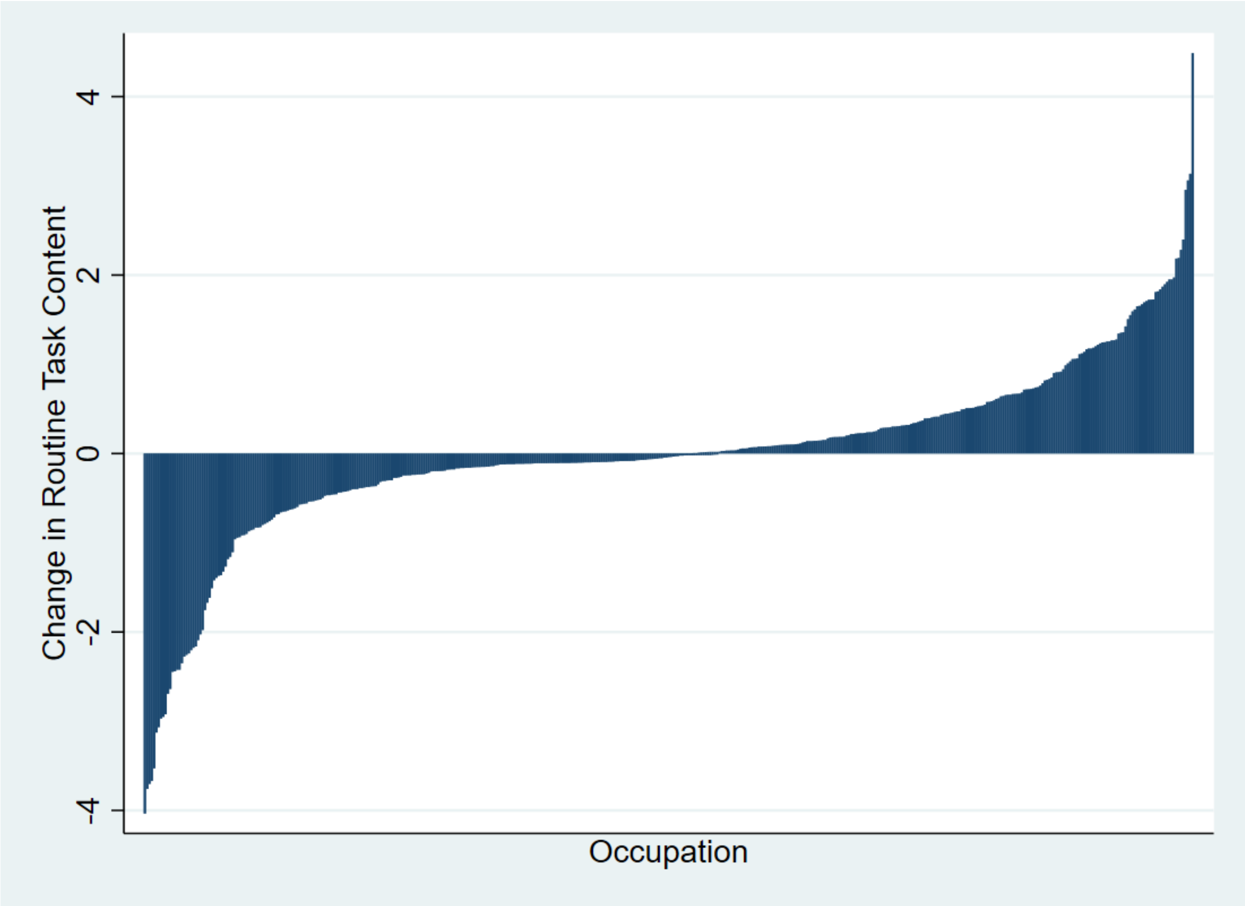
Note: The above graph shows the distribution of tasks for an occupation that at least one individual in the Health and Retirement Study survey is currently employed in. The task measure is standardized and then plotted over the years 2004, 2010, and 2016.

Figure 5: Within Changes of Abstract Task Content



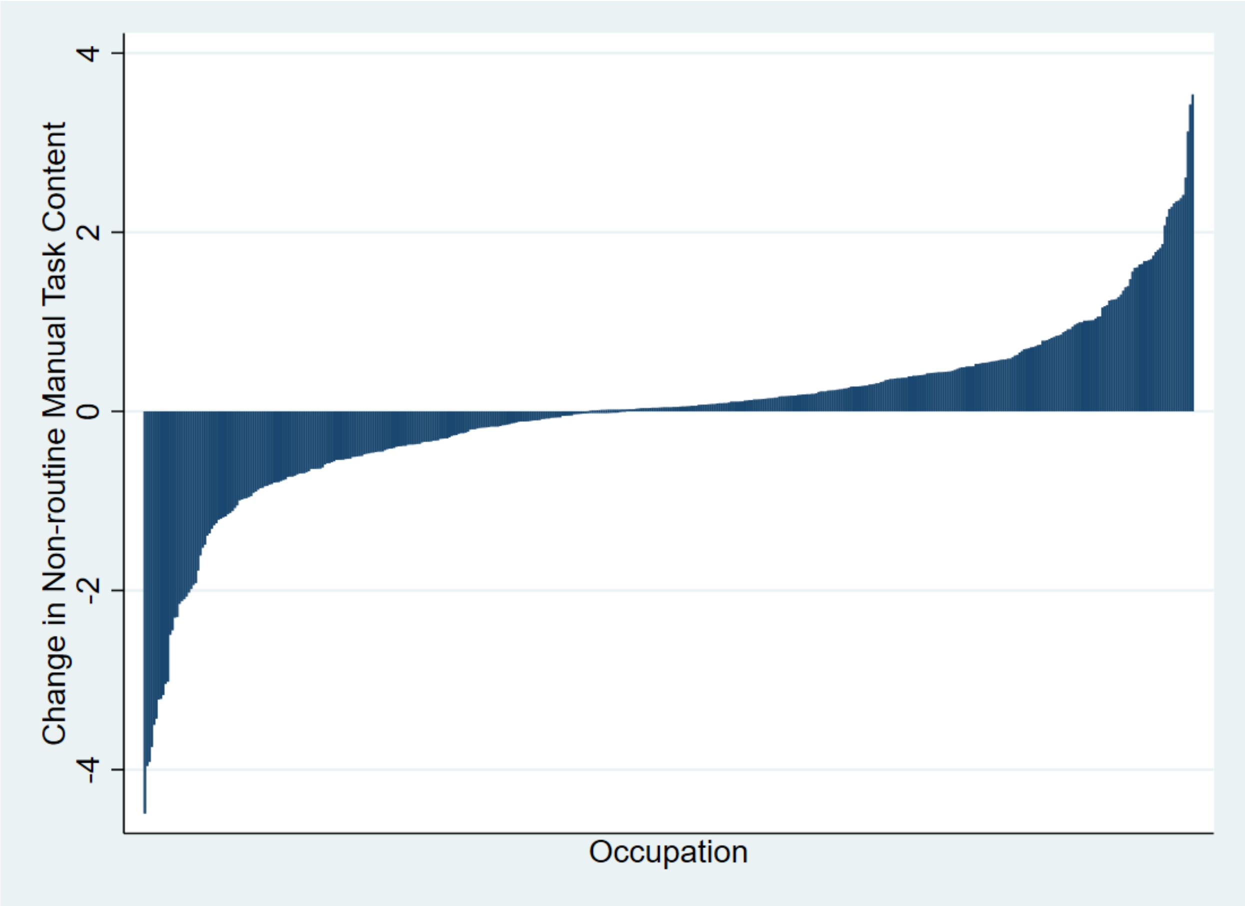
Note: The above graph shows the difference in task intensity for 2004 to 2016 for an occupation that at least one individual in the Health and Retirement Study survey is currently employed in. The task measure is standardized, and then each occupation is plotted by a ranking of how much task intensity has changed.

Figure 6: Within Changes of Routine Task Content



Note: The above graph shows the difference in task intensity for 2004 to 2016 for an occupation that at least one individual in the Health and Retirement Study survey is currently employed in. The task measure is standardized, and then each occupation is plotted by a ranking of how much task intensity has changed.

Figure 7: Within Changes of Non-routine Manual Task Content



Note: The above graph shows the difference in task intensity for 2004 to 2016 for an occupation that at least one individual in the Health and Retirement Study survey is currently employed in. The task measure is standardized, and then each occupation is plotted by a ranking of how much task intensity has changed.

Chapter 2

The Distribution of Occupational Tasks in the United States: Implications for a Diverse and Aging Population[16]

2.1 Introduction

Given further saturation of computer technology into daily life and increased exposure to international trade, work has changed dramatically in the 21st century (e.g., see Acemoglu & Restrepo, 2020, 2021; D. Autor et al., 2021). In the United States and other developed countries, these extensive secular changes in the labor market coincide with a growing older population. In fact, one out of every four U.S. workers will be over the age of 55 by 2026 (Collins & Casey, 2017).[17]

Economic research on aging is primarily concerned with the health and financial well-being of older people. However, less is known about how the task content of work is distributed by age and across demographic groups.[18] Our study fills this void by (a) examining how the distribution of occupational task intensity in the U.S. varies with age for different racial/ethnic and gender group and (b) documenting how the mental, physical and social requirements of occupations have changed over time for different age-race/ethnicity-gender groups. Our analysis is based on data from the Occupation Information Network (O*NET) and the American Community Surveys (ACS) from 2005—2019. The longitudinal data on occupations from O*NET are linked to the ACS waves via a crosswalk between the Standard Occupation Classification (SOC) system and the O*NET occupation codes (referred to as O*NET-SOC codes). Once the data sets are combined, we produce employment-weighted statistics for the task-content measures from Acemoglu & Autor (2011), as in Autor et al. (2003) and Deming (2017).

The age profiles of different worker tasks reveal several insights, but perhaps the main takeaway is that men and women of different races/ethnicities perform starkly different types of

[16] This Chapter was Coauthored with Samuel Cole, John Nunley, and R. Alan Seals.

[17] The age demographics may also be one of the drivers of automation. Acemoglu & Restrepo (2022) show that countries with older populations show an increase in automation, due to a shortage of middle-aged workers.

[18] Lahey & Oxley (2021) point out that the discrimination literature has focused on the intersectionality between race and gender, but not age. Lahey & Oxley (2021) find significant evidence of intersectional discrimination by age and race. In an eye-tracking laboratory experiment with randomized resumes, they find evidence that preferences for White-named job applicants, over Black-named applicants, fade as the job candidates are (artificially) aged.

work as they age. We find that White men transition to jobs with high non-routine cognitive analytical and non-routine cognitive interpersonal tasks around mid-career, and they remain in jobs requiring high levels of these tasks until they reach retirement age. White women, by contrast, tend to perform more routine cognitive tasks, and the intensity at which routine cognitive tasks are undertaken rises consistently as they age. Among men, each racial/ethnic groups begin working in occupations with high levels of physical task intensity early in their careers. Although White men and Asian men transition out of physical work steadily as they age, the same pattern does not hold for Hispanic and Black men. In fact, these minority groups, especially Hispanic men, tend to work in the most physically demanding occupations from the start of their careers and this continues until reaching retirement age. For the most part, the same pattern holds among women. The only exception is the intensity at which physical tasks are completed starts out at a lower level than it does for men.

We next investigate how the distribution of tasks across age and other demographic groups has changed over the last decade and a half. Our analysis of the changes in worker tasks follows the approach of Ross (2017) and Atalay et al. (2020), as these studies examine both flows of workers across occupations and changes in tasks within occupations. We find that White men of all ages experienced increases in non-routine cognitive task intensity and that Black and Hispanic women of all ages experienced large increases in routine cognitive tasks. Non-routine physical tasks increased for 55–67 year-old men; however, Black and Hispanic men did not experience much change in physical tasks over the sample period and remain near the top of the distribution for all age groups. Most of the across-time variation in task intensity is the result of the occupations themselves changing in lieu of workers shifting from one occupation to another, a finding consistent with Atalay et al. (2021).

Policymakers concerned about impending financial pressures on entitlement programs, related to demographics and other structural forces in the economy, may find it useful to keep track of the kinds of tasks older people perform at work. A better understanding of how tasks are distributed across demographic groups will be useful to mitigate disproportionate effects on minorities associated with the coming policy changes to Social Security and other entitlement systems.

2.2 Data Sources

We follow Ross (2017, 2020) and create a panel of occupations from 2005—2019 using data from O*NET. We then rely on the taxonomy of tasks provided in Acemoglu and Autor (2011). In Table 12, we list the tasks, their abbreviations used later in the paper, the survey questions used to create the composite task measures, the O*NET module from which the survey questions were taken, and the measurement scale. When possible, we use the level scale, as it measures the degree to which a task/knowledge/skill/ability is required or needed to perform the tasks of a given occupation. We use the level scale from the abilities, skills, and work activities modules in lieu of the importance scale, as it provides a better measure of *how much* a task is completed for a given occupation. It is not always possible to use the level scale, as neither the level nor importance scales are available for the variables taken from the work context module. In this module, the units of measurement vary across survey questions. In general, the context scale is based on frequency and the time spent doing certain tasks. Following Autor, Levy, and Murnane (2003), we convert the average scores of the survey questions to a 0—10 scale, reflecting their weighted percentile rank in each year.

The next step is to link the panel of occupation characteristics to the American Community Survey (ACS). The ACS has been administered since 2000 on an annual basis, and O*NET survey began in 1998. We start our analysis in 2005 for two reasons. First, the ACS underwent several different sampling designs in the early years. In 2000, the sample was based on a 1-in-750 random draw from the US population. Sampling changed in 2001 to 2004 and varied between sampling of 1-in-232 and 1-in-261 random draw of the US population. In 2005 and subsequent years, the sampling changed to a 1-in-100 random sample of the US population. Second, online documentation from O*NET cautions against using the data in a longitudinal format prior to 2003.[19] Online that using the occupation information in a longitudinal format is problematic for prior years. We link the panel of occupations to the individual-level ACS data via a detailed occupation code and year. We limit the ACS sample to respondents between 16—67 years-old, who are employed and report a valid Standard Occupation Classification (SOC) code. The sample

[19] As sensitivity checks, we checked our findings to the inclusion of 2003 and 2004 data from both O*NET and the ACSs. The inclusion of these additional data points does not affect our findings in a material way.

consists of 13,171,568 respondents. Using these data, we construct pseudo-lifecycle plots of worker tasks and measure the changes over time in task intensity for different age-race/ethnicity-gender groups.

When constructing the task measures, it is important to account for differences in the prevalence of occupations and, consequently, task content. For example, almost 50 percent of workers are employed in four major occupation groups: office and administration, sales, management, and healthcare practitioners. To account for differences in occupational prevalence, we follow Autor, Levy, and Murnane (2003) and construct labor-supply weights based on the number of hours usually worked and weeks worked during the previous year.[20] These weights are used in the analyses presented in the next two sections.

2.3 Task-Age Profiles

Using the individual-level ACS-O*NET linked data, we construct pseudo-lifecycle plots of the task intensities in which task intensities are plotted over age. The age profiles reflect the distribution of the task content of work in the U.S. labor market across the age distribution between 2005 and 2019. The task-age profiles are constructed for different workers from varying demographic backgrounds. In particular, we present task-age profiles by gender, race/ethnicity, and gender × race/ethnicity. The process to produce the task-age profiles involves three steps. The first step is to aggregate to the appropriate level. In our case, we conduct three separate aggregations to compute average task intensities by (a) age and gender (b) age and race/ethnicity, and (c) age, gender, and race/ethnicity. The sample sizes post-aggregation are 104, 364, and 520, respectively. The second step is to group the task intensity variables into centiles (100 bins), which creates a 0—100 scale. The third and final step is to fit a LOWESS curve through the data points with the task-intensity percentile measured on the *y*-axis and age measured on the *x*-axis.

From Figure 8, one observes that younger men and women are similar in terms of all task intensity variables, except those that require physical activity. For men, non-routine cognitive, whether analytical or interpersonal, tends to reach a plateau around mid-career, but they remain in

[20] Because the measure for weeks worked in the ACS is a factor variable in lieu of a continuous measure, we use the mid-point in the ranges for each of the measure's values (1—6). The vast majority workers report working between 50 and 52 weeks per year. As such, the weight for these workers would equal hours usually worked times 51 (the midpoint).

occupations with high levels of intensity in these tasks until they reach retirement age. By contrast, these intensities rise for women until around mid-career before falling steadily as retirement age approaches. The intensity at which women complete routine cognitive tasks rises with age, but the opposite is true for men. Workers, particularly men, tend to work in occupations with more extensive physical demands when younger but tend to transition out of performing these tasks as they age.

In Figure 9, we analyze the task intensity measures by race/ethnicity and age. We focus on four racial/ethnic groups: White, Black, Hispanic, and Asian.[21] From the panels in Figure 9, it is apparent that different racial/ethnic groups perform different types of tasks over their working lives. White and Asian workers experience significant upticks in the extent to which they perform non-routine cognitive tasks, and these intensities rise until the mid-30s to mid-40s and then decline thereafter. Black and Hispanic workers tend to work in occupations that are low in non-routine cognitive analytical and non-routine cognitive interpersonal task intensity. Instead, they tend to work in occupations that are high in physical task intensity. In fact, Hispanic workers are employed in occupations that are near the top of the physical task intensity over their entire working lives. Physical task intensity tends to fall for Black workers with age, but the decline in physical task intensity with age is slower than it is for White and Asian workers. Lastly, for routine cognitive task intensity, we observe all races/ethnicities tending to work in more cognitively routine occupations at young ages. This pattern continues until mid-career and it stabilizes for Asian and Black workers but reverses for White and Hispanic workers and continues to decline as retirement age approaches.

In Figure 10, we present task-age profiles by race/ethnicity and gender. The solid lines represent men, and the dashed lines represent women. For non-routine cognitive analytical and non-routine cognitive interpersonal task intensity, the task-age profiles for all race/ethnicity-gender groups, except White men, reveal a concave relationship. For White men, these intensities rise and either plateau or continue to rise until reaching retirement age. The other race/ethnicity-gender groups experience rising intensity in these tasks, but that pattern tends to reverse around mid-career. For non-routine cognitive tasks, we also note the "shallowness" of the task-age profiles

[21] For our findings with respect to race/ethnicity, we are unable to follow the Office of Management and Budget (OMB) standards, as the sample sizes for the American Indian and Alaska Native (AIAN) and Native Hawaiian or Other Pacific Islanders (NHOPI) groupings are small and, therefore, potentially unreliable. We, however, follow their definitions to identify the four racial/ethnic groups used in our analysis.

for Black and Hispanic men and women. Consider non-routine cognitive analytical task intensity. White men reach the 75th percentile around 40 years-old and then remain at a similar level of intensity as they age. Black and Hispanic workers, regardless of gender, reach approximately the 25th percentile around the mid-career, and then their task-age profiles plateau before falling as retirement age nears.

The intensity at which routine cognitive tasks are completed tends to rise in early career and then fall thereafter. The exceptions are White men and White women. For White men, routine cognitive task intensity begins around the 50th percentile but falls steadily until reaching the 1st percentile by age 67. White women, on the other hand, experience continually rising routine cognitive task intensity over their working lives: they begin around the 25th percentile, reach the 50th percentile around age 25, reach the 75th percentile around age 45, and then reach the 90th percentile in their early-60s.

In terms of physical work, we observe, for the most part, a negative relationship between the intensity of physical tasks, either routine manual or non-routine manual physical, and age. However, the rate at which the different racial/ethnic-gender groups transition out of physical work varies. White men and White women experience sharp drops in physical task intensity as they age. Alternatively, the rate at which the task intensity declines for Black and Hispanic people, both men and women, is much slower. For example, Hispanic men and Black men tend to work in some of the most physically demanding occupations in the economy throughout their entire working lives. Physical task intensity falls for Asian men initially, but the pattern stabilizes early in their early-30s, and they remain around the median for both routine manual and non-routine manual physical task intensity for the remainder of their working lives.

2.4 Changes in the Distribution of Tasks Over Time

We make comparisons of task intensities across demographic groups and time by examining two years of data: 2005 and 2019. We use the individual-level ACS-O*NET linked data, as in section 2.3. However, we limit the sample to workers employed in occupations observed in both 2005 and 2019. Ensuring the occupations are observed in both years allows for changes in the task intensities within occupations as well as changes resulting from workers switching from one occupation to another. In general, two methods have been proposed to study the evolution of task content in the

U.S. economy. The approach by Autor et al. (2003), which is based on changes in aggregate task demand caused by changes in employment across occupations over time, and the approaches by Atalay et al. (2020) and Ross (2017), which allow one to measure the sum of between-occupation shifts in employment, as in Autor et al. (2003), and changes in task intensity within the occupations themselves over time.

Our analysis, like those used in Atalay et al. (2020) and Ross (2017), gives the total change in task intensity over time in lieu of only the change in task intensity due solely to changes in employment shares across occupations over time.[22] We compute the employment-weighted mean of the task intensities for each age-race/ethnicity-gender group in each of the two years. The resulting data set consists of 832 age-race/ethnicity-gender-year observations (=52 age groups × 4 racial/ethnic groups × 2 genders × 2 years). Following these calculations, we then rank and assign the task intensities to percentiles (0—100) for each year. Due to the difficulty of presenting the results for each of the 51 age groups, we instead compute the median task intensity percentile for each race/ethnicity-gender-year group for following age groups: (i) 16-24, (ii) 25-34, (iii) 35-44, (iv) 45-54, and (v) 55-67.[23]

The median percentiles for each demographic group are reported in Table 13. In general, the discrepancies between the 2005 and 2019 percentiles vary widely across age, race/ethnicity, and gender. However, the largest discrepancies exist across racial/ethnic-gender groups. Rather than comment on each group, consider the 55-67 age group, White men tend to shift out of routine cognitive tasks into physical tasks (routine manual and non-routine physical). Hispanic men tend to shift out of non-routine cognitive tasks, both analytical and interpersonal, into routine cognitive, routine manual, and non-routine manual physical tasks. For Black men, the intensity at which cognitive and physical tasks are performed declines between the two years. Black and Hispanic women moved upward 36 percentiles and 29 percentiles, respectively, in the routine cognitive task intensity distribution between 2005 and 2019. Interestingly, Hispanic women move up the

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[22] The main difference in the two approaches is the use of a base year in Autor et al. (2003) and longitudinal data on occupations by Atalay et al. (2020) and Ross (2017). Autor et al.'s study is constrained by the lack of available data. Atalay et al. (2020) build on Autor et al.'s work by extracting the text from job advertisements posted in leading newspapers from 1950—2000.

[23] For example, consider non-routine cognitive analytical task intensity for 55-67 year-old White men. For 2005, the percentiles assigned to each age group range from 77—91. The median value for this group is 83 and the mode is 82. Thus, the percentile for non-routine cognitive analytical task intensity assigned to White men in the 55-67 year-old age group for 2005 is the median value (i.e. 83).

distribution for each of the five tasks. The same is largely true for Black women, except non-routine physical task intensity falls by 12 percentiles. The task intensities tend to rise for White women, but the change is relatively smaller than that for Black and Hispanic women.[24]

As a comparison to the overall changes from Table 13, we present the task intensities from 2005 and 2019 using the Autor et al. (2003) method, which captures changes in task intensity from workers changing occupations, in lieu of the occupations themselves changing. The results are presented in Table A1. In addition, we conduct a simple decomposition of the overall change into two components: the change from workers moving across occupations and the change from the occupations themselves evolving. These results are presented in Table A2. In lieu of commenting in detail on the supplementary calculations, we note that we find, as does Atalay et al. (2020), that changes in employment shares across occupations are an important part of the observed change. However, examining the within and between occupation changes in isolation can be misleading, as it is common for the within channel to dominate the between channel, and vice versa.

2.5 Conclusion

An extensive literature documents the relationship between occupational task intensity and labor market outcomes (e.g., D. Autor & Dorn, 2013; D. H. Autor et al., 2003; Deming, 2017). However, the distribution of labor market tasks by age and other demographics has received less attention (Hurst et al., 2021). With the exception of Hudomiet & Willis (2021), who focus on the computerization of occupations, to our knowledge, there has been no study focused specifically on the allocation of tasks for specific age-gender-race/ethnicity groups. Filling this void in our understanding of how work changes for people as they age will be particularly important for government policy.

We illustrate the age-specific distribution of occupational tasks in the United States from 2005-2019. Stark racial/ethnic and gender divides in the age-specific allocation of tasks offer a common theme from our results. As they age, White men work in the most cognitively demanding

[24] In Appendix 2 Figures 1—5, we plot the median percentiles for each demographic group but for the entire sample period in lieu of only two years (2005 and 2019). The five plots present the median task intensities for each race/ethnicity-gender group. The plots differ based on the age group under investigation.

jobs, while White women work in the least physically demanding occupations. Black and Hispanic men maintain the highest physical task intensity, whereas White men appear to transition to more cognitively intensive work early in their careers and remain in jobs with similar cognitive intensity until late career. On average, Black men and Hispanic men perform jobs with similar physical task intensity throughout their careers.

We also show that the kinds of work people of all ages perform has changed dramatically during the first part of the 21st century. An increase in routine cognitive and routine manual task intensity, particularly for the oldest group of workers, poses a significant challenge for policy makers. Older workers, a group that already suffers from rampant labor market discrimination (Lahey, 2008; Lahey & Oxley, 2021; Neumark et al., 2015) and lower productivity because of health limitations, may be more likely to be displaced by automation than younger workers. The more physically intense occupations of Black and Hispanic men over age 55 may be particularly susceptible to technological change, such as robotics (e.g., see Acemoglu & Restrepo, 2021); however, lower physical task intensity may also lengthen their work lives.

Policymakers in the United States and other developed countries will soon be challenged by financial stress on entitlement programs, largely due to the exit of baby boomers from the labor force. The relationship between worker tasks and relevant employment outcomes, such as earnings and labor force participation, will play an important role in determining the effects of the coming SSA reforms. Gender and racial/ethnic inequality in the distribution of tasks could contribute to racial/ethnic inequality in later-life disability (Kelley-Moore & Ferraro, 2004) and retirement savings (e.g., see Tamborini & Kim, 2020). Because in the U.S., Black and Hispanic retirees rely more on Social Security payments, which also depend on the length of work-life and career earnings, adjustments to retirement age and benefits will likely have disproportionate effects on these groups.

Table 12: Task Intensity Measure Definitions

Task	Abbreviation	Survey Questions	Module	Scale
Nonroutine Cognitive Analytical	NR COGA	Analyzing data/information	Work Activities	Level, 0—7
		Thinking creatively	Work Activities	Level, 0—7
		Interpreting information for others	Work Activities	Level, 0—7
Nonroutine Cognitive Interpersonal	NR COGI	Establishing and maintaining personal relationships	Work Activities	Level, 0—7
		Guiding, directing, and motivating others	Work Context	Context, 0—7
		Coaching/developing others	Work Context	Context, 0—7
Routine Cognitive	R COG	Importance of repeating same tasks	Work Context	Context, 0—5
		Importance of being exact or accurate	Work Context	Context, 0—5
		Structured vs. unstructured work (reverse scale)	Work Context	Context, 0—5
Routine Manual	R MAN	Pace determined by speed of equipment	Work Activities	Level, 0—7
		Controlling machines and processes	Work Context	Context, 0—7
		Spend time making repetitive motions	Work Context	Context, 0—5
Nonroutine Manual Physical	NR PHYS	Operating vehicles, mechanized devices, or equipment	Work Activities	Level, 0—7
		Spend time using hands to handle, control or feel objects, tools or controls	Work Context	Context, 0—5
		Manual dexterity	Abilities	Level, 0—7
		Spatial orientation	Abilities	Level, 0—7

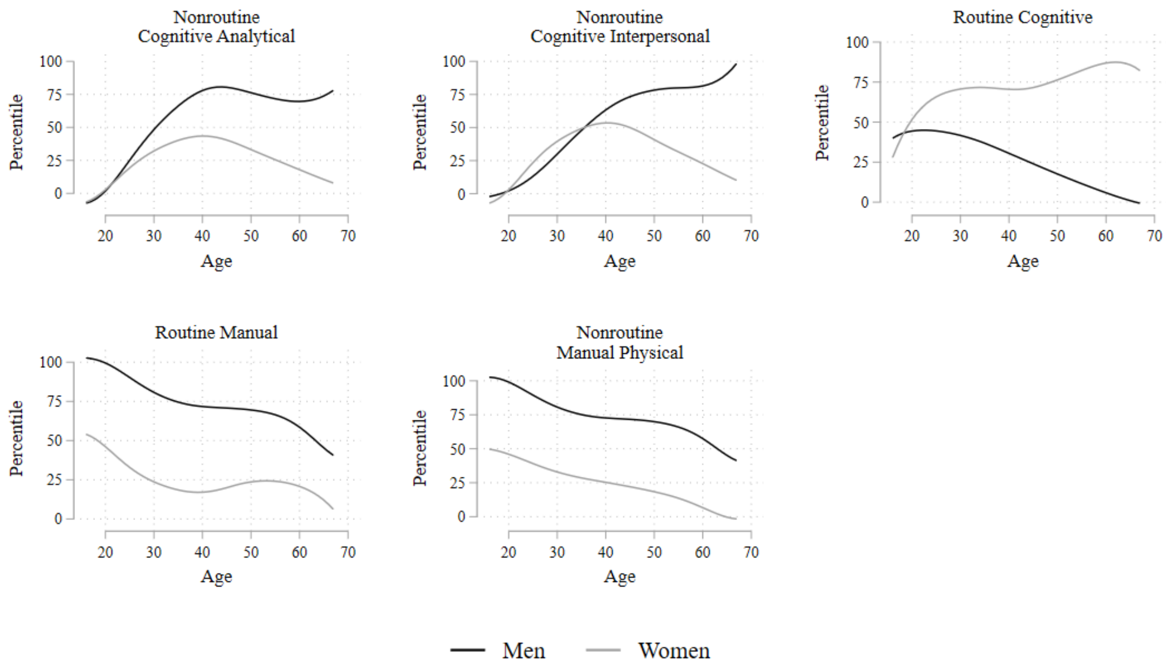
Note: The task measures are based on the taxonomy provided in Acemoglu and Autor (2011).

Table 13: Changes in Task Intensity Over Time by Age Group, Race/Ethnicity, and Gender

	Men												Women											
	White			Black			Asian			Hispanic			White			Black			Asian			Hispanic		
	2005	2019	Δ	2005	2019	Δ	2005	2019	Δ	2005	2019	Δ	2005	2019	Δ	2005	2019	Δ	2005	2019	Δ	2005	2019	Δ
16-24																								
NR COGA	17	14	-3	12	7	-5	13	13	0	14	11	-3	11	8	-3	13	9	-4	14	9	-5	14	8	-6
NR COGI	14	12	-2	8	7	-1	8	16	8	14	8	-6	16	12	-4	11	12	1	17	11	-6	12	11	-1
R COG	43	41	-2	56	63	7	58	83	25	51	49	-2	52	62	10	62	82	20	78	73	-5	66	84	18
R MAN	93	94	1	92	92	0	63	75	12	97	94	-3	35	59	24	38	55	17	26	46	20	47	61	14
NR PHYS	90	89	-1	85	81	-4	60	60	0	96	91	-5	46	51	5	46	46	0	28	39	11	43	49	6
25-34																								
NR COGA	87	77	-10	43	31	-13	98	98	1	34	39	5	87	76	-11	61	38	-24	98	97	-1	30	43	13
NR COGI	80	75	-5	35	27	-8	79	83	4	36	30	-6	82	81	-1	44	45	2	89	92	3	28	47	20
R COG	33	16	-17	59	52	-8	58	39	-20	42	30	-12	77	50	-28	85	85	0	94	64	-30	67	77	10
R MAN	66	59	-7	74	74	1	42	16	-26	93	82	-11	12	16	5	23	34	11	23	3	-20	40	34	-6
NR PHYS	68	68	1	74	73	-1	45	30	-16	93	84	-9	12	20	8	15	33	19	7	3	-5	26	30	4
35-44																								
NR COGA	91	89	-2	51	52	1	95	99	4	40	48	8	84	83	-2	59	58	-1	95	96	1	22	36	14
NR COGI	93	92	-2	47	38	-9	88	96	8	49	44	-5	84	87	4	50	65	15	74	91	18	23	39	17
R COG	25	9	-16	53	41	-12	39	23	-16	31	16	-15	82	54	-29	83	86	3	92	56	-36	50	66	17
R MAN	63	48	-15	77	71	-6	45	11	-35	90	87	-3	18	7	-11	27	24	-3	37	4	-34	53	44	-9
NR PHYS	65	63	-2	78	73	-5	53	35	-18	89	90	1	14	12	-2	26	21	-5	23	4	-19	41	37	-4
45-54																								
NR COGA	87	88	1	47	47	-1	74	93	19	43	46	3	84	77	-8	54	59	6	76	80	4	21	26	5
NR COGI	91	92	1	44	44	0	73	84	12	46	43	-4	86	76	-10	50	61	12	65	75	10	22	31	9
R COG	21	8	-13	47	33	-14	38	28	-10	33	16	-17	88	68	-20	74	88	14	87	69	-18	45	58	13
R MAN	61	51	-11	80	73	-8	58	36	-22	88	88	-1	18	10	-8	31	25	-6	47	22	-25	50	58	9
NR PHYS	63	64	1	82	77	-5	58	51	-7	87	92	5	16	9	-7	30	19	-11	39	18	-21	39	43	4
55-67																								
NR COGA	83	84	1	43	34	-9	66	68	2	34	33	-1	65	70	5	31	39	8	68	57	-11	14	19	5
NR COGI	89	86	-3	38	27	-11	59	57	-2	40	32	-8	67	69	2	35	42	7	60	56	-4	14	21	7
R COG	13	5	-8	46	39	-7	31	35	4	16	21	5	81	80	-1	56	85	29	76	79	3	21	57	36
R MAN	39	53	14	76	76	0	56	52	-4	83	84	1	13	15	2	28	31	3	45	30	-15	46	52	6
NR PHYS	54	67	13	82	78	-4	55	58	3	82	88	6	9	11	2	35	23	-12	38	26	-12	35	40	5

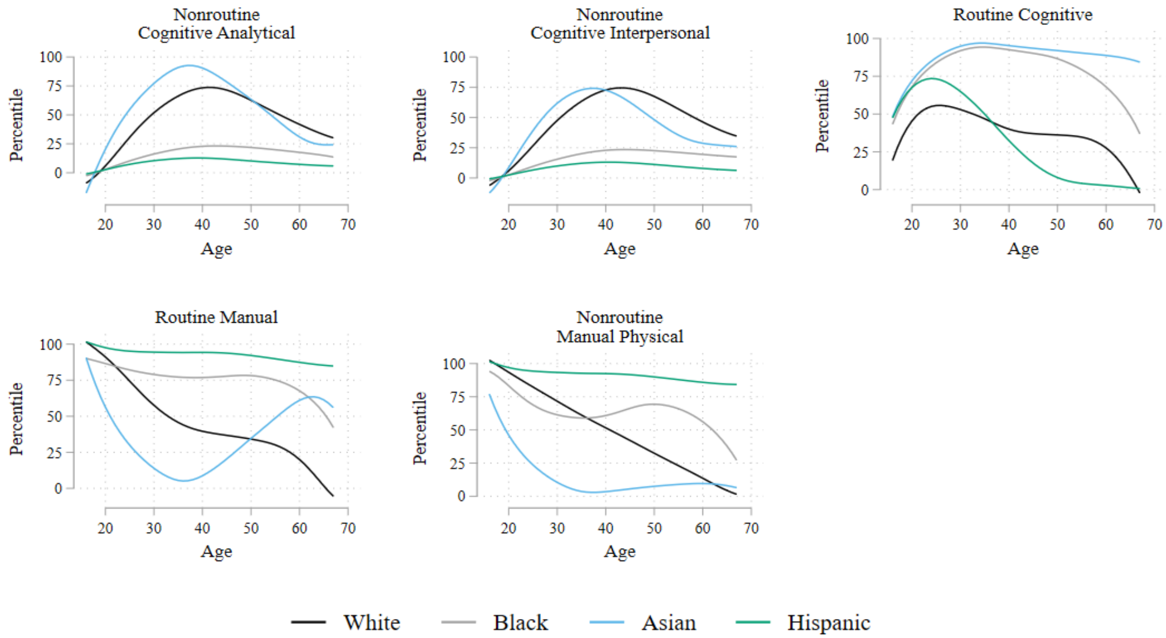
Note: The table presents the median task intensity percentile for each race/ethnicity-gender group from five age ranges (16-24, 25-34, 35-44, 45-54, and 55-67) in 2005 and 2019 as well as the change between the two years. Computing the median task intensity percentiles requires several steps. Using the individual-level ACS-O*NET linked data, we compute employment-weighted means of the task intensity measures for each age-race/ethnicity-gender group in each of the two years. The resulting data set consists of 832 age-race/ethnicity-gender-year observations (=52 age groups × 4 racial/ethnic groups × 2 genders × 2 years). Following these calculations, we then rank and assign the task intensities to percentiles (1—99) for each year. Within each of the five age groupings, we then compute the median task intensity percentiles for each race/ethnicity-gender group in each year.

Figure 8: Task Intensities and Aging by Gender



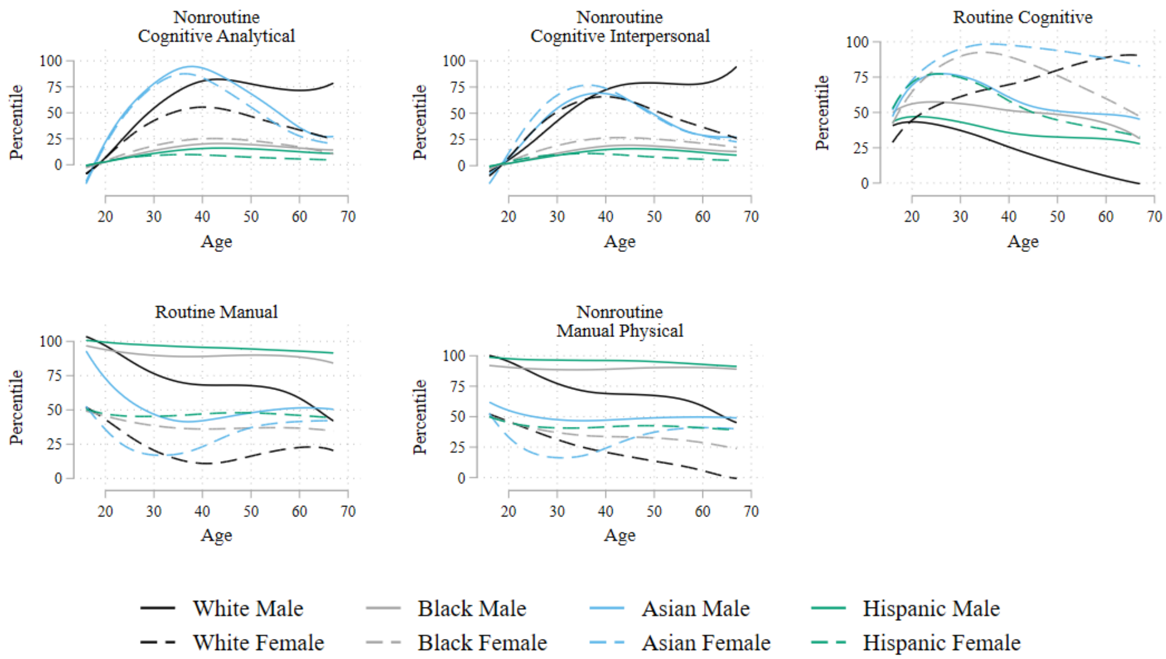
Note: Using the combined O*NET and ACS data sets from 2004-2019 (described previously), the figure presents the relationship between the task intensity measures and age for men and women. To create the figure, we first aggregate the data to the 104 age-sex cells, and then separate the task intensity measures into centiles (100 bins). The plotted lines rely on a LOWESS fit with the bandwidth set at 0.8.

Figure 9: Task Intensities and Aging by Race/Ethnicity



Note: Using the combined O*NET and ACS data sets from 2004-2019 (described previously), the figure presents the relationship between the task intensity measures and age for different races/ethnicities. To create the figure, we first aggregate the data to the 364 age-race/ethnicity cells, and then separate the task intensity measures into centiles (100 bins). The plotted lines rely on a LOWESS fit with the bandwidth set at 0.8.

Figure 10: Task Intensities and Aging by Gender and Race/Ethnicity



Note: Using the combined O*NET and ACS data sets from 2004-2019 (described previously), the figure presents the relationship between the task intensity measures and age for different races/ethnicities. To create the figure, we first aggregate the data to the 520 age-race/ethnicity-gender cells, and then separate the task intensity measures into centiles (100 bins). The plotted lines rely on a LOWESS fit with the bandwidth set at 0.8.

Chapter 3

The Emergency Switch to Remote Instruction Did Not Reduce Research Production: Evidence From the NBER Working Papers[25]

3.1 Introduction

The COVID-19 pandemic, especially in its early days in the Spring of 2020, had unprecedented disruptions in education. Because of the fear and uncertainty of the effects of the novel virus, virtually all colleges and universities across the country shut down their campuses and switched to remote instruction. Many recent papers have studied how the lives and learning outcomes of university students were impacted. The significant effects of COVID-19 on university students are now well documented.[26]

As much as university shutdowns and the change in modalities affected student outcomes, it is highly likely that the effects of these changes also extended to those teaching the courses, the faculty. In this paper, we focus on the changes in the research production of faculty due to universities' emergency switch to remote instruction and the differences in outcomes for male and female academics. Differences in the impact have critical implications when discussing how the COVID-19 pandemic may have disproportionately impacted one gender over the other. For example, papers such as Alon et al. (2020) suggest that working mothers were made disproportionately worse off because they are often primary caregivers. As society recovers from the effects of the virus research documenting measurable outcomes will serve as a way of disentangling how the genders were affected by the pandemic.

Some work has already provided insight into the effects of the pandemic on academics. Amano-Patino et al. (2020) have shown a larger decrease in the number of working papers published following the pandemic for women in economics compared to their male counterparts.

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[25] This Chapter was coauthored with Duha. T. Altindag.

[26] Recent studies have shown that the change in lifestyle and the unknown as to how long the pandemic would last has caused significant changes to student's expectations of the future Jaeger et al. (2021). Aucejo et al. (2020) show that students at a large public higher education institute had changes in their decisions on whether they chose to withdraw from classes, change their major, or delay the decision to graduate. Other work has focused on student's academic outcomes, Altindag, Filiz, and Tekin (2021) find that students' grades benefited from switching to online courses because of COVID-19. They show the increase in overall grades comes from instructor leniency in grading or lower standards of monitoring for academic integrity. Orlov et al. (2020), study a similar effect, but rather than examining grades, they estimate how students do on standardized exams. They find that students in remote instruction do worse than their in-person counterparts.

Additionally, Deryugina, Shurchkov, and Stearns (2021) through a survey of academics have found that women with children are spending significantly less time on research than those without children. Women with children also spend more time on childcare than men with children. For both men and women, less time was spent on work overall, and more on house care duties. Their work has suggested that we should expect that as countries began to lockdown and teaching moved online that research production should have slowed, and disproportionately so for women.

Though, it is unclear how the emergency switch to remote instruction due to the COVID-19 pandemic affected professors' ability to produce research. On the one hand, the shift to remote operations might have reduced research productivity, much less how genders differed. This is because professors might have increased the time they typically allocate on teaching-related activities at the expense of their research time to prepare for the remote delivery of their courses. For example, when a professor was forced to switch to an online teaching modality, she/he might have had difficulty adjusting her/his pedagogy of this new method. The overall changes in lifestyle due to the pandemic could have negatively impacted faculty's' productivity as well. Several unknowns and the panic around the new pathogen could have steered individuals to take time-consuming precautions (such as gathering/stocking supplies, learning about the COVID-19 virus, and so on) to guard against potential adverse effects of the pandemic. In addition, because the K-12 schools typically shut down or switched to remote instruction around the same time as the universities in the same city, researchers with young children might have had to spend much more time on child-rearing or other household production activities when the pandemic spread.

On the other hand, the inescapable switch to remote instruction during the start of the COVID-19 pandemic could have increased a professor's research production. For example, when classes started to be delivered online, and the campuses were shut down, a faculty member might have allocated less time to personal grooming (Pabilonia and Vernon 2020). In addition, when the professor did not have to be at work physically, she/he could have "saved" on commuting time, approximately 50 minutes per day, according to Pabilonia and Vernon (2020). Also, a professor could have chosen to reduce the time she/he put into teaching activities. For example, she/he might recognize that the forced switch to online instruction was a burden on students and reduced the content/material/assignment load for the students, or they might have canceled classes. Faculty members who were teaching more than one section of the same course had the opportunity to use the same lecture video for both classes, effectively turning two lecture periods into one. These efficiency gains are not only limited to those who are teaching classes. Other beneficiaries may include researchers who are not teaching but co-author papers with colleagues who teach and can save time by switching to online instruction.

In this paper, we estimate the impact of a university's switch to remote instruction on its faculty members' research productivity and examine the differences between men and women. Our identifying variation comes from the timing of universities' emergency switch to online modalities in the Spring of 2020. The exogeneity in the spatial and temporal spread of COVID-19 caused the variation in the timing of universities' shutdowns and their shift to remote instruction.[27] We use this variation to recover the causal effects. We hand-collected the dates of the switches of US universities from the announcements on their websites. The variation in the timing of the shift to remote instruction is depicted in Figure 11, which presents the cumulative share of schools operating remotely by week. While most switches took place in the week of March 23rd, some schools started remote instruction earlier in March and others in late March and April. In Figure 12, we show the geographic distributions of the schools in our sample. Each dot marks the location of a university. White, grey, and black dots indicate that the university shut down in-person classes before, in, and after the week of March 23rd, respectively. From Figure 12, it is clear that universities on the west coast switched to remote instruction at the earliest.

We supplement our analysis using IZA researchers. Rather than a university-level switch to remote instruction, we use the country-level decision to recommend or force universities and colleges to shut down. The variation in country-level shutdowns for these universities can be found in Figure 14. Nearly all of the IZA-affiliated schools are in Europe, where the COVID-19 pandemic started earlier than in the United States, a majority of schools shifted to remote instruction before or during the week of March 16th.

We measure the research production of the NBER-affiliated and IZA-affiliated professors using the number of working papers (WPs) and discussion papers (DPs) posted to their respective National Bureau of Economic Research (NBER) and Institute of Labor Economics (IZA) websites. There are pros and cons of this metric. For example, admittedly, this measure is narrowly focused on economics research and on the researchers that are affiliated with the NBER or IZA. It is usually

[27] For example, one of the earliest areas to have high levels of COVID-19 cases in the US was the northwest region. The University of Washington closed its campus as early as March 9, 2020, whereas a Midwest school, Northwestern University, did not shut down until as late as March 30, 2020.

accepted that the NBER and IZA affiliates are the leading researchers in economics, with IZA researchers being slightly less prestigious.[28] On the positive side, our research metric is a "real-time" measure because the NBER WPs and IZA DPs do not go through a refereeing process which typically takes a long time (Berk, Harvey, Hirshleifer 2017; Card and DellaVigna 2013; Ellison 2001). However, affiliates can post their WPs and DPs on their website immediately after they complete them. Specifically, a WP can be featured on Monday of week t if submitted to the NBER by the Thursday of week t-1. While a DP might be posted even sooner as they are not locked into a weekly scheduled release. Despite not undergoing review, the NBER WPs typically are of high quality. For example, according to Lusher, Yang, and Carrell's (2021) statistics, over 70% of the NBER WPs released over 2004-2017 were ultimately published in a peer-reviewed journal.

Using a researcher-level weekly panel data set, which spans the Winter and Spring of 2020, we show that the switch to emergency remote instruction in Spring 2020 *temporarily* increased the research production of NBER researchers. The effect lasted for only two weeks. Specifically, in the first week of the switch to remote instruction and the week immediately after, faculty posted 0.027 and 0.020 more WPs to the NBER website, respectively, relative to the week just before the switch to remote instruction (mean is 0.020). This increase of one additional paper per week appears to suggest that remote instruction is beneficial for research production. However, it is implausible for a researcher to complete a paper from scratch in such a short amount of time. Thus, the increase in research production is likely indicative of another mechanism. For example, at the time of the switch to remote teaching, the faculty may be completing their works-in-progress or putting the final additions on almost completed working papers.[29] These results are reaffirmed by results for IZA-affiliated researchers. IZA-affiliates see no significant reduction in their productivity following the switch to remote instruction. While these results are statistically significant, they are positive following the switch.

Importantly, there are significant differences in the research productivity of men and women NBER-affiliated researchers. Similar to the full sample, men see benefits in the first week

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[28] Becoming an NBER affiliate requires nomination by those who are already members of the NBER. We could not find any written rules about becoming an NBER researcher. However, it is commonly accepted that NBER researchers are well reviewed and competitive scholars in their fields (https://www.nber.org/about-nber).

[29] An anecdote about Sir Isaac Newton is along those lines. Specifically, as explained in a New Yorker article, Newton was extremely productive in his isolation during the bubonic plague in 1665-1667, bringing about new insights to mathematics and physics. One of the contributing factors to his success is said to be the years of hard work he had put in these ideas before he started his isolation.

of switching to remote instruction, but these effects again become indifferent from zero in the weeks following. Conversely, women produce 0.038 more papers in the initial week of moving online and continue to have statistically significant and positive effects from the switch to remote instruction. Men and women who are IZA-affiliates again have similarities to those in the NBER. Men produce significantly more papers in the week of beginning remote instruction and in the week following, becoming statistically insignificant in the subsequent week. Female IZA-affiliated researchers never have any statistically significant effects during the first weeks of remote instruction, but in the later weeks of remote instruction see an increase in the number of papers produced.

Due to the differential timing of the switch to remote instruction and the pre-determined start and end dates of the Spring semester in their institutions, researchers taught their classes online in varying amounts of time in Spring 2020. As an additional test of whether the switch to remote teaching increased the research productivity of NBER- and IZA-affiliates permanently or temporarily, we estimated the impact of the *duration* of remote instruction in the Spring 2020 semester. If remote instruction increases research production only temporarily, then its duration in the semester will not impact the number of working papers posted. This is because all universities had to switch to remote instruction in the Spring, although some operated remotely longer than others.

Our analysis shows that an additional week of remote instruction did not significantly increase or decrease the number of working papers a researcher posts on the NBER website, corroborating our earlier result: the switch of their universities to remote operations increased the research production of faculty members only temporarily. Men and women both see a non-effect as well. We additionally verified this finding with an instrumental variable's strategy. Specifically, we use the weeks between the start of the Spring 2020 semester and the first occurrence of a COVID-19 case in a university community as an instrument for the duration of remote instruction. We find that schools whose members were known to be infected by COVID-19 later in the Spring operated remotely for a shorter period than their counterparts where a member of the university was infected earlier. Despite a strong first-stage relationship, the 2SLS results show that the duration of remote instruction has a null impact on the NBER WPs.

Replicating our analysis for IZA authors using country-level shutdowns we find results that align with those from our NBER analysis. IZA researchers whose schools were in countries with longer shutdowns saw no relative increase in the number of IZA discussion papers posted. Weeks teaching remotely also had no discernable difference in the number of papers that men and women produce. In order to replicate our instrumental variables approach we create a proxy for the first case within a country using cases per million. As most universities in the United States switched to remote instruction around the week of March 16th, when COVID-19 cases were 10 cases per million, we proxy for the first case in a community by when a country's cases were first about 10 per million. We find a strong first stage, with results affirming those for NBER-affiliates.

Our results show a stark difference from much of the literature on how the pandemic impacted women compared to men. While much of the literature shows that women are worse off, we find that women, like men, have no change in their productivity following the start of the pandemic. In some cases, they appear to benefit more than men, with the initial switch to remote instruction having positive effects in later weeks. We caution against extrapolating our results to general outcomes for two reasons. The first is that our sample is relatively older, with about 20 years of experience, decreasing the likelihood of having small children in the home, the main contributor to shifting away time from an academic's research. Secondly, NBER and IZA researchers might be considered a higher caliber of researchers than the majority of academics. Their teaching loads are often smaller, with research production being their primary focus. They also often have teaching assistants that grade, teach, and sometimes hold office hours for their students.

A large literature exists on research related to women in the economics profession. This paper provides a new contribution to this literature by using a casual method to examine differences during the pandemic. Our findings stand in stark contrast to those in the literature. Work by Amano-Patino et al. (2020) using similar data, examining the number of working papers women and men produce before and after the start of the COVID-19 pandemic find that women have lower production levels during the pandemic. Their paper uses a hard cut off for before and after the pandemic, regardless of it affecting certain areas of the country at different times. This follows a number of other articles, that have found women in academia overall have had more negative outcomes than males (Hechtman et al. 2018; Huang et al. 2020).

Our work also contributes to the literature on productivity of work from home. Telework or work-from-home practices have been increasingly allowed by firms in recent decades (Frazis 2020). Besides documenting the impact of the novel COVID-19 pandemic on research production, our paper contributes to a line of study that examines the productivity effects of telework or work-from-home policies on university professors. A recent article by Bloom et al. (2020) finds that working from home increased productivity for call center workers. These productivity gains are due to taking fewer breaks and taking the calls more efficiently. Other work has examined how worker productivity under teleworking is impacted by the type of tasks conducted. For example, Dutcher (2012) shows that more creative tasks lead to more productive teleworking employees. In contrast, more dull tasks tend to have negative consequences. Bailey and Kurland (2002) provide a more thorough review of telework studies across academic fields, with results generally showing workers benefit from telework.

In the rest of the paper, in Section 2, we discuss issues related to our data. Section 3 presents the empirical analyses and results for the effect of the switch to remote instruction. Sections 4 and 5 show our findings for the length of remote instruction as well as an instrumental variables approach, respectively. In Section 6, we provide a summary and discussion of our findings.

3.2 Data Sources

The primary source of our data set is the working paper archives of the National Bureau of Economic Research (NBER).[30] NBER announces the titles and authors of the working papers (WPs) posted each week on its website. We identified whether a paper is COVID-19-related using the information on another NBER web page, where if a working paper is related to the COVID-19 pandemic is tracked.[31] Our data set spans the period between January 2020 and July 2020.[32] During this period, NBER researchers in our estimation sample have produced a total of 891 papers, 189 of which are COVID-19-related.

We found the institutions of each NBER-affiliated scholar from their profiles on the NBER website. We excluded from our analysis the institutions out of the US (for example, the University of Toronto in Canada and the University of Oxford in the UK) and those that are not universities or colleges (such as the Federal Reserve institutions and the RAND Corporation). This exclusion

[30] https://www.nber.org/papers
[31] https://www.nber.org/nber-studies-related-covid-19-pandemic-topic-area
[32] We stopped in late July 2020, because most schools' fall semesters start in early August. The policy of each school allowed a spectrum of teaching modalities in Fall 2020. These modalities often did not apply to all faculty members. Thus, it is hard to identify different treatments in this semester.

left us with a total of 1,517 NBER researchers from 127 US universities. The locations of these schools are depicted in Figure 12. Schools are dispersed throughout the United States, concentrating on the east and west coasts and other population centers.

From the researchers' CVs and profiles on their university webpages, we obtained information on their sex (subjectively from their photographs) and the year in which they received their PhDs. Also, using the US Census's Frequently Occurring Surnames Database, we imputed the race of each researcher.[33]

We further augmented our data with university characteristics. For example, from each university's website (the registrar, academic calendar, or the universities' news pages) or the local newspapers, we manually collected the dates on which the schools shut down their campuses and started remote instruction, as well as the start and end dates of their Spring Break and the Spring semester. We acquired university characteristics, such as the average SAT scores of the incoming freshman class, the average cost of attendance, and average monthly faculty salary from the Department of Education database, College Scorecard, for the 2019-2020 academic year.[34] We also collected the number of COVID-19 cases in the universities' counties from The New York Times COVID-19 database.[35] Lastly, we include county characteristics complied by the Economic Research Service for the US Department of Agriculture.[36]

In Table 14, we present the descriptions and summary statistics of the variables we use in our analysis. Between the beginning of the Spring semester in January 2020 and the end of July 2020, an NBER researcher authored or co-authored 0.77 working papers 0.18 of these were COVID-19 related. The universities delivered their classes remotely for about 8.2 weeks. The overwhelming majority of the researchers in our sample are male and white, and they received their doctoral degrees more than two decades ago. The schools for which they work are highly selective. For example, the average SAT score of the incoming freshman class is 1,450, and their admittance rate is 20%. The universities are relatively large (15,019 students). The average cost of enrollment totals $58,158 a year. The faculty in these institutions earn an average monthly (pre-

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[33] We merge the last names of our researchers with the U.S. Census Frequently Occurring Surnames from the 2010 Census (https://www.census.gov/topics/population/genealogy/data/2010_surnames.html). This data set compiled surnames that occurred 100 or more times in the 2010 U.S. Census. The Census then breaks out what percent of respondents of that surname were of a particular race. We matched the researchers with races that had the same last name the most.

[34] https://collegescorecard.ed.gov/

[35] https://github.com/nytimes/COVID-19-data

[36] https://www.ers.usda.gov/data-products/county-level-data-sets/download-data.aspx

tax) salary of $16,308, and 81% of them are full-time professors. Most researchers work at schools that are ranked within the top 50 schools (according to the USA Today rankings) and 28% at Ivy League universities. In the counties where the universities are located, residents are primarily white. The economic conditions in these counties are generally better than the US average (3.33% unemployment rate and a median household income of $82,788 as of 2019).

The process of collecting dates for the IZA discussion papers differ from the NBER working papers as the exact dates when the papers are posted on the IZA discussion paper website are unavailable.[37] In contrast to the NBER, which posts papers to its website every Monday and indicates which Monday they are posted, to our knowledge, IZA discussion papers are posted to its website at various times throughout the week. On the IZA papers, only the month and the year that they were posted are listed. To obtain the date on which an IZA paper was posted, we downloaded each paper between January and August 2020. From the paper's properties (that can be viewed through Acrobat), we obtained the date the pdf file was created and modified (See Appendix Figure 1 for an example). The creation date is when the authors of a paper either use Acrobat for Word or LaTex to create the pdf file. In our empirical analysis, we use the date that a paper is created as it gives a more accurate time as to when the paper is produced.[38]

Unlike the sample of NBER-affiliates, we include IZA-affiliated researchers from institutions outside of the United States while still excluding those who are not working in universities or colleges. After these restrictions our sample is left with a total of 1,289 researchers from 488 different schools. These schools are distributed across 54 different countries, but most are located in the United States. Of the 1,289 IZA-affiliated researchers, only 184 were also found in the NBER sample. Researcher characteristics of IZA affiliates, such as sex and the year in which they received their Ph.D. is acquired from their CV'S and pictures on their IZA homepage. Additionally, we presume race through IZA profile pictures.

Due to the sheer number of schools within the IZA sample, collecting school academic calendar dates and when the schools shifted from in-person instruction to remote instruction would

[37] https://www.iza.org/publications/dp

[38] We take the date that a paper is modified as the date the IZA cover page is applied, as papers that are in consecutive paper order are modified around the same date and time. Additionally, during March 2020 there is a large gap in the middle of the month in which working papers were not posted to the IZA discussion paper depository. There are no papers that are modified from March 2nd until March 16th at which point only two papers are modified. We attribute the lack of IZA working papers posted during this time to the COVID-19 pandemic, giving an inaccurate representation of the number of papers that are produced.

be an immensely time-consuming effort. For this reason, we operate as though all schools are in session from the beginning of 2020 and the week of July 27th, 2020. Additionally, to proxy for when the schools move to online teaching, we use dates provided by OxCGRT that indicate when a country's government recommended or forced higher education to stop in-person instruction.[39]

We collect school rank, number of full-time students, the percent of students who originate from a different country, and the student-to-faculty ratio from the Times Higher Education.[40] We also collect country-level unemployment rates, GDP per capita, and population from the World Bank.[41] The number of COVID-19 cases per million people in each country was obtained from Our World in Data.[42]

On average, IZA-affiliated researchers produce about 0.52 papers, of which 0.44 are not related to COVID-19. Much like our NBER sample, IZA researchers are predominately male and white, with about 21 years since they received their PhDs. These researchers produced 678 unique papers between January and July of 2020, of which 107 are related to COVID-19 by IZA's own definition.[43] The universities that they work at have about 25,768 students. A little over 20% of their students are international, and there is approximately one faculty member for every 20 students. Over 50% of the sample work in a university that is considered in the top 200 in the world according to the classification in Timer Higher Education in 2020. During the week of March 9th, 2020, when the World Health Organization declared COVID-19 a global pandemic, there were about 50 cases per million people on average in the countries where these universities are located. In 2020, the unemployment rate was 4.96%, and the GDP per capita was 53,171.55.

[39] Thomas Hale, Noam Angrist, Rafael Goldszmidt, Beatriz Kira, Anna Petherick, Toby Phillips, Samuel Webster, Emily Cameron-Blake, Laura Hallas, Saptarshi Majumdar, and Helen Tatlow. (2021). "A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker)." Nature Human Behaviour. https://www.bsg.ox.ac.uk/research/research-projects/covid-19-government-response-tracker
OxCGRT is a database on government responses to COVID-19. They collect data through various news articles, and government announcements.

[40] https://www.timeshighereducation.com/

[41] https://databank.worldbank.org/source/world-development-indicators

[42] https://ourworldindata.org/covid-cases

[43] https://covid-19.iza.org/

3.3 The Timing of the Switch to Remote Instruction Empirical Analysis

3.3.1. NBER-affiliated Researchers

Figure 11 depicts the cumulative share of schools in our sample (N=127) that switched to remote instruction by week in Spring 2020. The earliest switches were in the week that started on March 9th, 2020 (Stanford University and the University of Washington). The latest ones switched in the week of April 6th, 2020 (Yale University, Cornell University, and Northwestern University). We investigate whether the timing of the switches is correlated with school characteristics by running regressions as depicted below:

(1) $Y_s = \beta_1 EarlyRemote_s + \beta_2 LateRemote_s + u_s$

where $EarlyRemote_s$ and $LateRemote_s$ indicate whether the school s started remote instruction in Spring 2020 before and after the week of March 23rd, 2020, respectively. The comparison category is made up of the schools that switched to online instruction in the week of March 23rd. There are approximately 54 (43%) and 21 (17%) schools in the early- and late-remote groups, respectively.

The outcomes in equation (1), Y_s, are the school attributes. Specifically, we consider the admission rates, the average SAT score of the incoming freshman class, the number of undergraduates, the average cost of attendance, the average monthly faculty salary, and the proportion of full-time faculty. We also analyze the NBER researcher characteristics, such as the proportion of males and blacks, as well as the average number of years after obtaining a PhD. Other variables are the characteristics of the county where the school is located, such as the per capita COVID-19 cases that accumulated as of March 9th, median household income, the unemployment rate, and the share of black residents of the county.

Results obtained from equation (1) are depicted in Figures 13A, 13B, and 13C, where each mini graph within the panels presents the coefficients (the dots) and the 95% confidence intervals (horizontal lines) for $EarlyRemote_s$ and $LateRemote_s$.[44] The vertical red line marks zero. The outcomes in Figures 13A, 13B, and 13C are researcher, university, and county characteristics, respectively.

[44] We also present the coefficients in Appendix Table 1.

The estimates in these Figures 13A-13C indicate that the timing of the switch to remote instruction is not correlated with these characteristics. Specifically, the characteristics of the researchers and the schools that shifted to remote operations before and after March 23rd (early- and late-switchers) are no different from one another and their counterpart schools that switched on March 23rd. They are equally selective, similar in size, type, quality, and similarly expensive. The average monthly salaries, perhaps a measure of faculty productivity, in these universities are about the same as well as the share of full-time faculty. The sex and racial composition of the NBER researchers in the universities and their experience are approximately equal as well. The only difference between these schools is in the number of COVID-19 cases in the county that they are located. Not surprisingly, the colleges that shifted to online teaching earlier were located in the counties with higher known cases of COVID-19 infections as of early March, compared to universities that switched to remote instruction later. Later in the paper, we show that a school's decision to shut down its on-campus operations depends on the occurrence of COVID-19 cases in its community.

3.3.2 IZA-affiliated Researchers

Using the country-level decision to recommend or force universities and colleges to shut down, we demonstrate the cumulative number of school closings over the month of March in Figure 14 (N=54). The two outlier countries are China and Hong Kong, which shut down in-person instruction on the week of January 27th. We separate those that switched to online instruction early versus late using the March 16th date as the cut-off. Specifically, if a country recommended or mandated the shutdown of its universities before (after) the week of March 16, then a university from that country is classified as early (late) remote. Those that shifted to remote instruction during the week of March 16 constitute the third category. Using equation (1), we estimate differences between these schools across a number of researcher, school, and country characteristics.

Researcher level characteristics include whether a researcher is male, whether they are nonwhite, and the number of years of work experience. The university or college characteristics are the number of full-time students per faculty member, the percentage of students that are international, and whether the university ranks within the top 200 of all schools in the world. The country characteristics we consider include the number of COVID-19 cases per million during the week of March 9th, the unemployment rate, and the GDP per capita.

Coefficients obtained from equation 1 using the IZA sample are plotted in Figures 16A-16C. We find that countries that switch to remote instruction before or after March 16th are not largely statistically different from those that switched on the week of 16th. There are two exceptions. Countries that switch at an earlier date tend to have more researchers who are not white. On the other hand, schools in countries that switch after March 16th tend to have schools that are considered in the Top 200.

3.3.3 Working Paper Production in 2019 vs. 2020

Figure 17 presents the number of National Bureau of Economic Research working papers (NBER WPs) by month. The solid blue and red dashed lines represent the papers produced in the 2019-2020 and 2018-2019 academic years, respectively. The solid vertical red line marks March when in 2020, the COVID-19 pandemic first became a national threat, and universities started to shut down their campuses (see Figure 1). In the 2019-2020 academic year, the number of WPs increased beginning in March 2020 and peaked in the summer. The red dashed line shows that this is not the case in 2018-2019. In that academic year, the number of WPs did not increase dramatically after March. The comparison of the patterns in these academic years suggests that NBER researchers produced more WPs in Spring 2020 than Spring 2019, after March, when the universities switched to remote instruction in 2020.

Figure 18 shows the number of COVID-19 related WPs in 2020. Not surprisingly, COVID-19-related WPs started to increase after March 2020, when the pandemic became widespread around the globe. This is probably because of the increased demand for COVID-19 research. For example, in the Spring of 2020, there were a large number of unknowns about COVID-19. To motivate researchers to study COVID-19 related issues, the academic community prioritized COVID-19 research. Several journals announced calls for COVID-19 related papers, indicating that they would fast-track them and make special issues about COVID-19.[45]

[45] Examples of the call for COVID-19 related papers and special issues: Journal of Public Economics and American Journal of Health Economics.

In Figure 19, we compare the number of WPs that are not about COVID-19 in the academic year 2018-2019 (red-dashed line) to 2019-2020 (blue-solid line). This figure clearly shows the trends in WPs in these academic years are the same, except perhaps a temporary increase in March 2020. This finding suggests that researchers did not substitute away from their regular research agendas, i.e., non-COVID-19-related working papers.

Replicating this exercise with the IZA discussion papers, we find a similar trend, albeit somewhat smaller in the difference in counts of papers in the two academic years. In Figure 20, as we did in Figure 17, we show all papers during the 2019-2020 academic year compared to those during the 2018-2019 academic year. Before March, the number of papers produced each month is similar to the year before but in the following months (April – July), there were significantly more papers produced during the 2019-2020 academic year compared to the 2018-2019 academic year. A substantial portion of the difference can be attributed to COVID-19-related discussion papers. Figure 21 shows, like Figure 18, that COVID-19-related discussion papers start to appear during March and increase in the following months. When we factor out the production of COVID-19-related discussion papers as in Figure 22, there is still a small but persistent difference in the number of papers produced following March.

3.3.4 Impact of the Switch to Remote Instruction on Research Production – NBER Researchers

In this section, we formally investigate the impact of the emergency switch to remote instruction on research production by analyzing the WPs posted around the time when a researcher's school began delivering classes remotely. Using an event study analysis approach, we estimate the following regression:

$$(2) \qquad Working\ Papers_{ist} = \beta Time\ Relative\ to\ Remote\ Start_{st} + \gamma X_{st} + \theta_i + \tau_t + \varepsilon_{ist},$$

where the outcome variable, $Working\ Papers_{ist}$, is the number of WPs posted on the NBER website by researcher i from school s in week t. The variables of interest are in vector $Time\ Relative\ to\ Remote\ Start_{st}$, which includes a set of weekly dummy variables normalized around when a school starts remote instruction. Precisely, we control for separate dummies for the first through fifth weeks and a dummy for the sixth week or after the adoption of remote education.

We include similar relative time dummies for the weeks prior.[46] We omit the week immediately preceding the treatment (the first full week of remote instruction) as our comparison category.

The vector X_{st} in equation (2) is a set of control variables for important university dates, such as indicators for the week of Spring Break and summer break, another one for the week of Spring Break extension.[47] In some schools, there is a gap between the dates of the campus's shutdown for in-person operations and the start of remote delivery of classes.[48] In the regressions, we control for whether the campus was shut down for in-person operations. Vector X_{st} also contains the number of COVID-19 cases per 100,000 people in the county where the university is located and a dummy for whether a researcher has posted a working paper on the NBER website in the last three months. θ_i stands for the individual-level fixed effects, isolating the time-invariant differences in researchers. τ_t is a weekly time dummy. Standard errors are clustered at the school level.

The complete set of estimates from equation (2) are reported in Appendix Table 3. We plot the estimates of the variables of interest, the relative time dummies, in Figure 23. Our outcome variable, the number of working papers, can be found on the vertical axis. The horizontal axis depicts the week relative to the one when remote instruction began. Our point estimates are represented by the dots, with vertical lines showing the 95% confidence intervals. These point estimates compare the impact in each week relative to the week immediately before starting remote instruction.

Figure 23 shows that the coefficients of the weekly time dummies before the start of remote instruction are primarily not statistically significant and are close to zero. This finding demonstrates that there was no anticipation of the switch to remote instruction that impacted the WPs on the NBER site. This evidence ascertains that the "parallel trends" assumption is satisfied. In addition, the coefficients for the week starting remote instruction and, in the week, directly following are positive and significant. That is, in the first two weeks of beginning remote

[46] For example, the week immediately following a school's move to remote instruction is denoted by the dummy $One\ Week\ After_{st}$. In that week, this dummy is equal to one. The $Two\ Weeks\ After_{st}$ dummy is equal to one in the second week following the start of remote instruction, and so on. Similarly, for the time before moving to remote instruction, we include a set of before dummies. For example, the $Two\ Weeks\ Before_{st}$ indicator takes the value of one, two weeks before the move to remote instruction.

[47] Some schools, such as the Stony Brook University, extended their spring breaks by one week.

[48] Examples of such schools include Louisiana State University and the University of Maryland.

instruction, researchers publish more WPs than they are before teaching remotely. After the first two weeks, the coefficients are virtually zero.

Does the increase in WPs in the first two weeks of the switch imply a higher research production? We believe not. Two weeks is an implausibly short time to complete a working paper from scratch. We instead interpret this finding as a temporary increase in paper production. For example, researchers may be using the initial periods of remote instruction to finish their almost completed WPs. In the weeks after, researchers do not publish a statistically greater number of WPs from our comparison period in the following weeks.

Figures 17, 18, and 19 indicate differences between the production of WPs that are related to COVID-19 versus those that are not. To better understand the impact of the shift to remote instruction on COVID-19 and non-COVID-19 WPs, we separately estimate equation (2) using the number of COVID-19- and non-COVID-19-related WPs as the outcome variables. The results, which are graphically presented in Figures 24A and 24B, show that in the week of a school's switch to remote instruction, the number of both COVID-19- and non-COVID-19-related papers increases.[49] However, in the following weeks, our coefficients become insignificant and close to zero for both types of papers.

To examine the differential effect the switch to remote instruction might have had for men and women, we estimate equation (2) in these samples separately. In Figures 25A and 25B, the coefficients for men and women for all working papers can be found, respectively. Men produce approximately 0.024 more WPs during the initial week of their school moving online. In the weeks following, the coefficients become close to zero, and they are not statistically significant. Conversely, women produce 0.038 more papers in the initial week of moving online and 0.041 more in the following week. Unlike men, women researchers' production of working papers in weeks 3 and 4 after switching are statistically significant and positive. Suggesting that while men might not see a benefit to remote instruction, women appear to find some value from being able to work from home.

We repeat this analysis for COVID-19-related and non-COVID-19-related WPs. Figures 26A and Figure 27A show that men produce 0.005 more COVID-19-related WPs and 0.018 non-COVID-19-related WPs in the initial week of switching to remote instruction, respectively. For both paper types, in the weeks following the switch to remote instruction, there was no statistically

[49] We present the coefficient estimates in Appendix Table 2.

significant increase in the production of papers. Women, on the other hand, see no increase in the amount of COVID-19-related working papers due to the switch to remote instruction. They produce 0.037 more non-COVID-19-related working papers in the initial week of switching and 0.040 in the week directly following. The third week after the switch, women also have a 0.040 increase in the number of papers they produce.

3.3.5 Impact of the Switch to Remote Instruction on Research Production - IZA Researchers

There are several differences between the researchers in the NBER and IZA. Most importantly, those who are a part of the IZA and the working papers they produce are focused on labor markets and the world of work, whereas researchers that are a member of NBER conduct research in all fields of economics. Secondly, one could argue becoming an NBER affiliate is harder because the NBER's process is more selective. Nevertheless, they are considered leading experts in their field and go through a selection process of their own to join the IZA, making them a good comparison group. To supplement our previous results, we replicate our analysis using the sample of IZA-affiliated researchers.

Given the amount of IZA fellows that come from a diverse set of schools and countries, we make use of country-level data rather than the school-level information. We use a comparable estimation strategy to that of equation (2) rather than using the variation from schools switching to remote instruction we use country-level differences. We estimate the following equation:

$$(3)\ Discussion\ Papers_{ict} = \beta Time\ Relative\ to\ Remote\ Start_{ct} + \gamma X_{ct} + \theta_i + \tau_t + \varepsilon_{ict}$$

Our outcome variable is the number of discussion papers that are created during that week, not when they are posted to the IZA discussion paper directory. The dependent variable of interest $Time\ Relative\ to\ Remote\ Start_{ct}$, is a set of weekly dummy variables the same as equation (2). One key difference in the dependent variables in equations (2) and (3) is that in equation (3), the time relative to the remote instruction period is computed using the first week that a country requires or recommends universities and colleges to close.

Within X_{ct}, we control for the number of COVID-19 cases per million within a country. As the severity of COVID-19 could impact the quality of life of the researchers or the strictness of lockdowns within a country, it can also be correlated with how much research they are able to produce. In addition, like equation (2), we control for if an IZA-affiliated researcher created a discussion paper within the last three months.

We find results that are consistent with those we found in Figure 23 for our NBER-affiliated sample. Coefficients, plotted in Figure 28, demonstrate that IZA-affiliated authors are not negatively impacted by the switch to remote instruction. In the weeks that follow the switch, the coefficients show that remote instruction had a positive but statistically insignificant effect on the number of discussion papers created. Using IZA's own definition of COVID-19-related papers, we can distinguish and create separate outcomes for COVID-19-related and non-COVID-19-related papers. Re-estimating equation (3) with COVID-19-related discussion papers as the dependent variable, Figure 29A shows that coefficients are negative and statistically significant, but they are small and nearly zero. Using non-COVID-19-related papers as the outcome variable, we find that the effect of switching to remote instruction has a positive but statistically insignificant effect (Figure 29B).

We again estimate our event studies with subsamples of both men and women. Interestingly, we find similar patterns to those of the men and women members of the NBER. Coefficients for men can be found in Figure 30A and for women in Figure 30B. Like the male researchers in the NBER, IZA male researchers have positive coefficients in the initial week of switching to remote instruction as well as the subsequent week. Unlike the NBER sample, men in the IZA sample never have negative coefficients. Although none of the weeks are statistically different from zero. Women IZA-affiliated researchers differ significantly in the start of remote instruction and the week following when compared to their NBER peers. While women in the NBER see positive impacts, women of the IZA have a negative, statistically insignificant effect on the number of working papers published. In the weeks following, they are similar in that they have a positive effect on the number of papers they produce, yet somewhat smaller for IZA affiliates.[50] These results reaffirm those found for our NBER sample, women benefit from the ability to work remotely, while men have consistent production from before the switch.

For both men and women, we estimate how an additional week of remote instruction impacts the number of COVID-19-related and non-COVID-19-related discussion papers.

[50] Using a pooled sample of NBER and IZA affiliates we find comparable results. For example, the effect of remote instruction for both men and women are insignificant and close to zero in the first weeks, but the coefficient for 4 weeks after has a large positive effect for women.

Coefficients for COVID-19-related papers for men can be found in Figure 31A and are nearly zero. In Figure 32A, we plot estimates for non-COVID-19-related papers for our sample of men. Our event study analysis shows that in the initial week of switching to remote instruction and in those following, the effect is positive. Coefficients for the sample of women can be found in Figure 31B for COVID-19-related papers and Figure 32B for non-COVID-19-related papers. For the outcome of COVID-19-related papers, the shift to remote instruction has a small, nearly zero effect on the number of working papers produced. In comparison, those that are non-COVID-19-related are positively affected and growing in magnitude in later weeks.

3.4 The Length of Remote Instruction Empirical Analysis

3.4.1 Impact of the Duration of Remote Instruction on Research Production – NBER Researchers

Results of the previous section show that the switch to remote instruction caused only a short-living increase in the number of working papers. In this section, we conduct an indirect test for whether the rise in research production due to the switch to remote instruction is indeed temporary. Specifically, we utilize the idea that the length of remote instruction in the semester in a school should not impact the number of working papers posted by the researchers in that school if the effect is transitory. This is because *all* universities in our sample switched to online teaching at some point in Spring 2020 (See Figure 11), but some schools operated under remote instruction for a shorter period than others. The distribution of the number of weeks of remote instruction is presented in Figure 33. Professors in some schools, such as the University of Pittsburgh and the University of Alabama, delivered their courses remotely for as little as four weeks. In other schools, the remote instruction period was as long as 13 weeks (for example, the University of California – Irvine and Dartmouth University).

Many factors generate the variation in the number of weeks universities delivered classes remotely in Spring 2020. These factors include the timing of the switch to remote learning and the length of the spring semester, which is a function of the start and the end dates of the semester. The beginning and the end dates of semesters were determined before the academic year began. We reviewed the news from the universities' websites regarding whether schools adjusted the length of their semesters and found that no school in our sample altered the end-of-semester dates due to COVID-19. As discussed above, some schools switched to remote instruction earlier than others. We show in Figure 13 and Appendix Table 1 that the timing of this decision is unrelated to school characteristics and the attributes of the researchers.

To estimate the impact of the duration of remote instruction weeks on the research output of the faculty, we run the equation below:

(4) $$Papers_{is} = \beta_1 Remote\ Instruction\ Weeks_s + \beta_2 X_s + \beta_3 R_i + \varepsilon_{is}$$

where $Papers_{is}$ is the number of WPs that the researcher *i* of the school *s* produced and posted on the NBER web page between the start of the Spring 2020 semester and the end of July 2020.[51] $Remote\ Instruction\ Weeks_s$ is a continuous variable that measures the duration of the remote instruction at the university. The vector X_s contains university characteristics that were considered in the balancing tests (Figure 13). We also control whether a school operates on a quarter system and the number of weeks in their semester. Thus, the coefficient of $Remote\ Instruction\ Weeks_s$ shows the impact of one additional week of remote instruction holding constant the total duration of the semester. The vector R_i represents characteristics of the researcher, and it comprises years of experience (years after obtaining their Ph.D.), their sex, and race. Standard errors are clustered at the university level.

We present the estimates for the variable of interest, $Remote\ Instruction\ Weeks_s$, from equation (3) in Table 16 and the complete set of coefficients in Appendix Table 9. In Column (1) of Table 16, where the outcome is the total number of working papers produced in Spring 2020, the coefficient of $Remote\ Instruction\ Weeks_s$ is small and statistically insignificant. This finding suggests that researchers in universities that delivered their courses for a more extended period produced similar amounts of research than their counterparts in other schools with a shorter remote instruction period. The outcomes in Columns (2) and (3) are the numbers of COVID-19 and non-COVID-19-related papers, respectively. Same as the results in Column (1), coefficients show that the impact of the duration of the remote instruction is statistically indistinguishable from zero.

In Table 17A and 17B, we estimate equation (4) again but limit the estimation sample to men and women separately.[52] In columns (1) of each table, we present the impact of

[51] Note that some schools operate in a quarter system rather than a semester system. These schools are in a minority in our sample (17 out of 127). For these schools, we considered the second and third semesters as the spring semester.

[52] Complete set of coefficients can be found in Appendix Table 10 for men and 11 for women.

$Remote\ Instruction\ Weeks_s$ on the number of papers that each gender submits to the NBER during Spring 2020. We find that this estimate is statistically insignificant for both men and women, but for women, it is much larger than for men. Coefficients for the outcomes of COVID-19-related and non-COVID-19-related working papers are found in Columns (2) and (3), respectively. Similar to the results from the full sample of combined genders, the length that a university relies on remote instruction has a small and statistically insignificant effect on the number of COVID-19-related working papers published for both genders. Non-COVID-19-related papers estimates for men are consistent with those for the full sample. In contrast, shown in Column (3) of Table 16B, the number of weeks of remote instruction has a statistically significant positive impact on the amount of non-COVID-19-related WPs that are published by the female NBER researchers. An additional week of remote instruction would lead to approximately 0.09 more working papers, considerably small compared to our mean (0.59).

3.4.2 Impact of the Duration of Remote Instruction on Research Production – IZA Researchers

Using our IZA researcher sample, we estimate a regression similar to equation (3). Rather than using the school-level variation in dates, we use the country-level variation of closing to calculate the number of weeks that a school is remote. The value for $Remote\ Instruction\ Weeks_c$ is computed as the number of weeks between when a country requires or recommends school closings and the end of our sample period, July 27th, 2020. Furthermore, variables that are plotted in Figure 16A-16C are used as controls for the IZA-affiliated researchers.

Table 18 and Appendix Table 12 contain our estimates for the effect that $Remote\ Instruction\ Weeks_c$ had on the number of discussion papers a researcher creates after switching to online instruction, as well as the effect on COVID-19-related and non-COVID-19-related papers. Column (1) shows results that are consistent with those shown in Table 16 for NBER-affiliated researchers, the number of weeks of remote instruction had no impact on the number of total papers published. Both columns (2) and (3), where outcomes were COVID-19-related and non-COVID-19-related papers, match results for the NBER in that they are small and statistically insignificant. Table 18 corroborates the results we found for NBER-affiliated researchers.

We additionally tested if the responses to the shift to online instruction of the men and women in the IZA sample resemble those in the NBER sample. Column (1) of Panel A presents the effect for men and Panel B for women in Table 19.[53] Same as in Table 18, both Panels of Table 19 show that an additional week of remote teaching has no significant effect on the number of discussion papers that are created. Column (2) of both panels present results like those obtained from the NBER sample. That is, neither gender's discussion paper production changes due to the length that they instruct remotely. Unlike women in the NBER, female IZA researchers' non-COVID-19-related paper production does not increase. Consistent with their NBER counterparts, the duration of remote instruction has no effect on the paper production of men in the IZA.[54]

3.5 Instrumental Variables Estimation

3.5.1 NBER-affiliated Researchers

As an additional robustness check, we re-estimated equation (3) using a 2SLS strategy. Specifically, we instrumented $Remote\ Instruction\ Weeks_s$ with the variable, $Weeks\ Until\ First\ Case_s$, which measures the time between the start of the Spring semester and the first incidence of a COVID-19 infection in the school community. To construct this variable, we obtained information about whether and when an individual in the campus community (a student, a faculty, a staff member) was reported to be infected with COVID-19. The sources of this information are the universities' news pages and alert systems, the student-run newspapers of the universities, and the local media.[55] We checked whether our instrument, the number of weeks before a school had its first case, is correlated with any of our researcher, school, or county characteristics, by estimating regressions where university characteristics are regressed on

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[53] Appendix Table 13 and 14 present a full set of coefficients for men and women, respectively.

[54] The pooled sample of IZA and NBER affiliated researchers provide similar patterns with remote weeks not having an effect on the number of papers produced. For example, in the pooled sample, the coefficient on the number of work weeks for all papers for men is 0.017 and for women 0.05, both being statistically insignificant.

[55] Several universities announced the first case of COVID-19 in the community, but, of course, they did not name the person. For example, Brown University notified their students through their public COVID-19 alert system that their first case was seen in a community member. Tallahassee Democrat, a local newspaper, ran a story about Florida State University's first cases. It was reported to be students. We learned about Michigan State University's first infections from its president's message: "…two confirmed cases of novel coronavirus connected to their university." Similarly, Stanford University president announced, "We learned late today of the first positive COVID-19 test for an undergraduate student in our community."

$Weeks\ Until\ First\ Case_s$. Estimates obtained from this exercise are depicted in Figure 20 (and Appendix Table 4), which shows that our instrument is uncorrelated with most variables.

Our instrumental variables strategy is operationalized based on the idea that universities are more likely to take precautions, such as shutting down their campuses and switching to remote instruction, when it is documented that COVID-19 is spreading in their community. Perhaps out of panic or to reduce their liabilities, school administrators are more likely to shift their institutions to operate remotely when COVID-19 infections arise during their normal operations. Under this assumption, there should be a negative mechanical relationship between $Remote\ Instruction\ Weeks_s$ and $Weeks\ Until\ First\ Case_s$. This is because the later the first COVID-19 case is observed among the university community members, the fewer weeks are left in the semester for remote instruction. We test this idea by estimating the first-stage regression in equation (4):

(4) $$Remote\ Instruction\ Weeks_s = \gamma_1 Weeks\ Until\ First\ Case_s + \gamma_2 X_s + \gamma_3 R_i + v_{is}$$

The control variables are identical to those in the structural equation (3). Note that the number of observations entering this regression is 1,513, lower than the number of observations in Table 16 (1,517). This is because there were no announced cases of COVID-19 infections in some schools, and the instrument was undefined in such cases.[56]

The estimate obtained from equation (4) is given in Column (1) of Panel A of Table 22.[57] The coefficient of $Weeks\ Until\ First\ Case_s$ is -0.179. This finding indicates the later the first COVID-19 case of the university is observed, the fewer weeks classes are delivered remotely, other things such as the prevalence of COVID-19 spread within the county is held constant. In addition, the relationship between the instrument and the endogenous variable is strong. Specifically, the F statistic for the instrument's significance in the first stage is 43, well above the rule of thumb of 10 suggested by Staiger and Stock (1997).

In columns (2)-(4) of Panel A in Table 22, we show the reduced form estimates, where the WP outcome variables are regressed on the instrument and other control variables. In all regressions, the coefficient of $Weeks\ Until\ First\ Case_s$ is small and statistically insignificant.

[56] These schools are Chapman University, Case Western University, Spelman College, and University of Texas – Dallas

[57] We present the full set of estimates in Appendix Table 19.

Panel B of Table 22 presents the 2SLS estimates of $Remote\ Instruction\ Weeks_s$ in equation (3). These estimates are also statistically insignificant, corroborating our OLS results in Table 15.

Table 23 presents estimates from equation (4) for only men. Column (1) of Panel A presents the reduced form results. The coefficient for $Weeks\ Until\ First\ Case_s$ corresponds to the full sample result (-0.163), with an F statistic of 31. All other columns of panel A are reduced form estimates showing that $Weeks\ Until\ First\ Case_s$ has no distinguishable impact on the number of WPs produced. Panel B presents the 2SLS results for All WPs, COVID-19-related WPs, and non-COVID-19-related WPs. In any regression, there is no impact to speak of. Table 24 replicates this analysis for the female NBER researchers. Column (1) of Panel A shows that an additional week until the first case reduces the number of weeks of remote instruction by 0.23 weeks. The F statistic is smaller than the full sample and the sample of men (10.75). Columns (2) through (4) of Panel A present our reduced form estimates. Panel B contains the coefficients from our 2SLS estimates, while the coefficients are large, they are statistically insignificant. For example, the coefficient in Column (1) shows that an additional week of remote leads to 0.734 more working papers but is indistinguishable from zero.

3.5.2 IZA-affiliated Researchers

As we did with NBER-affiliated researchers, we estimate our OLS results using a 2SLS approach. The instrument, $Weeks\ Until\ First\ Case_c$, differs from the NBER sample in a significant way. Because we did not retrieve school level data, we lack information as to when schools had their first case, we therefore create a proxy using data on country-level COVID-19 cases per million. In Figure 11 we show that most schools in our NBER sample switch in the week of March 16^{th}, within this week there are about 10 cases per million. For this reason we chose this as a threshold to proxy for when a school would have its first case. For example, in Morocco during the week of March 30^{th} there are 14 cases per million people, we consider all weeks leading up to March 30^{th} as weeks that a school within this country did not have any COVID-19 cases in their community. Therefore, weeks until first case for IZA schools is all weeks leading up to the first week the respective country has 10 or more cases per million.

The coefficients for the effect $Weeks\ Until\ First\ Case_c$ within a country can be found in Column (1) of Panel A of Table 23. Analogous to the sample of NBER-affiliated researchers, an additional week until the first cases decrease the number of weeks of remote instruction by 0.311, with an F statistic of 27. Columns (2) – (4) show the reduced form, ensuring that $Weeks\ Until\ First\ Case_c$ does not have any impact on our outcome variables. In Panel B, our instrumented $Remote\ Instruction\ Weeks_c$ has no effect on our outcome variables. Demonstrating that our results using the IZA-affiliated sample support those found in Table 20.[58]

We further place IZA-affiliated results for men in Table 24 and women in Table 25. Column (1) of both tables' present estimates for the first stage, for men the coefficient on weeks until the first case is -0.282, whereas for women it is -0.374. The F statistic is 14 and 16 for men and women, respectively. The other columns of Panel A show for both genders the amount of time before the first case has no statistically significant effect on the number of papers produced. Additionally, Panel B of both Tables shows the same result, that an additional week of remote instruction does not change the number of discussion papers that are produced.[59]

3.6 Summary and Discussion

Although the impact of universities' emergency switch to remote instruction in Spring 2020 on students' learning outcomes is well documented, little is known about its effect on research production. In this paper, we fill in the gaps using National Bureau of Economic Research Working Papers (NBER WPs) and the Institute of Labor Economics Discussion Papers (IZA DPs) data that span the period between January and July 2020. Using the plausibly exogenous variation in the timing of universities' switch to remote operations, we show that the research production of the NBER affiliated professors in the US higher institutions did not decrease. On the contrary, the shift to remote operations caused a temporary increase in the number of completed WPs in the week of and one week after a school's switch to remote instruction. This is likely because researchers put the finishing touches to their almost completed papers when their schools move to remote education, perhaps due to pessimistically predicting the worsening of the COVID-19 situation in the future. Furthermore, when examining differences between men and women, we find no large

[58]A full set of estimates can be found in Appendix Table 20.
[59] Results for the pooled sample of NBER and IZA researchers is similar with an F-statistic larger than the threshold of 10 for both sexes. Additionally, the instrumented remote instruction variable is statistically insignificant coefficient for both sexes. When the outcome is for all papers, an additional week of remote instruction reduces the number of papers men produce by -0.214 and for women increase the number produced by 0.035.

differences. Conflicting with some of the literature that has suggested women in economics have been made worse off by the pandemic. All results are substantiated using country level closures for IZA researchers.

If the shift to remote instruction did not have any permanent effect on research production, then the duration of remote instruction in the Spring 2020 semester should not affect the number of NBER WPs. This is because all universities in the US have switched to remote teaching in that semester, although some were exposed to it longer than others. We, indeed, show that the duration of remote instruction does not affect NBER WP production. This finding is also corroborated by our 2SLS estimates that use the occurrence of the first COVID-19 case in the university community as the instrument for the duration of remote instruction.

Note that our findings show that the research productivity of faculty did not decrease, *even during the COVID-19 pandemic*. To the extent that our results apply to non-pandemic periods, they imply that working-from-home could benefit research production. This is because, in addition to forcing professors to work from home, the COVID-19 pandemic caused reductions in research time. For example, professors were forced to adapt to online teaching suddenly, and those with young children had to allocate more time to child-rearing activities. Absent such adverse effects, working from home during non-pandemic periods may increase scientific research production.

Another important implication of our results is that NBER- and IZA-affiliated men and women did not have significantly different outcomes. Opposing some conclusions in the literature, we find that women had some positive effects due to the switch to remote instruction. This is an important finding when putting into context how individuals benefit from the flexibility of work from home. If women are more predominately the homemakers or the primary child caretaker, they may have found the flexibility of remote work more advantageous for balancing work and homelife.

In our concluding remarks, we highlight that there are caveats to these interpretations. For example, even though the pandemic did not affect the research production, it might have negatively impacted publications. For instance, if the pandemic increased the time that journal editors and reviewers take to evaluate the merits of papers, then it would still adversely influence a professor's publication record. In addition, during the pandemic, several journals have announced that they prioritize COVID-19 related research. Thus, the publication of research that is unrelated to COVID-19 might have been delayed. If researchers could not quickly adjust their research toward the study of the pandemic, their publication records could suffer, even though they could continue to produce the same amount of research. An additional limitation of our paper is its narrow focus on economics research conducted by the NBER- and IZA-affiliated researchers. It is commonly accepted that NBER researchers are of "higher quality" than the average. For example, Lusher, Yang, and Carrell (2021) show that more than two-thirds of all NBER WPs produced between 2004 and 2017 were published, and they were commonly placed in high-ranking journals. In addition, the average professor in a US higher education institution may not be able to command the resources that are available to NBER or IZA researchers. Our comparison of the universities that include at least one NBER researcher to those with none appears to support this view. For example, NBER schools are more selective, larger, and more costly to attend compared to others.[60] These findings imply that our results may not be generalizable to all faculty members in the universities and colleges.

[60] In a (non-)NBER school, the average SAT score of the undergraduate students is (1,132) (1,350), the number of students is (3,593) 17,096, and the cost of attendance is ($35,591) $45,126.

Table 14: Descriptions and Summary Statistics for NBER Sample

Variable	Description	Mean	Std. Dev.
Outcome Variables			
Working Papers (WPs)	The number of WPs the researcher authored or co-authored.	0.77	1.16
COVID-19-related WPs	The number of COVID-19-related WPs the researcher authored or co-authored.	0.18	0.58
Non-COVID-19-related WPs	The number of WPs that are not related to COVID-19 the researcher authored or co-authored.	0.59	0.89
Treatment Variable			
Weeks of Remote Instruction	The number of weeks a school is in remote instruction.	8.19	2.42
Researcher Characteristics			
Male	=1 if a researcher is male.	0.77	0.42
Experience	The number of years after a researcher receives their Ph.D.	21.67	12.78
Black	=1 if a researcher is black.	0.01	0.11
University Characteristics			
Admission Rate	The ratio of the number of students admitted to the number of applications at the researcher's university.	0.20	0.20
SAT	The average SAT score of admitted students at the researcher's university.	1449.78	90.52
Enrollment	The number of undergraduate students enrolled in the researcher's university.	15018.99	11195.12
Cost of Attendance	The average annual cost of attendance to the researcher's university.	$58158.89	$19334.35
Faculty Salary	The average faculty salary per month at the researcher's university.	$16308.25	$3151.27
% Full-Time Faculty	The share of faculty that are full-time at the university.	0.81	.14
Public School	=1 if the researcher's university is a public school.	0.31	0.46
Ivy League School	=1 if the researcher's university is an Ivy League school.	0.28	0.45
Top 50 School	=1 if the researcher's university is ranked in the top 50 from USA Today.	0.86	0.35

Table 1 Continued			
Variable	Description	Mean	Std. Dev.
County Characteristics			
COVID-19 per capita	The number of COVID-19 cases per 100,000 residents of the county where the university is located.	0.06	0.12
Unemployment Rate	The 2019 unemployment rate in county where the researcher's university is located.	3.33	.85
Household Income	The median household income in 2019 in the county where the researcher's university is located.	$82788.59	21482.3
% Black (County)	The percent of a county that is black.	0.16	0.13

Note: The unit of observation is a researcher. There are 1,517 observations.

Table 15: Descriptions and Summary Statistics for IZA Sample

Variable	Description	Mean	Std. Dev.
Outcome Variables			
Working Papers (WPs)	The number of WPs the researcher authored or co-authored.	0.52	0.94
COVID-19-related WPs	The number of COVID-19-related WPs the researcher authored or co-authored.	0.08	0.39
Non-COVID-19-related WPs	The number of WPs that are not related to COVID-19 the researcher authored or co-authored.	0.44	0.81
Treatment Variable			
Weeks of Remote Instruction	The number of weeks a school is in remote instruction.	20.64	1.62
Researcher Characteristics			
Male	=1 if a researcher is male.	0.72	0.45
Experience	The number of years after a researcher receives their Ph.D.	21.37	11.82
Nonwhite	=1 if a researcher is not white.	0.11	0.32
University Characteristics			
Enrollment	The number of full-time students enrolled in the researcher's university.	25,768.58	12,546.23
Students Per Teacher	The ratio of full-time students to the number of staff.	19.58	12.49
% International	The percent of students at a researcher's university that originate from a different country than their school.	0.20	0.12
Top 200 School	=1 if the school is within the top 200 of schools, internationally.	0.51	0.50
Country Characteristics			
COVID-19 per capita	The number of COVID-19 cases per 100,000 residents of the county where the university is located.	49.84	73.46
Unemployment Rate	The 2019 unemployment rate in country where the researcher's university is located.	4.96	2.94
GDP Per Capita	The median household income in 2019 in the county where the researcher's university is located.	53,171.55	12,658.35
Population	The population of the country in which the university or college of the researcher is located per 100,000.	1161.286	3182.058

Note: The unit of observation is a researcher. There are 1,289 observations.

Table 16: The Effect of Number of Weeks Remote on the Number of NBER Working Papers

	(1)	(2)	(3)
	All Papers	COVID-19 Papers	Non-COVID-19 Papers
Remote Instruction Weeks	-0.001	-0.024	0.023
	(0.041)	(0.024)	(0.025)
Controls	Yes	Yes	Yes
N	1,517	1,517	1,517

Note: The unit of observation is a faculty member who is affiliated with the NBER. Column (1) uses the outcome of total number of working papers a faculty member publishes during Spring 2020. Column (2) is the coefficient for when the outcome is the number of papers that the NBER classifies as being related to COVID-19 and is published during Spring 2020. Column (3) uses the outcome for number of papers that are not related to COVID-19 published during Spring 2020. Standard errors clustered at the school level. * p<0.1 ** p<0.05 *** p<0.01. Each regression uses a full set of controls found in Figure 13, with a full set of estimates found in the appendix.

Table 17: The Effect of Number of Weeks Remote on the Number of NBER Working Papers by Gender

Panel A: Men

	(1)	(2)	(3)
	All Papers	COVID-19 Papers	Non-COVID-19 Papers
Remote Instruction Weeks	-0.021	-0.028	0.008
	(0.043)	(0.023)	(0.028)
Controls	Yes	Yes	Yes
N	1,170	1,170	1,170

Note: The unit of observation is a male faculty member who is affiliated with the NBER. Column (1) uses the outcome of total number of working papers a male faculty member who is affiliated with the NBER publishes during Spring 2020. Column (2) is the coefficient for when the outcome is the number of papers that the NBER classifies as being related to COVID-19 and is published during Spring 2020. Column (3) uses the outcome for number of papers that are not related to COVID-19 published during Spring 2020. Standard errors clustered at the school level. * p<0.1 ** p<0.05 *** p<0.01. Each regression uses a full set of controls found in Figure 13, with a full set of estimates found in the appendix.

Panel A: Women

	(1)	(2)	(3)
	All Papers	COVID-19 Papers	Non-COVID-19 Papers
Remote Instruction Weeks	0.089	0.000	0.089**
	(0.063)	(0.037)	(0.041)
Controls	Yes	Yes	Yes
N	347	347	347

Note: The unit of observation is a male faculty member who is affiliated with the NBER. Column (1) uses the outcome of total number of working papers a female faculty member publishes during Spring 2020. Column (2) is the coefficient for when the outcome is the number of papers that the NBER classifies as being related to COVID-19 and is published during Spring 2020. Column (3) uses the outcome for number of papers that are not related to COVID-19 published during Spring 2020. Standard errors clustered at the school level. * p<0.1 ** p<0.05 *** p<0.01. Each regression uses a full set of controls found in Figure 13, with a full set of estimates found in the appendix.

Table 18: The Effect of Number of Weeks Remote on the Number of IZA Working Papers

	(1)	(2)	(3)
	All Papers	COVID-19 Papers	Non-COVID-19 Papers
Remote Instruction Weeks	-0.011	0.005	-0.017
	(0.020)	(0.007)	(0.018)
Controls	Yes	Yes	Yes
N	1289	1289	1289

Note: The unit of observation is a faculty member who is affiliated with the IZA. Column (1) uses the outcome of total number of working papers a faculty member creates during Spring 2020. Column (2) is the coefficient for when the outcome is the number of papers that the IZA classifies as being related to COVID-19 and is published during Spring 2020. Column (3) uses the outcome for number of papers that are not related to COVID-19 published during Spring 2020. Standard errors clustered at the school level. * p<0.1 ** p<0.05 *** p<0.01. Each regression uses a full set of controls found in Figure 16, with a full set of estimates found in the appendix.

Table 19: The Effect of Number of Weeks Remote on the Number of IZA Working Papers by Gender

Panel A: Men

	(1)	(2)	(3)
	All Papers	COVID-19 Papers	Non-COVID-19 Papers
Remote Instruction Weeks	-0.013	0.009	-0.022
	(0.022)	(0.008)	(0.019)
Controls	Yes	Yes	Yes
N	934	934	934

Note: The unit of observation is a male faculty member who is affiliated with the IZA. Column (1) uses the outcome of total number of working papers a faculty member publishes during Spring 2020. Column (2) is the coefficient for when the outcome is the number of papers that the IZA classifies as being related to COVID-19 and is published during Spring 2020. Column (3) uses the outcome for number of papers that are not related to COVID-19 published during Spring 2020. Standard errors clustered at the school level. * p<0.1 ** p<0.05 *** p<0.01. Each regression uses a full set of controls found in Figure 16, with a full set of estimates found in the appendix.

Panel A: Women

	(1)	(2)	(3)
	All Papers	COVID-19 Papers	Non-COVID-19 Papers
Remote Instruction Weeks	-0.005	-0.004	-0.001
	(0.039)	(0.012)	(0.031)
Controls	Yes	Yes	Yes
N	355	355	355

Note: The unit of observation is a female faculty member who is affiliated with the IZA. Column (1) uses the outcome of total number of working papers a faculty member publishes during Spring 2020. Column (2) is the coefficient for when the outcome is the number of papers that the IZA classifies as being related to COVID-19 and is published during Spring 2020. Column (3) uses the outcome for number of papers that are not related to COVID-19 published during Spring 2020. Standard errors clustered at the school level. * p<0.1 ** p<0.05 *** p<0.01. Each regression uses a full set of controls found in Figure 16, with a full set of estimates found in the appendix.

Table 20: The Effect of Weeks Until First Case on Weeks of Remote Instruction
Instrumental Variables Estimates for NBER-affiliates
Panel A: Reduced Form Results

	(1)	(2)	(3)	(4)
	First Stage	Reduced Form		
	Number of Weeks Remote	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Weeks Until the First Case	-0.179***	-0.039	-0.022	-0.017
	(0.027)	(0.028)	(0.017)	(0.017)
N	1,513	1,513	1,513	1,513

Note: The unit of observation is a faculty member that is affiliated with the NBER. The outcome variable in Column (1) is the number of full weeks that a faculty member's school uses remote instruction. Columns (2), (3) and (4) use the number of papers that a faculty member publishes in the Spring of 2020. Estimates are regressed on the number of weeks since the start of the semester to the week that a school reports its first positive COVID-19. Standard errors clustered at the school level. * p<0.1 ** p<0.05 *** p<0.01. Each regression uses a full set of controls found in Figure 13, with a full set of estimates found in the appendix.

Panel B: 2SLS Results

	(1)	(2)	(3)
	2SLS Estimates		
	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Number of Weeks Remote	0.217	0.123	0.094
	(0.214)	(0.135)	(0.106)
N	1,513	1,513	1,513

Note: The unit of observation is a faculty member that is affiliated with the NBER. Column (1) shows results for all working papers published in the Spring of 2020. Columns (2) and (3) are results for papers split by if they are COVID-19 related or not, respectively. Each regression uses a full set of controls found in Figure 13, with a full set of estimates found in the appendix.

Table 21: The Effect of Weeks Until First Case on Weeks of Remote Instruction
Instrumental Variables Estimates for Men that are NBER-affiliates
Panel A: Reduced Form Results

	(1)	(2)	(3)	(4)
	First Stage	Reduced Form		
	Number of Weeks Remote	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Weeks Until the First Case	-0.163***	-0.019	-0.009	-0.010
	(0.029)	(0.030)	(0.016)	(0.021)
N	1,167	1,167	1,167	1,167

Note: The unit of observation is a male faculty member that is affiliated with the NBER. The outcome variable in Column (1) is the number of full weeks that a faculty member's school uses remote instruction. Columns (2), (3) and (4) use the number of papers that a faculty member publishes in the Spring of 2020. Estimates are regressed on the number of weeks since the start of the semester to the week that a school reports its first positive COVID-19. Standard errors clustered at the school level. * p<0.1 ** p<0.05 *** p<0.01. Each regression uses a full set of controls found in Figure 13, with a full set of estimates found in the appendix.

Panel B: 2SLS Results

	(1)	(2)	(3)
	2SLS Estimates		
	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Number of Weeks Remote	0.117	0.054	0.062
	(0.213)	(0.113)	(0.136)
N	1,167	1,167	1,167

Note: The unit of observation is a male faculty member that is affiliated with the NBER. Column (1) shows results for all working papers published in the Spring of 2020. Columns (2) and (3) are results for papers split by if they are COVID-19 related or not, respectively. Each regression uses a full set of controls found in Figure 13, with a full set of estimates found in the appendix.

Table 22: The Effect of Weeks Until First Case on Weeks of Remote Instruction
Instrumental Variables Estimates for Women that are NBER-affiliates
Panel A: Reduced Form Results

	(1)	(2)	(3)	(4)
	First Stage	Reduced Form		
	Number of Weeks Remote	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Weeks Until the First Case	-0.230***	-0.169***	-0.083*	-0.086**
	(0.070)	(0.057)	(0.042)	(0.035)
N	346	346	346	346

Note: The unit of observation is a female faculty member that is affiliated with the NBER. The outcome variable in Column (1) is the number of full weeks that a faculty member's school uses remote instruction. Columns (2), (3) and (4) use the number of papers that a faculty member publishes in the Spring of 2020. Estimates are regressed on the number of weeks since the start of the semester to the week that a school reports its first positive COVID-19. Standard errors clustered at the school level. * p<0.1 ** p<0.05 *** p<0.01. Each regression uses a full set of controls found in Figure 13, with a full set of estimates found in the appendix.

Panel B: 2SLS Results

	(1)	(2)	(3)
	2SLS Estimates		
	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Number of Weeks Remote	0.734	0.360	0.374
	(0.488)	(0.291)	(0.240)
N	346	346	346

Note: The unit of observation is a female faculty member that is affiliated with the NBER. Column (1) shows results for all working papers published in the Spring of 2020. Columns (2) and (3) are results for papers split by if they are COVID-19 related or not, respectively. Each regression uses a full set of controls found in Figure 13, with a full set of estimates found in the appendix.

Table 23: The Effect of Weeks Until First Case on Weeks of Remote Instruction
Instrumental Variables Estimates for IZA-affiliates
Panel A: Reduced Form Results

	(1)	(2)	(3)	(4)
	First Stage	Reduced Form		
	Number of Weeks Remote	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Weeks Until the First Case	-0.311***	-0.006	-0.002	-0.004
	(0.060)	(0.020)	(0.006)	(0.018)
N	1289	1289	1289	1289

Note: The unit of observation is a female faculty member that is affiliated with the IZA. The outcome variable in Column (1) is the number of full weeks that a faculty member's school uses remote instruction. Columns (2), (3) and (4) use the number of papers that a faculty member publishes in the Spring of 2020. Estimates are regressed on the number of weeks since the start of the semester to the week that a country have more than 10 COVID-19 cases per million. Standard errors clustered at the school level. * p<0.1 ** p<0.05 *** p<0.01. Each regression uses a full set of controls found in Figure 16, with a full set of estimates found in the appendix.

Panel B: 2SLS Results

	(1)	(2)	(3)
	2SLS Estimates		
	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Number of Weeks Remote	0.020	0.008	0.013
	(0.063)	(0.020)	(0.056)
N	1289	1289	1289

Note: The unit of observation is a female faculty member that is affiliated with the IZA. Column (1) shows results for all working papers published in the Spring of 2020. Columns (2) and (3) are results for papers split by if they are COVID-19 related or not, respectively. Each regression uses a full set of controls found in Figure 16, with a full set of estimates found in the appendix.

Table 24: The Effect of Weeks Until First Case on Weeks of Remote Instruction
Instrumental Variables Estimates for Men that are IZA-affiliates
Panel A: Reduced Form Results

	(1)	(2)	(3)	(4)
	First Stage	Reduced Form		
	Number of Weeks Remote	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Weeks Until the First Case	-0.282***	0.008	-0.004	0.013
	(0.075)	(0.025)	(0.009)	(0.021)
N	934	934	934	934

Note: The unit of observation is a male faculty member that is affiliated with the IZA. The outcome variable in Column (1) is the number of full weeks that a faculty member's school uses remote instruction. Columns (2), (3) and (4) use the number of papers that a faculty member publishes in the Spring of 2020. Estimates are regressed on the number of weeks since the start of the semester to the week that a school reports its first positive COVID-19. Standard errors clustered at the school level. * p<0.1 ** p<0.05 *** p<0.01. Each regression uses a full set of controls found in Figure 16, with a full set of estimates found in the appendix.

Panel B: 2SLS Results

	(1)	(2)	(3)
	2SLS Estimates		
	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Number of Weeks Remote	-0.030	0.016	-0.046
	(0.091)	(0.032)	(0.078)
N	934	934	934

Note: The unit of observation is a male faculty member that is affiliated with the IZA. Column (1) shows results for all working papers published in the Spring of 2020. Columns (2) and (3) are results for papers split by if they are COVID-19 related or not, respectively. Each regression uses a full set of controls found in Figure 16, with a full set of estimates found in the appendix.

Table 25: The Effect of Weeks Until First Case on Weeks of Remote Instruction
Instrumental Variables Estimates for Women that are IZA-affiliates
Panel A: Reduced Form Results

	(1)	(2)	(3)	(4)
	First Stage	Reduced Form		
	Number of Weeks Remote	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Weeks Until the First Case	-0.374***	-0.041	0.002	-0.043*
	(0.094)	(0.025)	(0.006)	(0.026)
N	355	355	355	355

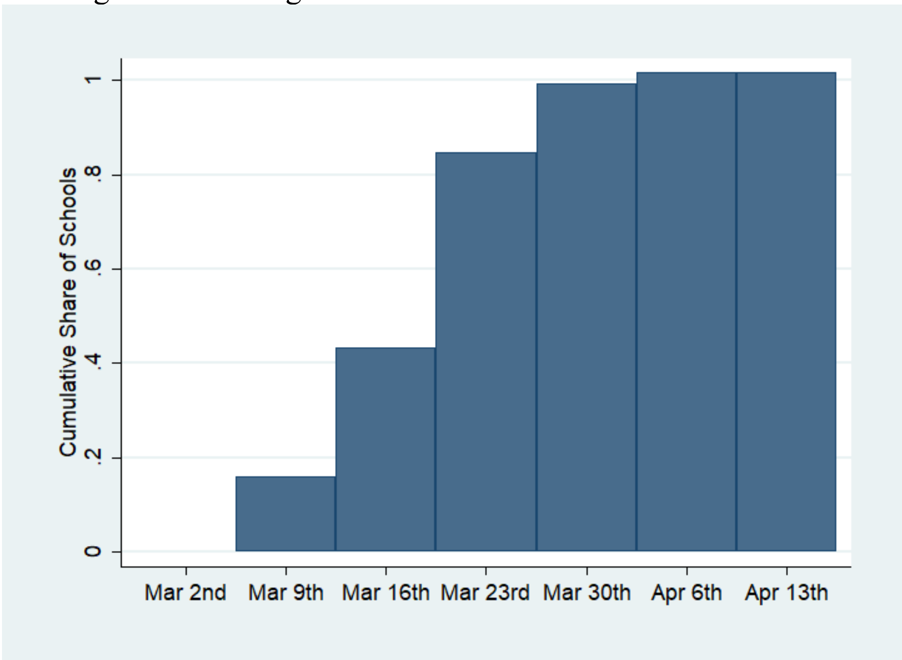
Note: The unit of observation is a female faculty member that is affiliated with the IZA. The outcome variable in Column (1) is the number of full weeks that a faculty member's school uses remote instruction. Columns (2), (3) and (4) use the number of papers that a faculty member publishes in the Spring of 2020. Estimates are regressed on the number of weeks since the start of the semester to the week that a country have more than 10 COVID-19 cases per million. Standard errors clustered at the school level. * p<0.1 ** p<0.05 *** p<0.01. Each regression uses a full set of controls found in Figure 16, with a full set of estimates found in the appendix.

Panel B: 2SLS Results

	(1)	(2)	(3)
	2SLS Estimates		
	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Number of Weeks Remote	0.109	-0.006	0.115
	(0.075)	(0.015)	(0.078)
N	355	355	355

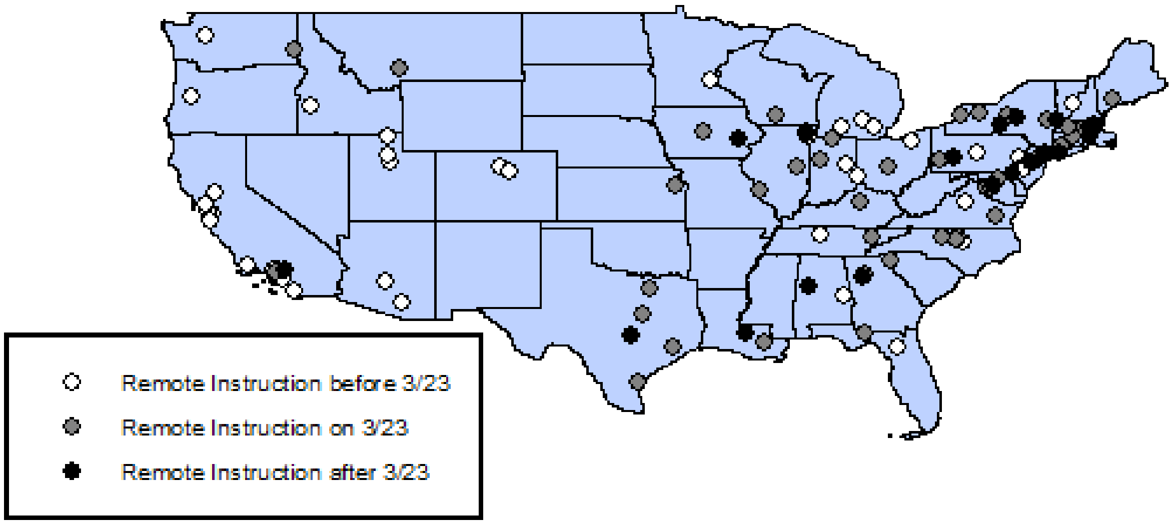
Note: The unit of observation is a female faculty member that is affiliated with the IZA. Column (1) shows results for all working papers published in the Spring of 2020. Columns (2) and (3) are results for papers split by if they are COVID-19 related or not, respectively. Each regression uses a full set of controls found in Figure 16, with a full set of estimates found in the appendix.

Figure 11: Timing of Schools' Switch to Remote Instruction



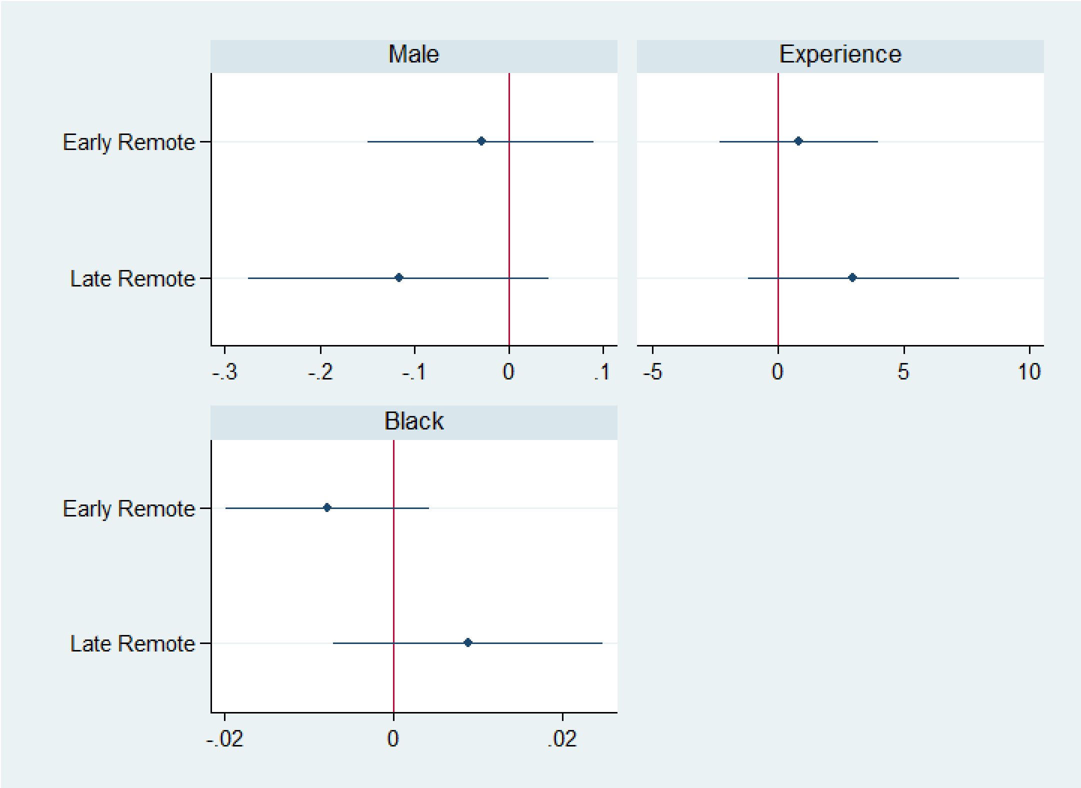
Note: The figure presents the cumulative share of schools in our sample that switched to remote instruction. The earliest switch was in the week of March 9th, 2020, and the latest was in the week of April 6th, 2020. By April 6th, all universities were delivering their courses remotely.

Figure 12: The Locations of the Universities with NBER Researchers



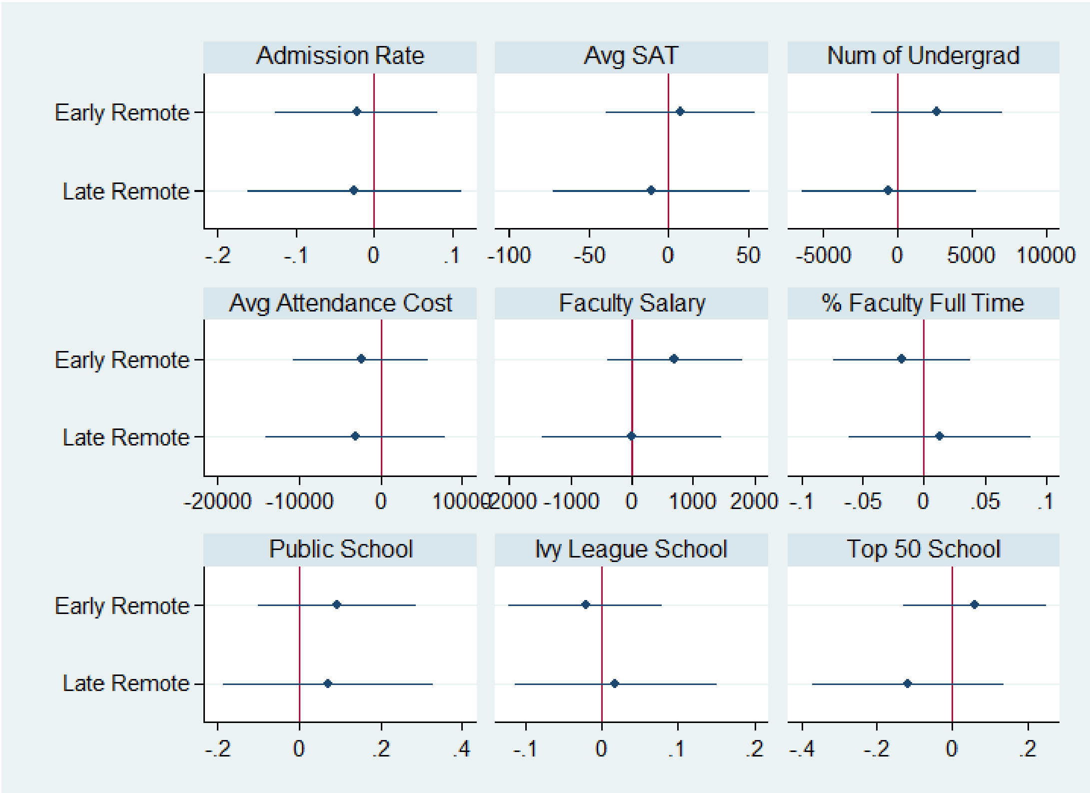
Note: Map depicts locations of all schools used within our analysis. White, gray, and black dots indicate that the school switched to online instruction before, on, and after the week of March 23rd, 2020.

Figure 13A: The Correlation between the Timing of the Switch to Remote Instruction and NBER Researcher Characteristics



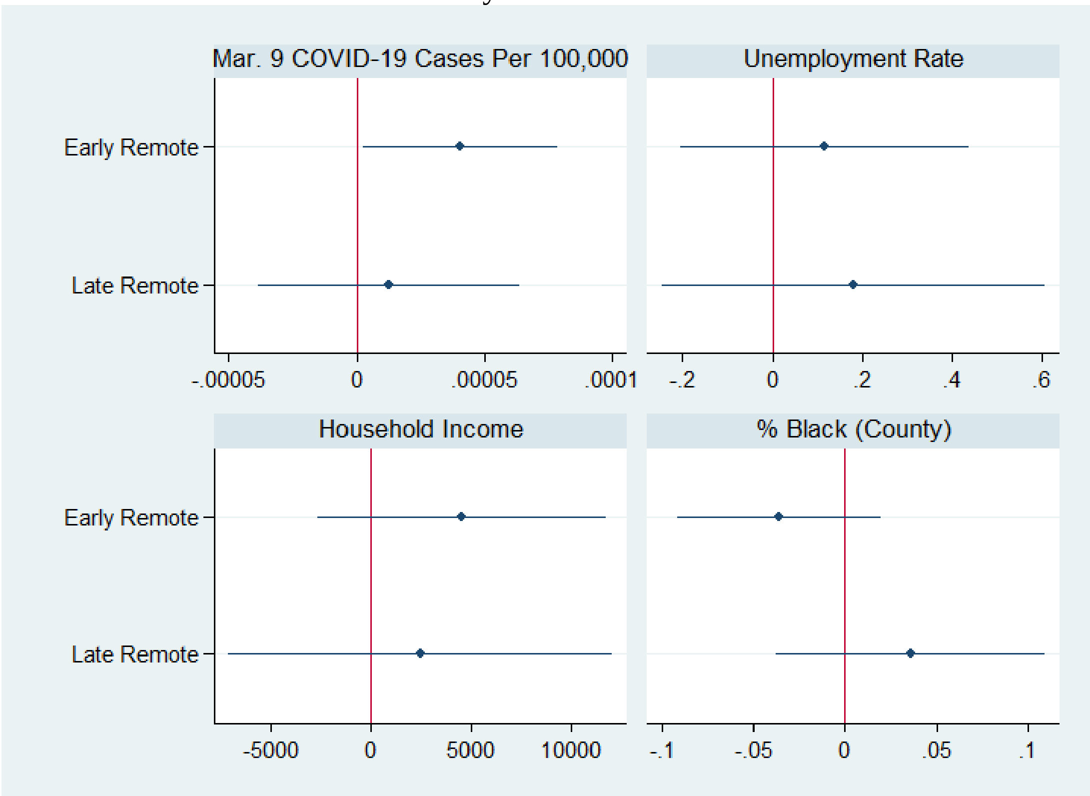
Note: Each mini-graph represents results from one regression. The unit of observation is a school. The outcomes are listed at the top of each mini-graph. The only control variables are indicators for whether a school switched to remote instruction earlier or later than the week of March 23rd, 2020. The omitted category is the schools that moved to remote instruction in the week of March 23rd. Dots (horizontal lines) indicate the point estimates (95% confidence intervals). The vertical red lines mark zero.

Figure 13B: The Correlation between the Timing of the Switch to Remote Instruction and School Characteristics



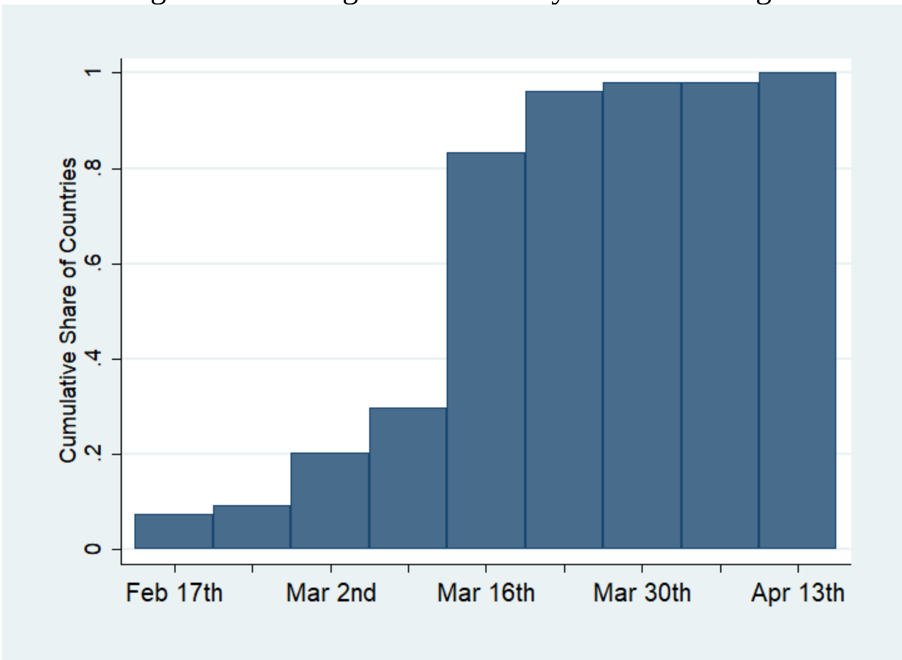
See notes to Figure 13A.

Figure 13C: The Correlation between the Timing of the Switch to Remote Instruction and County Characteristics



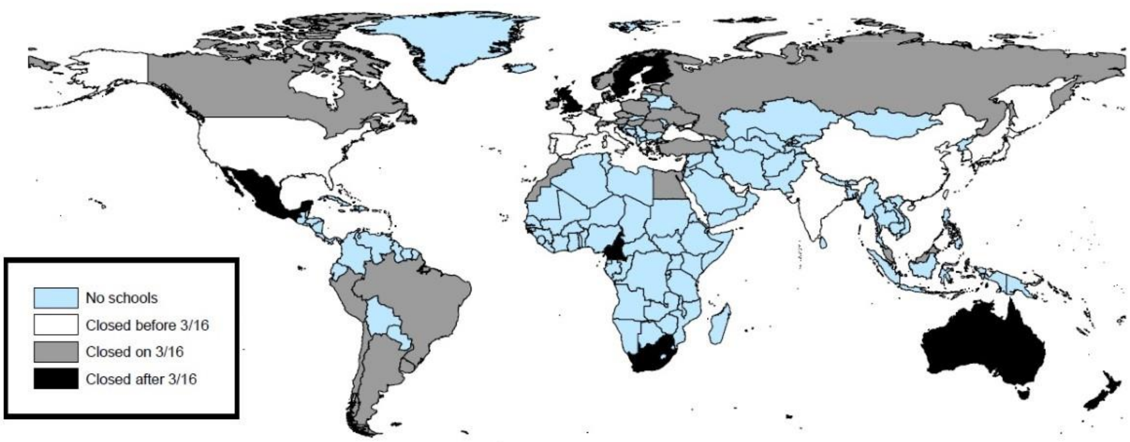
See notes to Figure 13A.

Figure 14: Timing of IZA Country School Closings



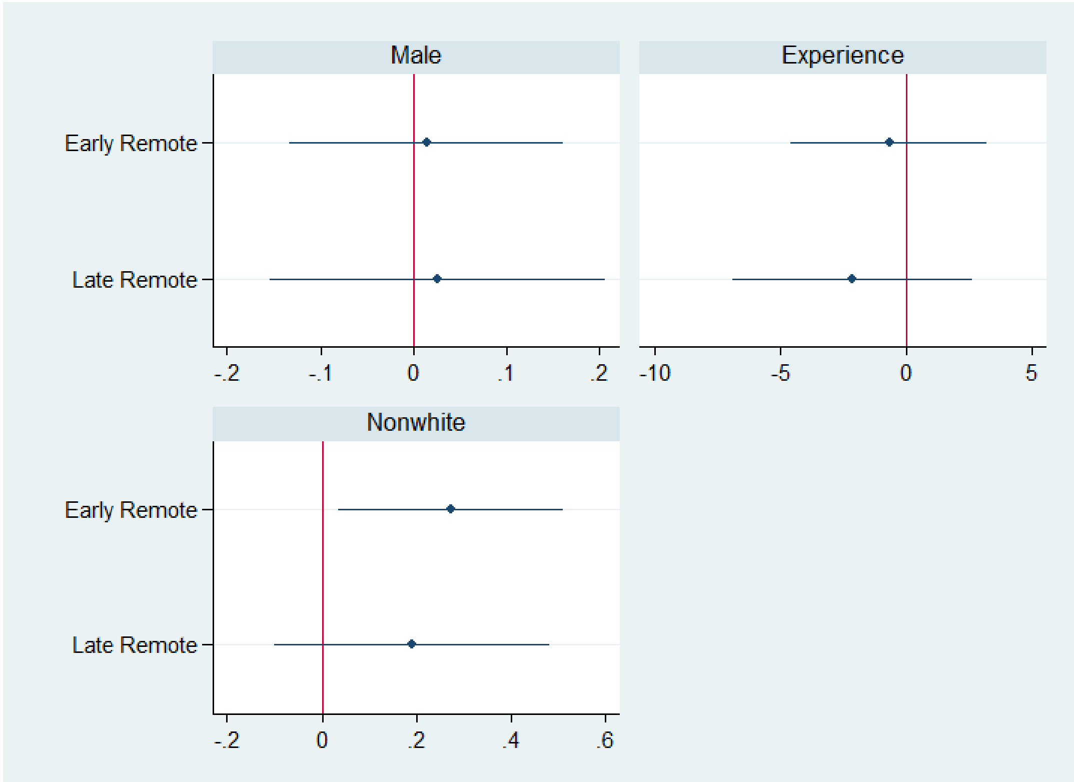
Note: The figure presents the cumulative share of countries in our IZA-affiliate sample that enforced university or colleges to close. The earliest closure was in the week of January 25th, 2020, and the latest was in the week of April 13th, 2020. By April 13th, all countries within the sample had require closure.

Figure 15: The Countries of IZA-affiliated Researchers



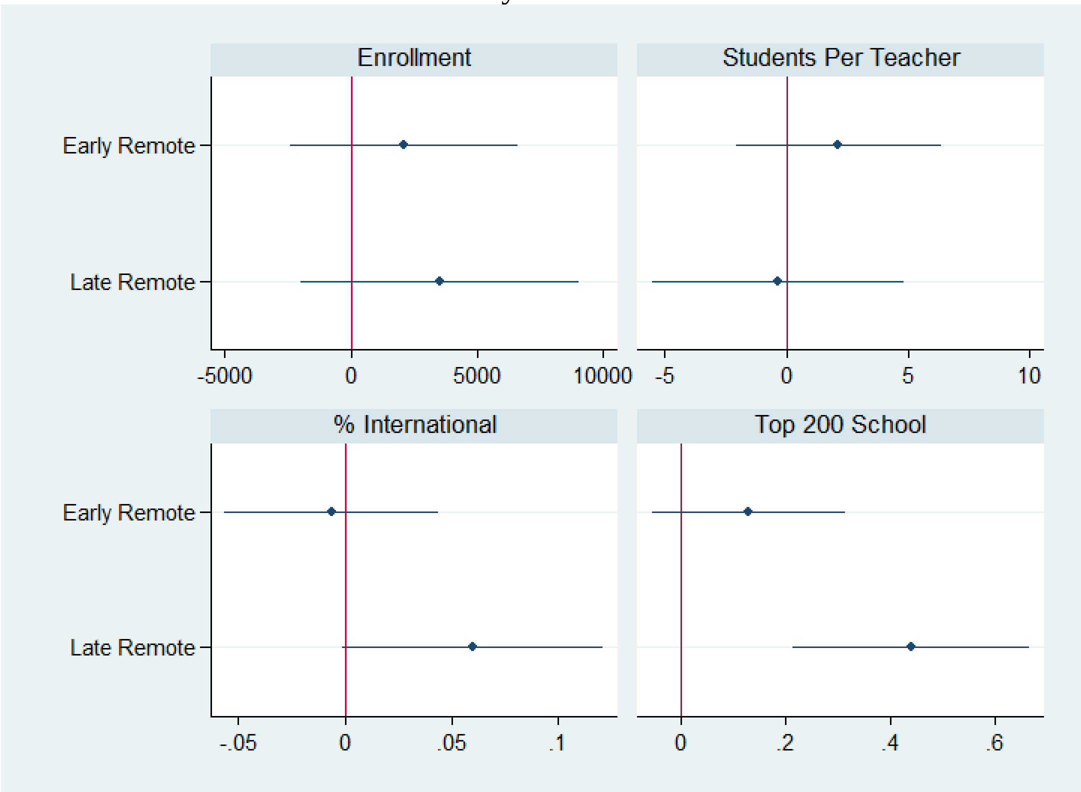
Note: Map depicts locations of all countries used within our IZA analysis. White, gray, and black filled countries indicate that the school lies in a country that closed switched to before, on, and after the week of March 16th, 2020.

Figure 16A: The Correlation between Country Enforced Closure and IZA Researcher Characteristics



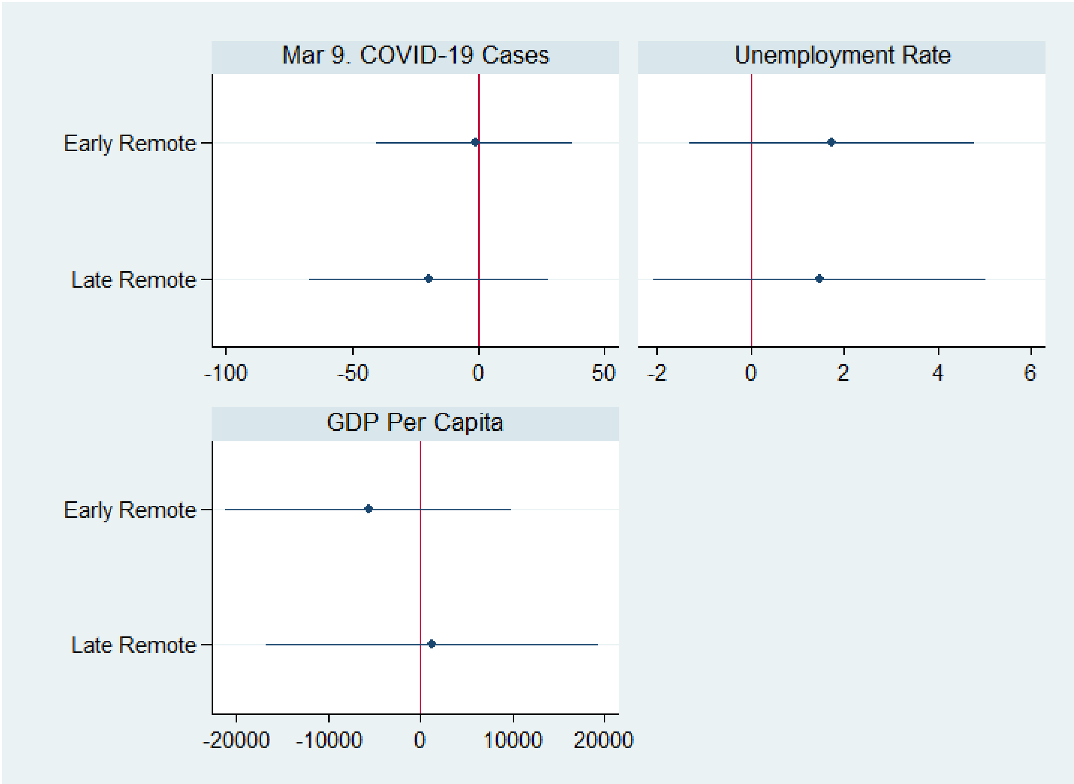
Note: Each mini-graph represents results from one regression. The unit of observation is a school. The outcomes are listed at the top of each mini-graph. The only control variables are indicators for whether a school had enforced closure earlier or later than the week of March 16th, 2020. The omitted category is the schools that moved to remote instruction in the week of March 16th. Dots (horizontal lines) indicate the point estimates (95% confidence intervals). The vertical red lines mark zero.

Figure 16B: The Correlation between Country Enforced Closure and IZA School Characteristics



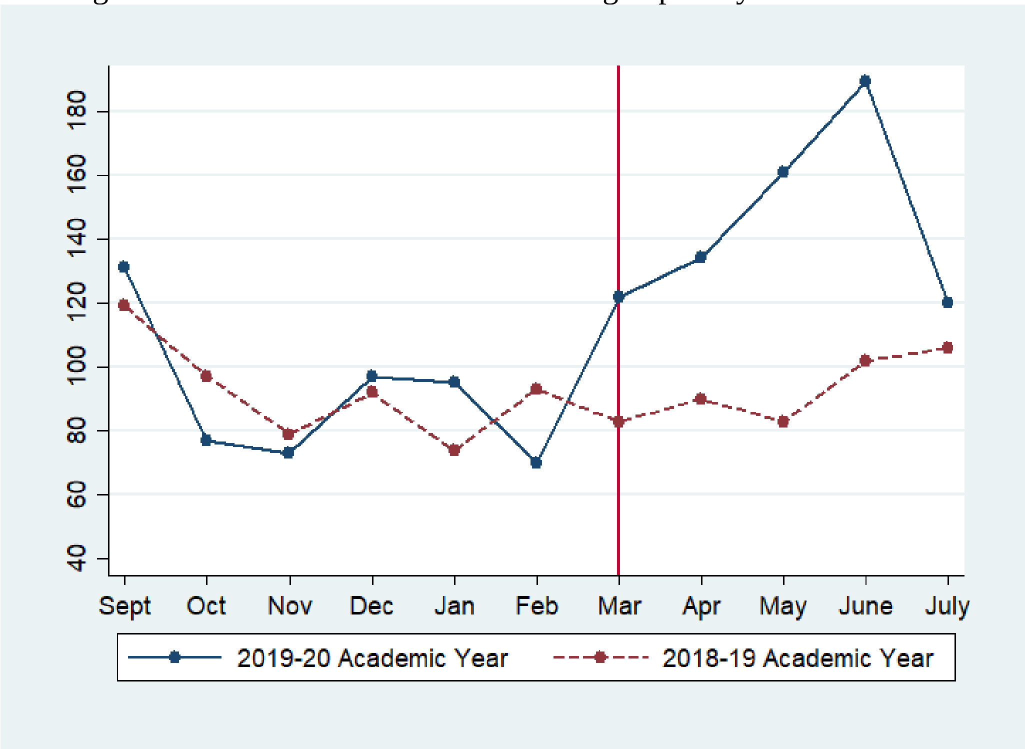
See notes to Figure 16A.

Figure 16C: The Correlation between Country Enforced Closure and IZA Country Characteristics



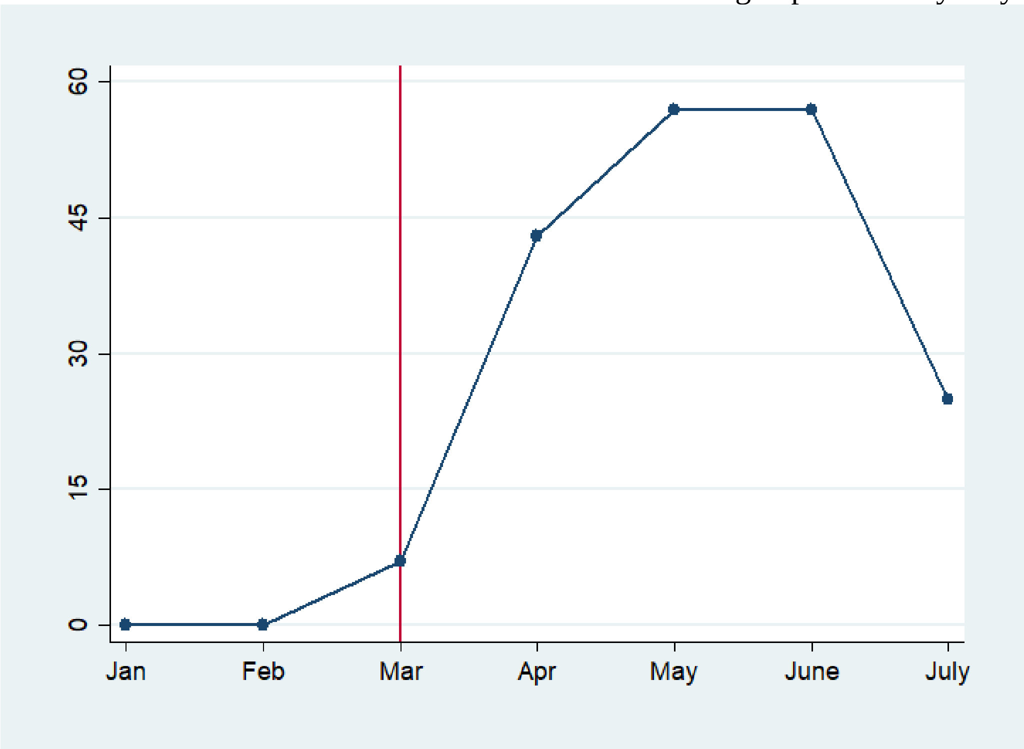
See notes to Figure 16A.

Figure 17: The Number of NBER Working Papers by Academic Year



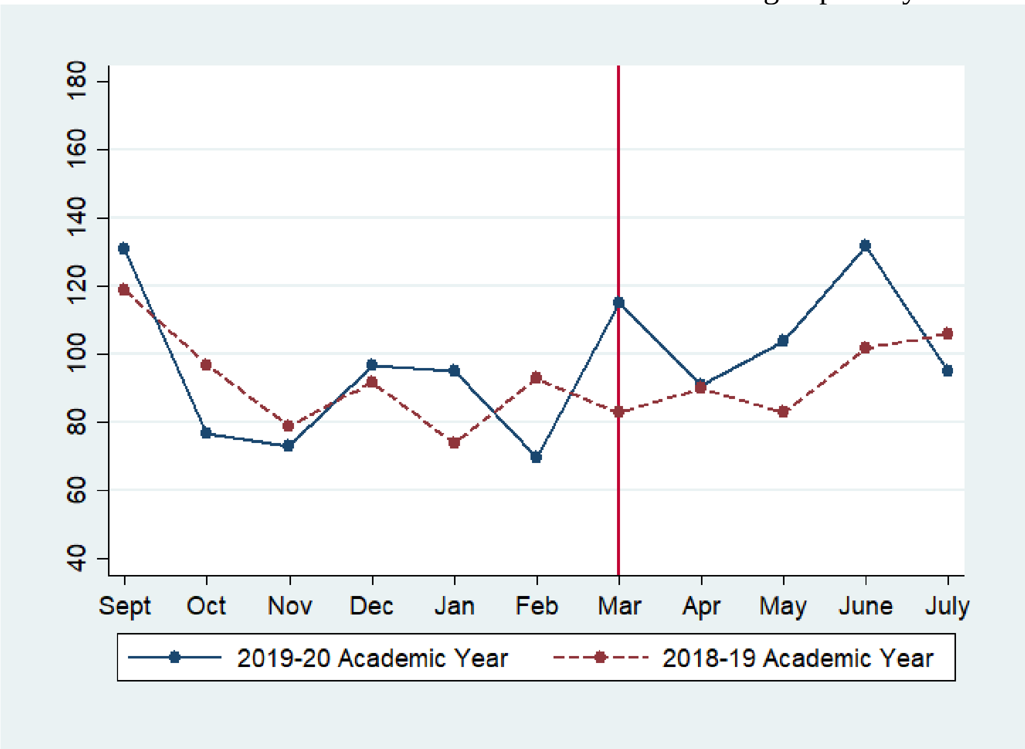
Note: The figure presents the monthly number of NBER working papers published over the period of September to July. The solid blue line is the number of NBER working papers published per month in the Academic year of 2019-2020. The dashed red line is the number of NBER working papers published per month in the Academic year of 2018-2019. The vertical red line indicates the month of March.

Figure 18: The Number of COVID-19-Related NBER Working Papers January-July 2020



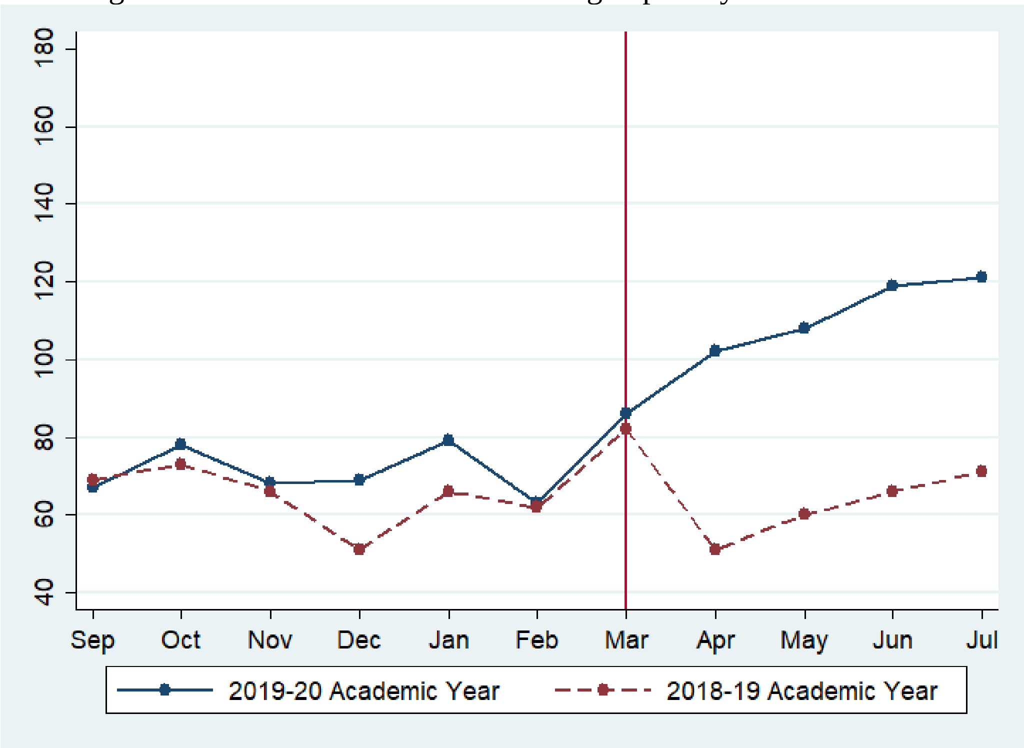
Note: The graph demonstrates the total amount of COVID-19-related NBER working papers per month between January and July 2020. The red line indicates the month of March. COVID-19-related NBER papers are first published in the month of March.

Figure 19: The Number of Non-COVID-19-Related NBER Working Papers By Academic Year



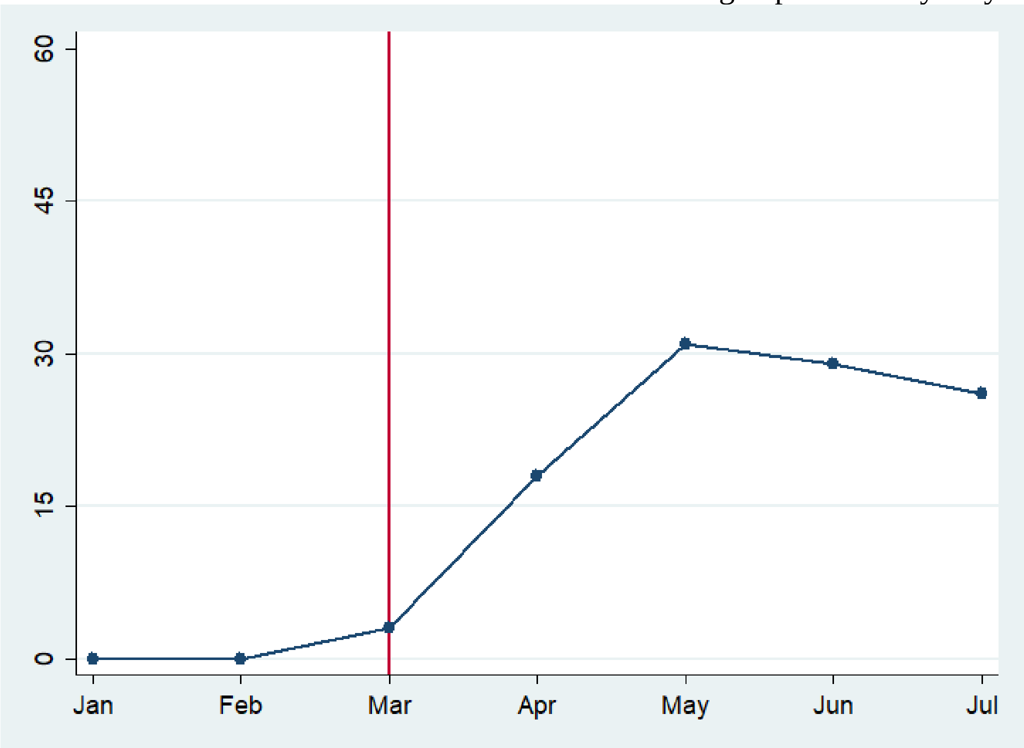
Note: The figure presents the monthly number of non-COVID-19-related NBER working papers posted in academic years 2018-2019 and 2019-2020. The solid blue line is the number of NBER working papers produced per month in the Academic year of 2019-2020. The dashed red line is the number of NBER working papers posted per month in the Academic year of 2018-2019. The vertical red line indicates the month of March.

Figure 20: The Number of IZA Working Papers by Academic Year



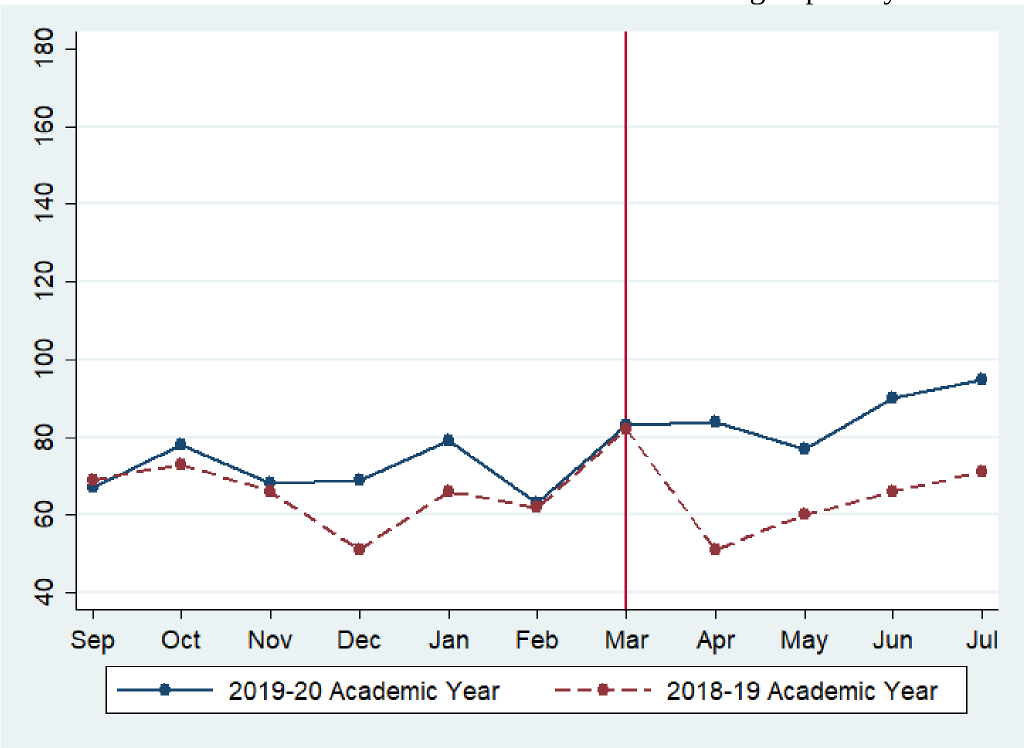
Note: The figure presents the monthly number of IZA working papers created over the period of September to July. The solid blue line is the number of IZA working papers created per month in the Academic year of 2019-2020. The dashed red line is the number of working papers created per month in the Academic year of 2018-2019. The vertical red line indicates the month of March.

Figure 21: The Number of COVID-19-Related IZA Working Papers January-July 2020



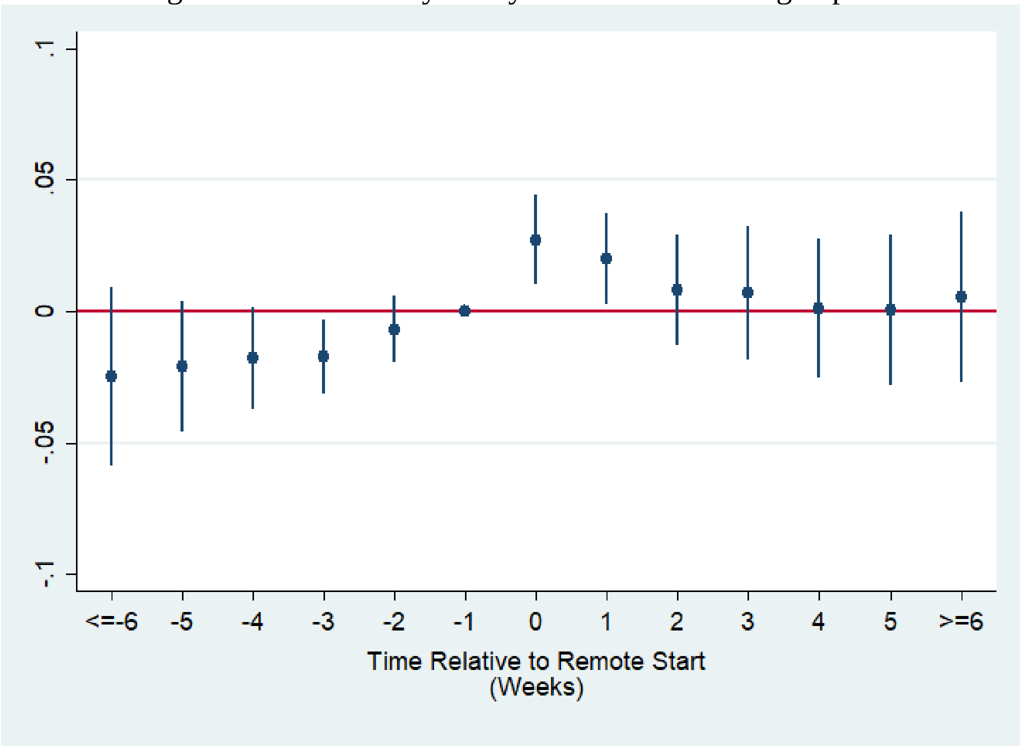
Note: The graph demonstrates the total amount of COVID-19-related IZA working papers per month between January and July 2020. The red line indicates the month of March. COVID-19-related IZA papers are first published in the month of March.

Figure 22: The Number of Non-COVID-19-Related IZA Working Papers by Academic Year



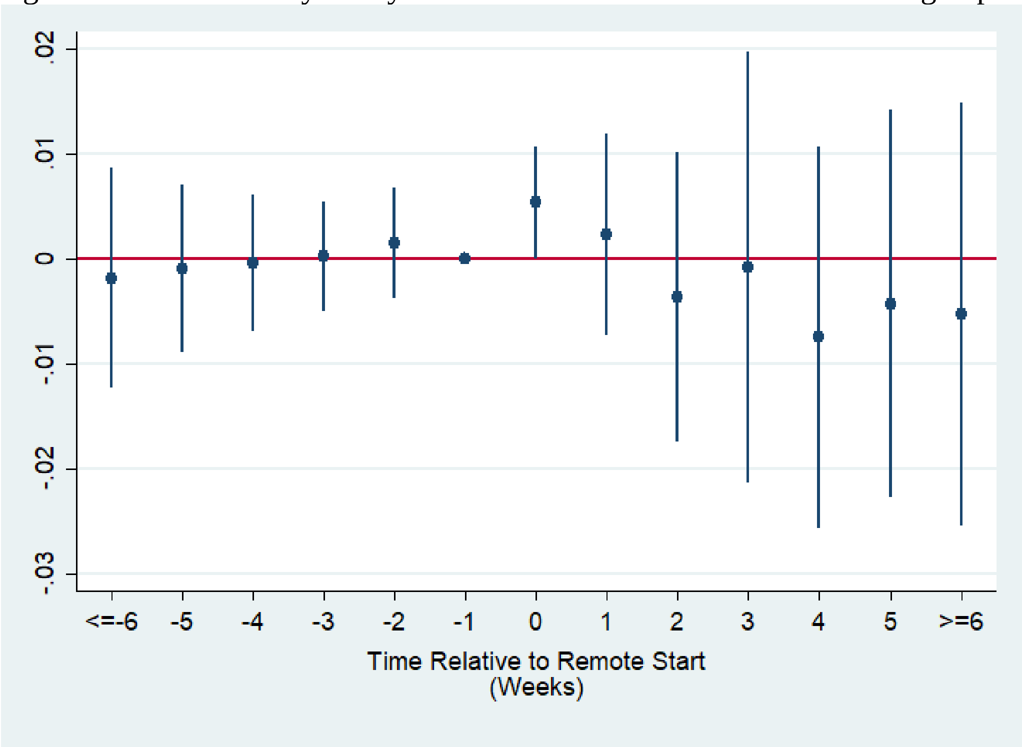
Note: The figure presents the monthly number of non-COVID-19-related IZA working papers created in academic years 2018-2019 and 2019-2020. The solid blue line is the number of IZA working papers produced per month in the Academic year of 2019-2020. The dashed red line is the number of working papers posted per month in the Academic year of 2018-2019. The vertical red line indicates the month of March.

Figure 23: Event Study Analysis - NBER Working Papers



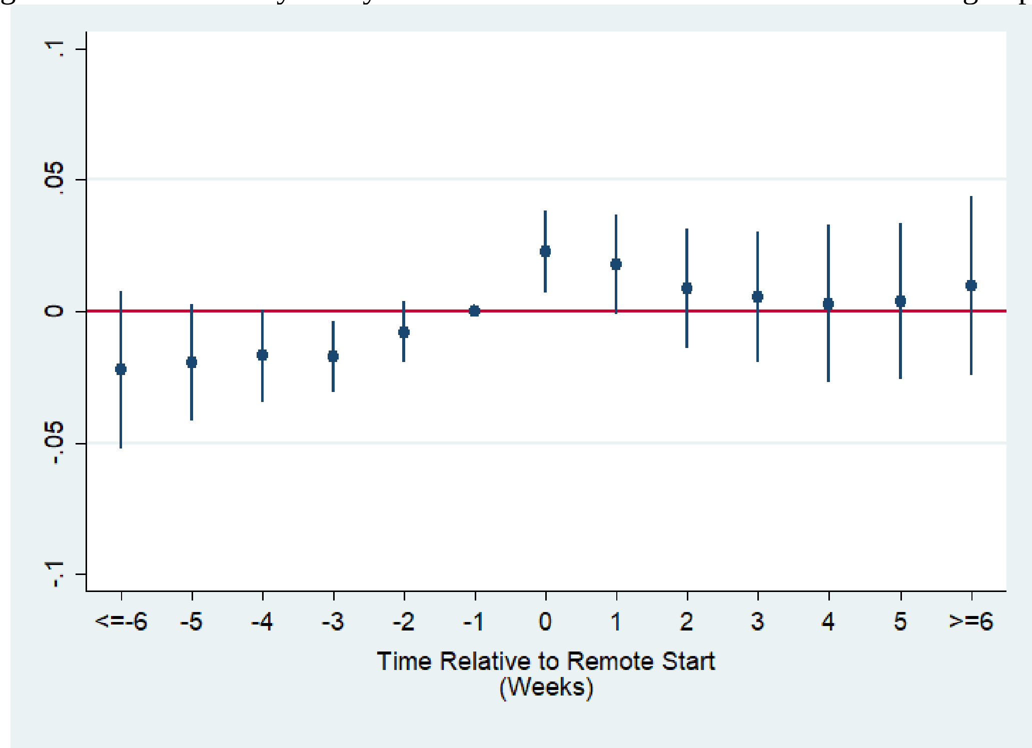
Note: Blue dots (vertical blue lines) represent the point estimates (95% confidence intervals) obtained from the regression of the production of a NBER working paper on week dummies relative to a school switching to remote instruction (Eq. (3)). The omitted category is one week before remote instruction begins.

Figure 24A: Event Study Analysis – COVID-19-Related NBER Working Papers



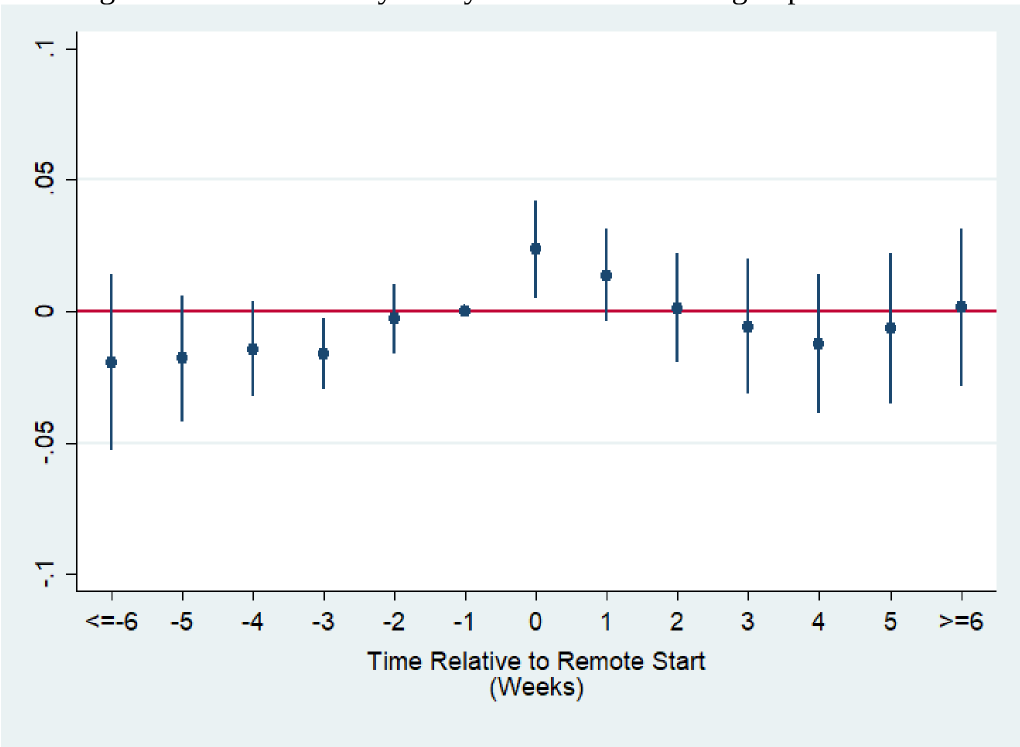
Note: Blue dots (vertical blue lines) represent the point estimates (95% confidence intervals) obtained from the regression of the production of a COVID-19-related NBER working paper on week dummies relative to a school switching to remote instruction (Eq. (3)). The omitted category is one week before remote instruction begins.

Figure 24B: Event Study Analysis – Non-COVID-19-Related NBER Working Papers



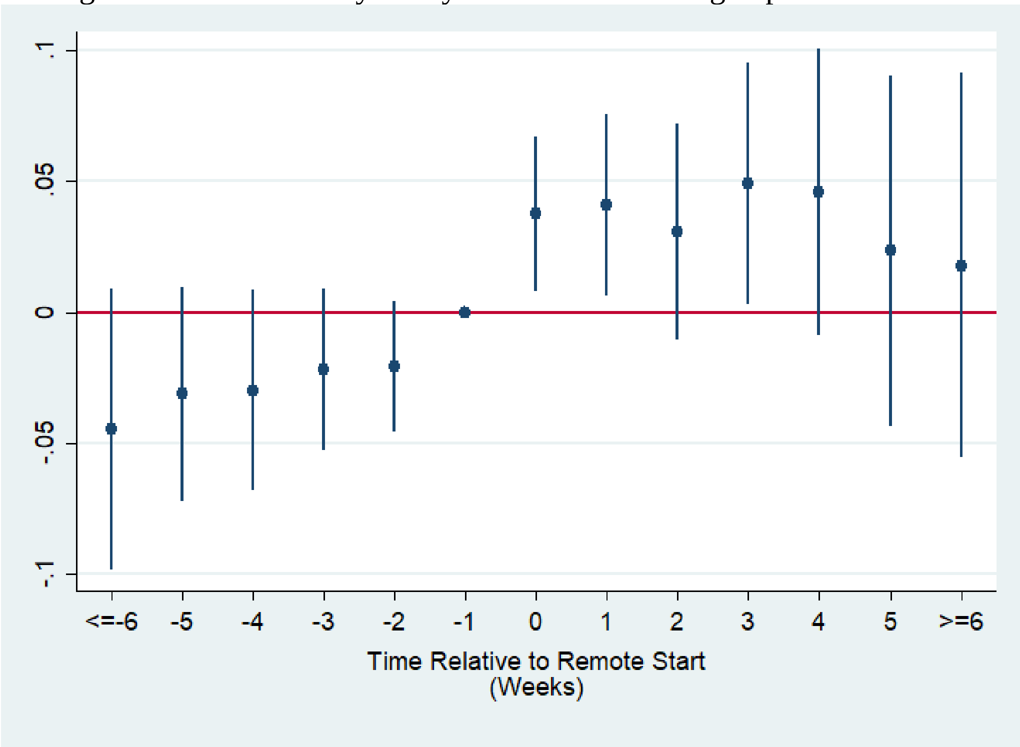
Note: Blue dots (vertical blue lines) represent the point estimates (95% confidence intervals) obtained from the regression of the production of a non-COVID-19-related NBER working paper on week dummies relative to a school switching to remote instruction (Eq. (3)). The omitted category is one week before remote instruction begins.

Figure 25A: Event Study Analysis - NBER Working Papers for Men



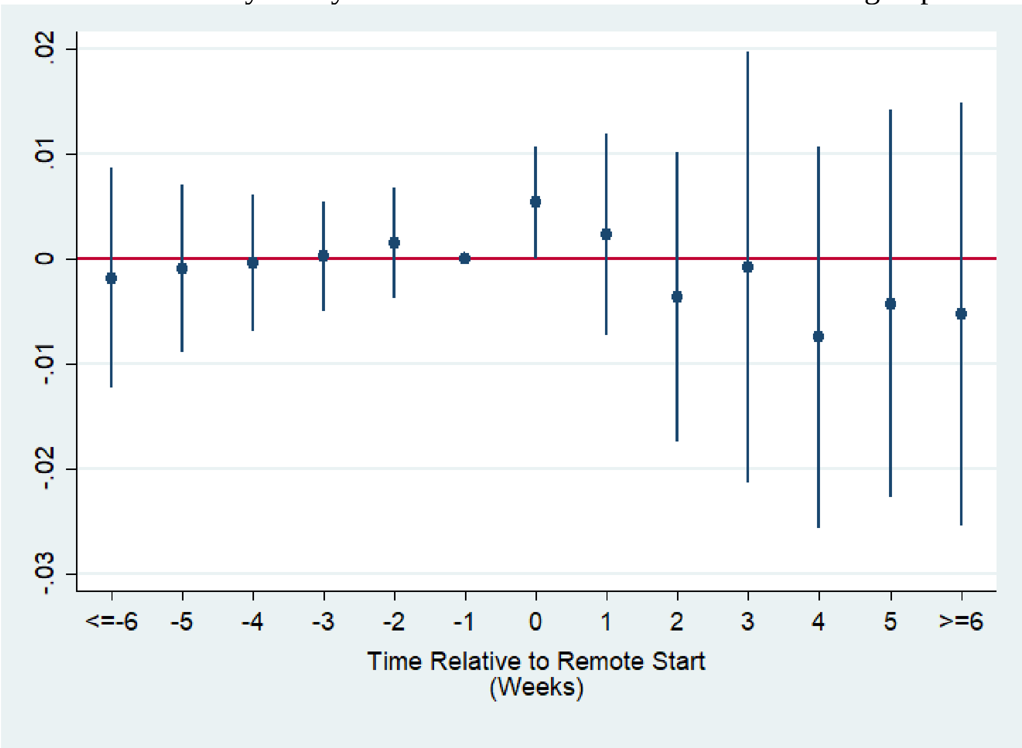
Note: Blue dots (vertical blue lines) represent the point estimates (95% confidence intervals) obtained from the regression of the production of a NBER working paper on week dummies relative to a school switching to remote instruction for a sample of only men (Eq. (3)). The omitted category is one week before remote instruction begins.

Figure 25B: Event Study Analysis - NBER Working Papers for Women



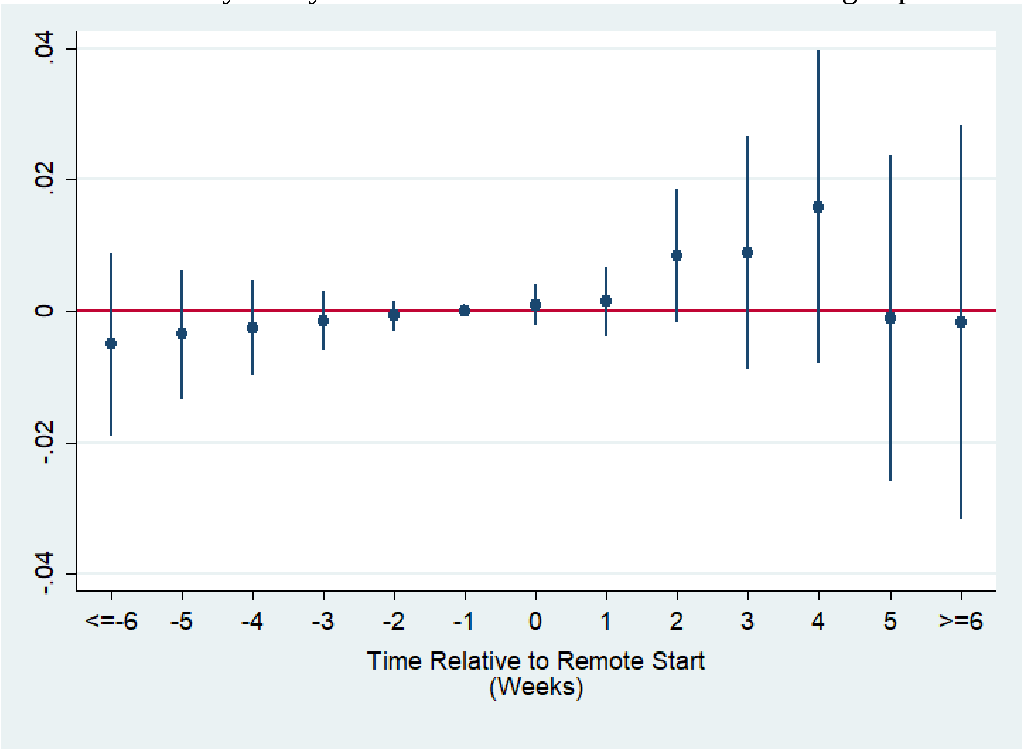
Note: Blue dots (vertical blue lines) represent the point estimates (95% confidence intervals) obtained from the regression of the production of a NBER working paper on week dummies relative to a school switching to remote instruction for a sample of only women (Eq. (3)). The omitted category is one week before remote instruction begins.

Figure 26A: Event Study Analysis – COVID-19-Related NBER Working Papers for Men



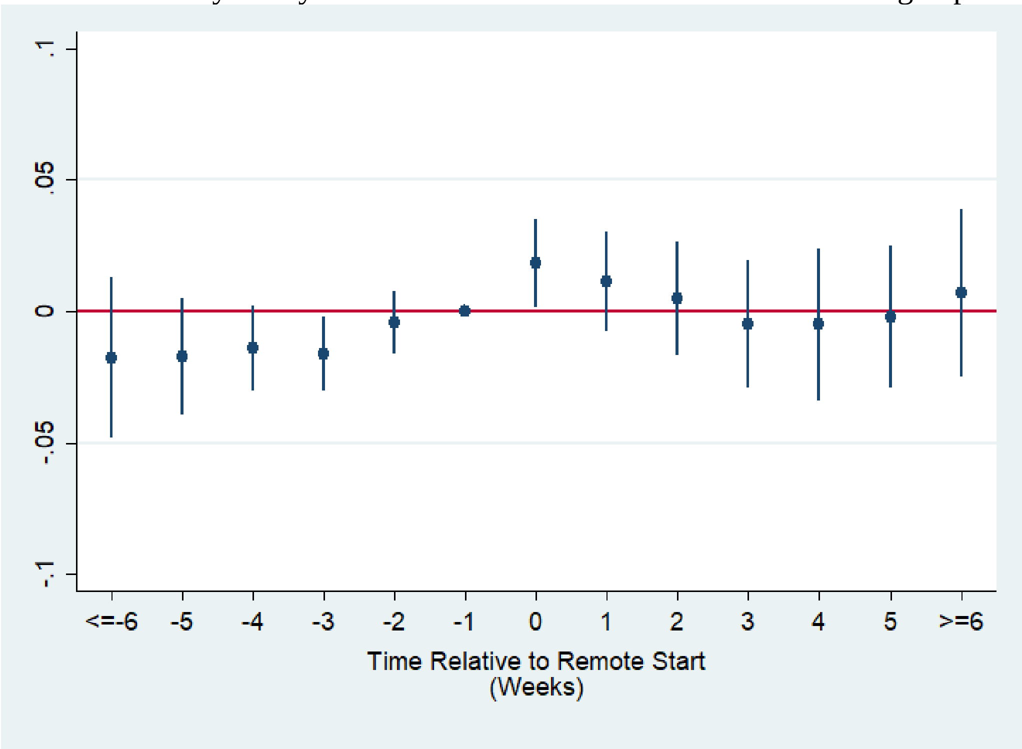
Note: Blue dots (vertical blue lines) represent the point estimates (95% confidence intervals) obtained from the regression of the production of a COVID-19-related working paper on week dummies relative to a school switching to remote instruction for a sample of only men (Eq. (3)). The omitted category is one week before remote instruction begins.

Figure 26B: Event Study Analysis – COVID-19-Related NBER Working Papers for Women



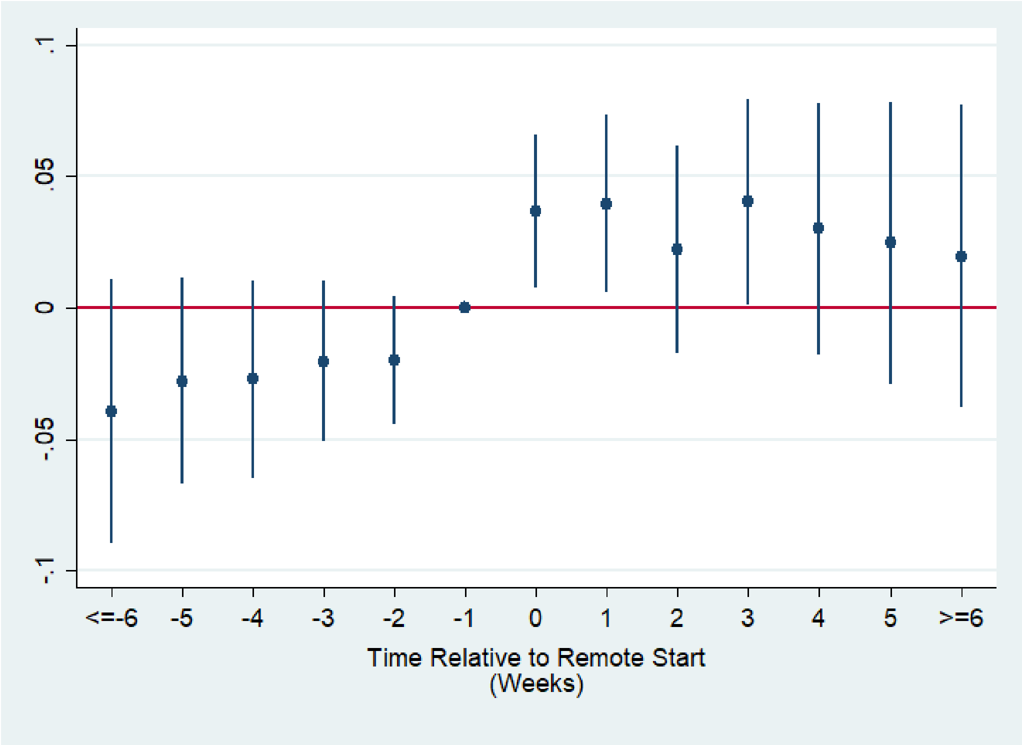
Note: Blue dots (vertical blue lines) represent the point estimates (95% confidence intervals) obtained from the regression of the production of a COVID-19-related working paper on week dummies relative to a school switching to remote instruction for a sample of only women (Eq. (3)). The omitted category is one week before remote instruction begins.

Figure 27A: Event Study Analysis – Non-COVID-19-Related NBER Working Papers for Men



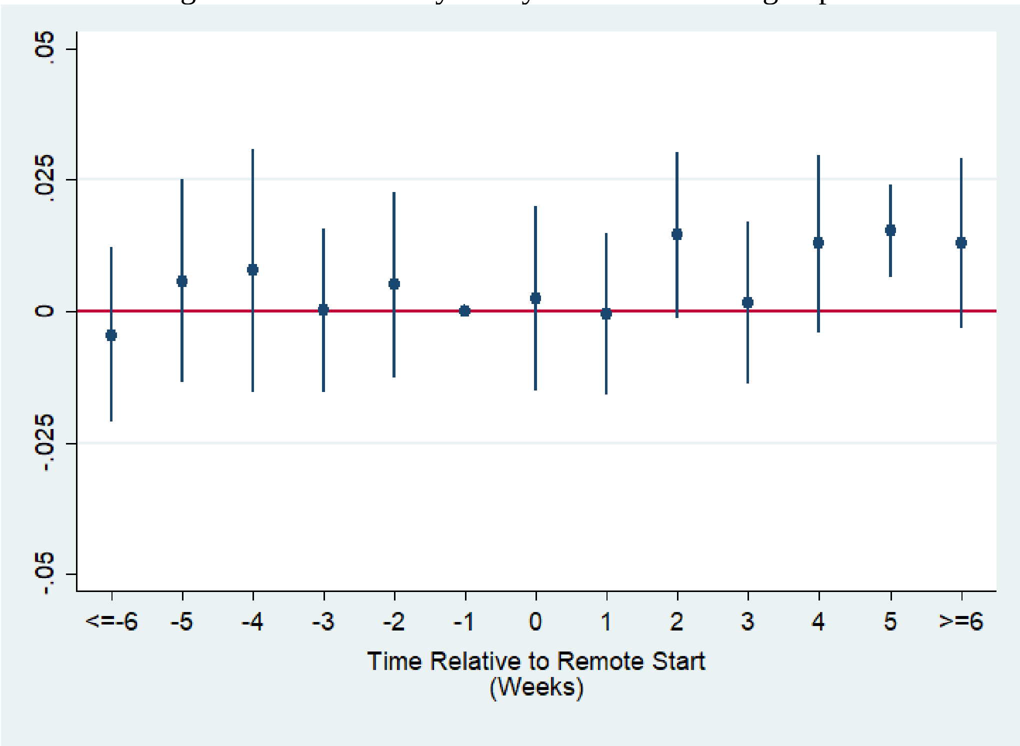
Note: Blue dots (vertical blue lines) represent the point estimates (95% confidence intervals) obtained from the regression of the production of a non-COVID-19-related working paper on week dummies relative to a school switching to remote instruction for a sample of only men (Eq. (3)). The omitted category is one week before remote instruction begins.

Figure 27B: Event Study Analysis – Non-COVID-19-Related NBER Working Papers for Women



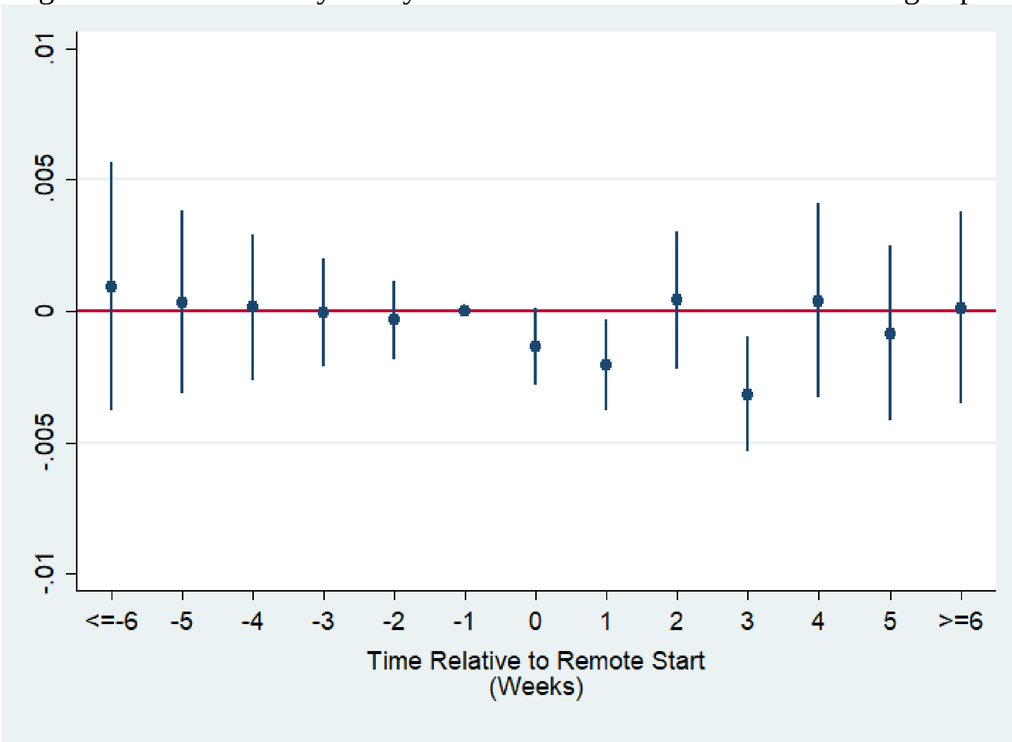
Note: Blue dots (vertical blue lines) represent the point estimates (95% confidence intervals) obtained from the regression of the production of a non-COVID-19-related working paper on week dummies relative to a school switching to remote instruction for a sample of only women (Eq. (3)). The omitted category is one week before remote instruction begins.

Figure 28: Event Study Analysis – IZA Working Papers



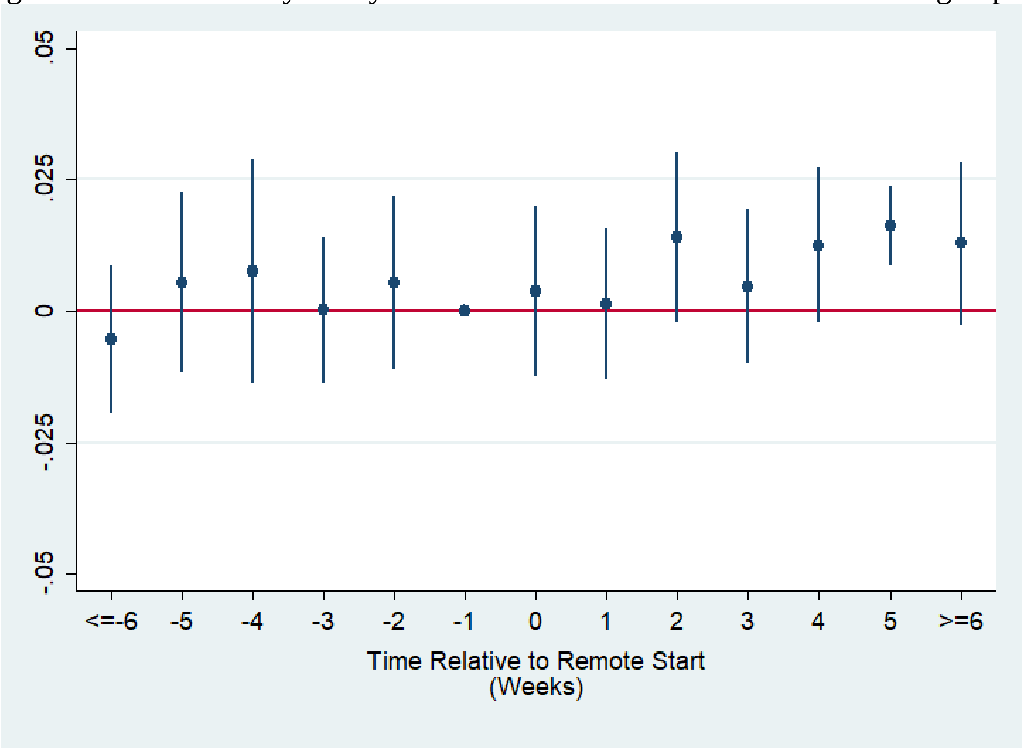
Note: Blue dots (vertical blue lines) represent the point estimates (95% confidence intervals) obtained from the regression of the production of an IZA working paper on week dummies relative a country enforcing university shutdowns (Eq. (4)). The omitted category is one week before enforcement begins.

Figure 29A: Event Study Analysis – COVID-19-Related IZA Working Papers



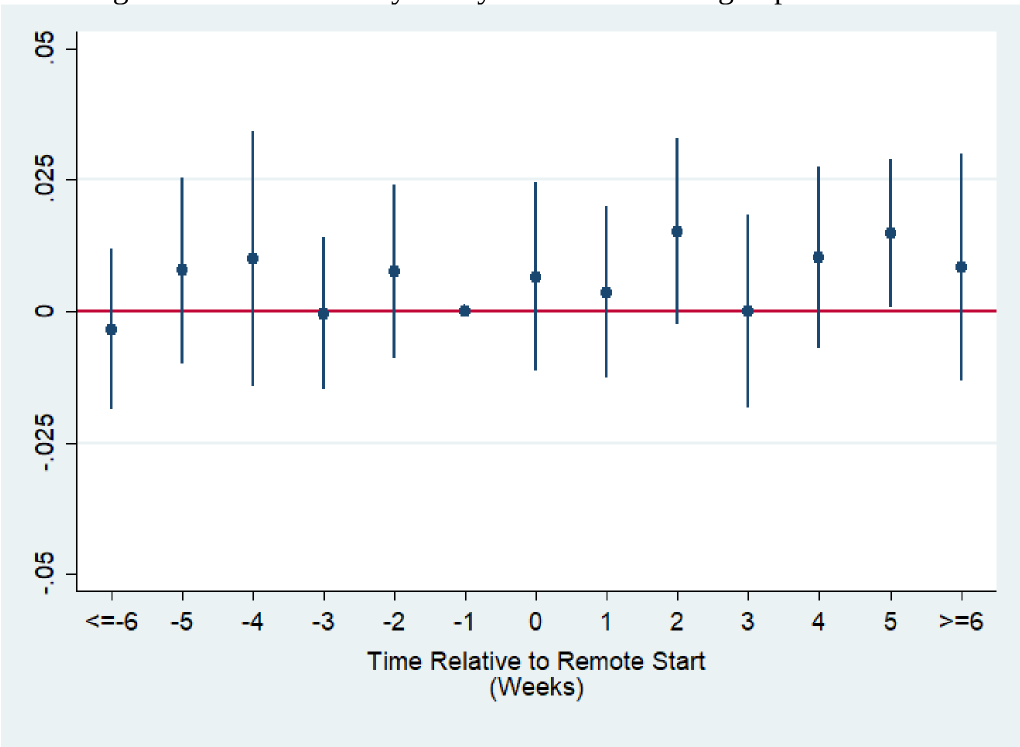
Note: Blue dots (vertical blue lines) represent the point estimates (95% confidence intervals) obtained from the regression of the production of a COVID-19-related IZA working paper on week dummies relative a country enforcing university shutdowns (Eq. (4)). The omitted category is one week before enforcement begins.

Figure 29B: Event Study Analysis – Non-COVID-19-Related IZA Working Papers



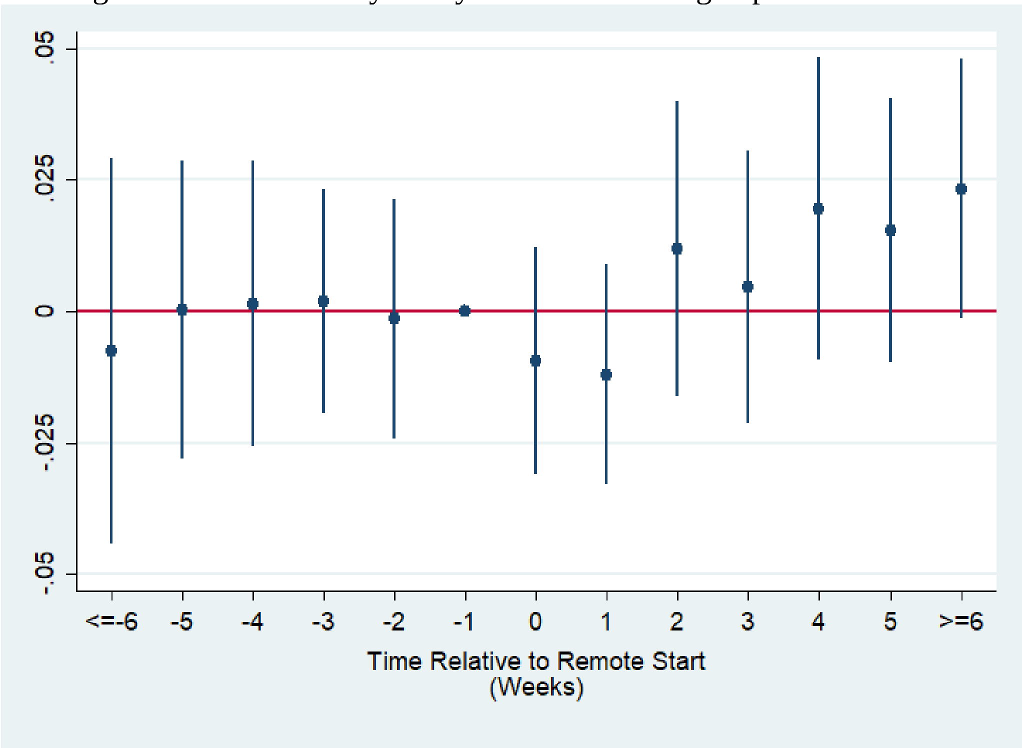
Note: Blue dots (vertical blue lines) represent the point estimates (95% confidence intervals) obtained from the regression of the production of a non-COVID-19-related IZA working paper on week dummies relative a country enforcing university shutdowns (Eq. (4)). The omitted category is one week before enforcement begins.

Figure 30A: Event Study Analysis – IZA Working Papers for Men



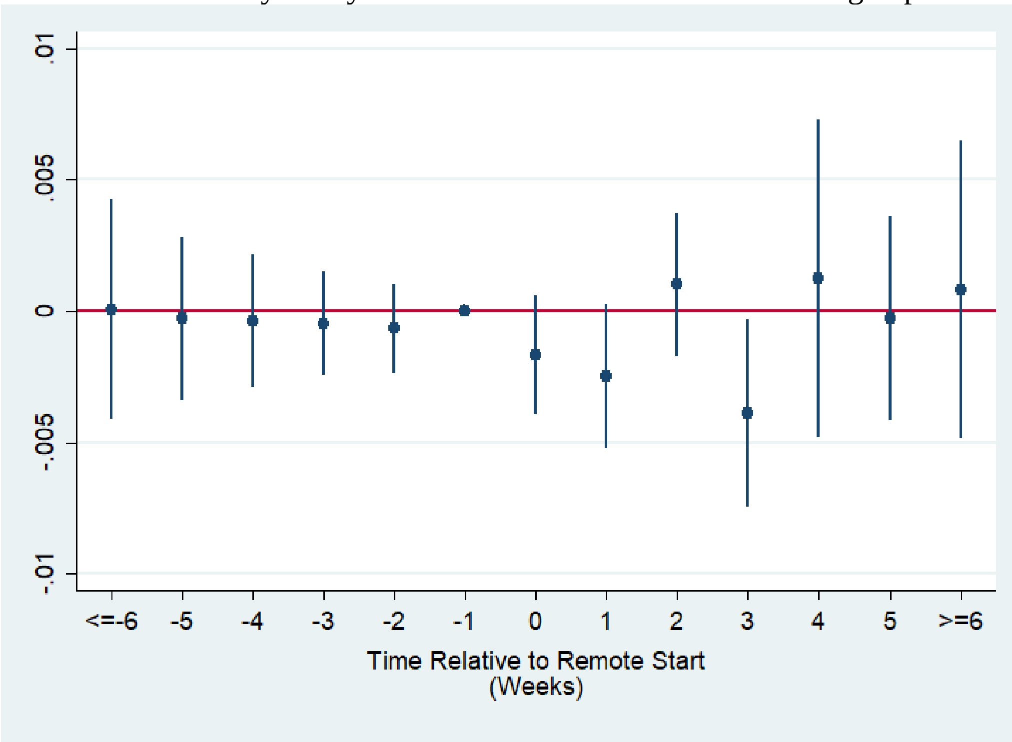
Note: Blue dots (vertical blue lines) represent the point estimates (95% confidence intervals) obtained from the regression of the production of an IZA working paper on week dummies relative a country enforcing university shutdowns for a sample of only men (Eq. (4)). The omitted category is one week before enforcement begins.

Figure 30B: Event Study Analysis – IZA Working Papers for Women



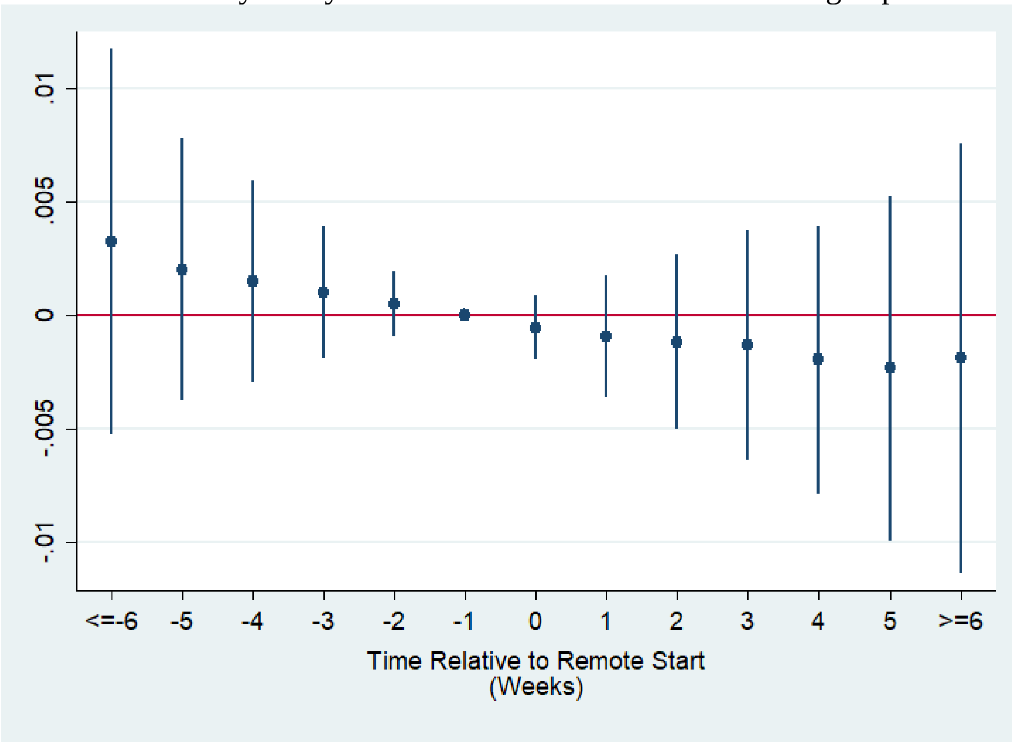
Note: Blue dots (vertical blue lines) represent the point estimates (95% confidence intervals) obtained from the regression of the production of an IZA working paper on week dummies relative a country enforcing university shutdowns for a sample of only women (Eq. (4)). The omitted category is one week before enforcement begins.

Figure 31A: Event Study Analysis – COVID-19-Related IZA Working Papers for Men



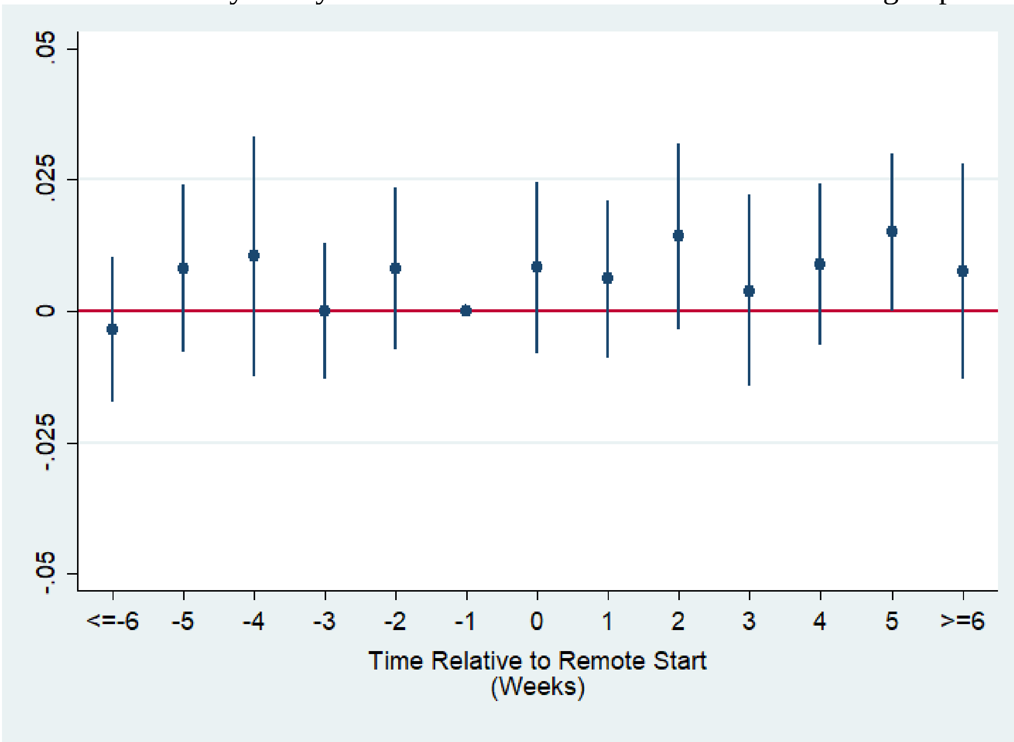
Note: Blue dots (vertical blue lines) represent the point estimates (95% confidence intervals) obtained from the regression of the production of a COVID-19-related IZA working paper on week dummies relative a country enforcing university shutdowns for a sample of only men (Eq. (4)). The omitted category is one week before enforcement begins.

Figure 31B: Event Study Analysis – COVID-19-Related IZA Working Papers for Women



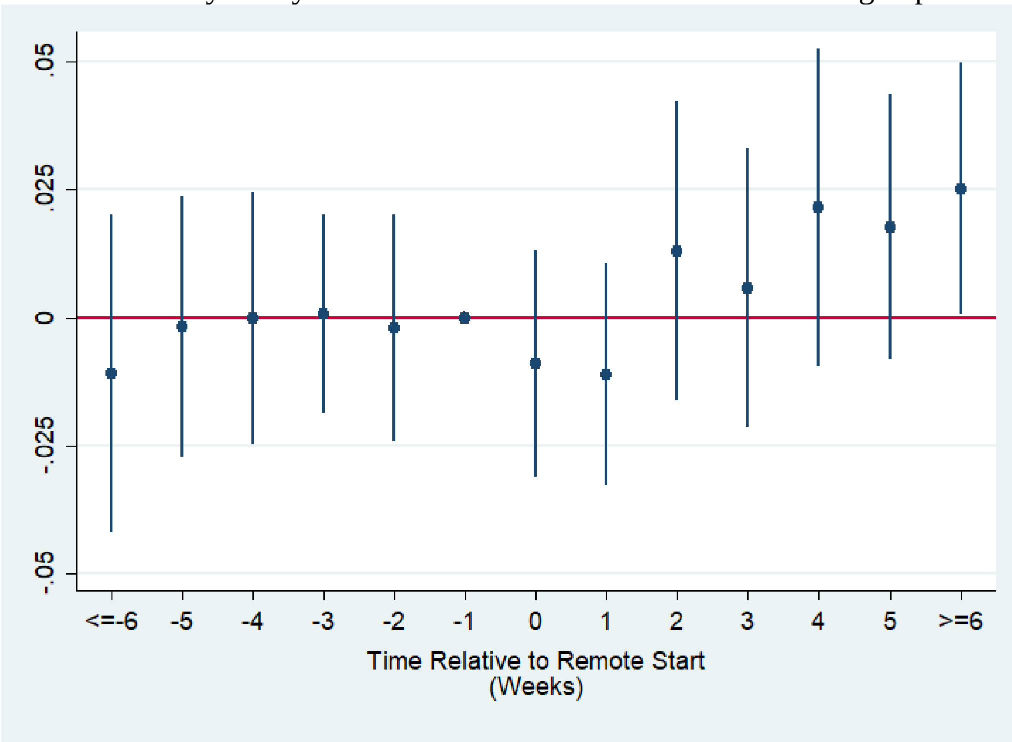
Note: Blue dots (vertical blue lines) represent the point estimates (95% confidence intervals) obtained from the regression of the production of a COVID-19-related IZA working paper on week dummies relative a country enforcing university shutdowns for a sample of only women (Eq. (4)). The omitted category is one week before enforcement begins.

Figure 32A: Event Study Analysis – Non-COVID-19-Related IZA Working Papers for Men



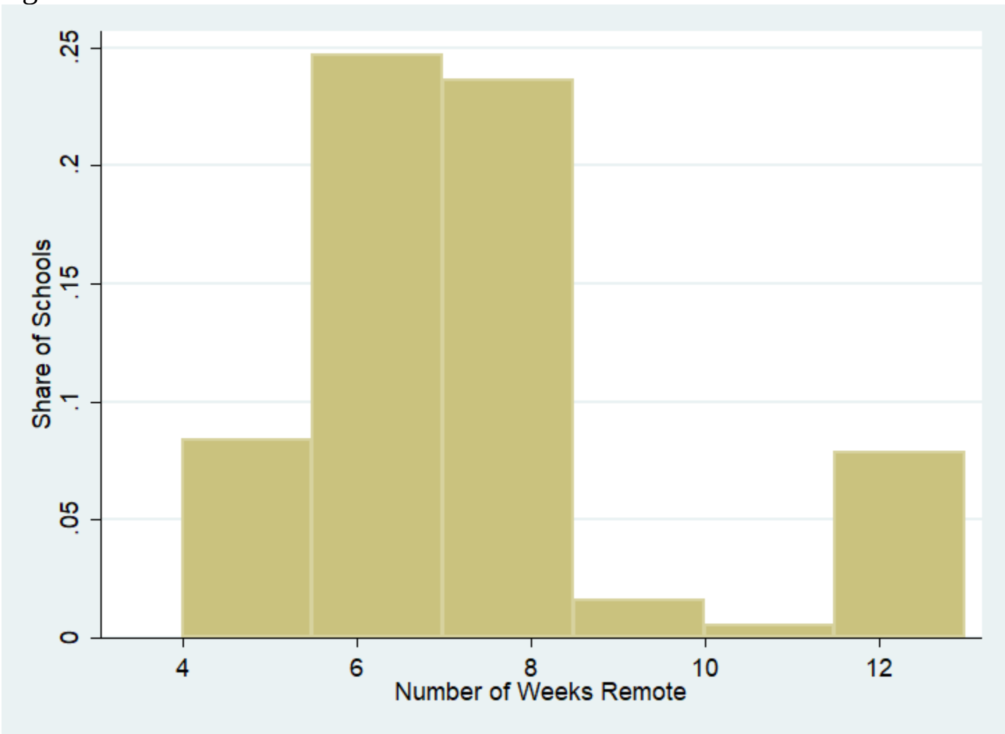
Note: Blue dots (vertical blue lines) represent the point estimates (95% confidence intervals) obtained from the regression of the production of a non-COVID-19-related IZA working paper on week dummies relative a country enforcing university shutdowns for a sample of only men (Eq. (4)). The omitted category is one week before enforcement begins.

Figure 32B: Event Study Analysis – Non-COVID-19-Related IZA Working Papers for Women



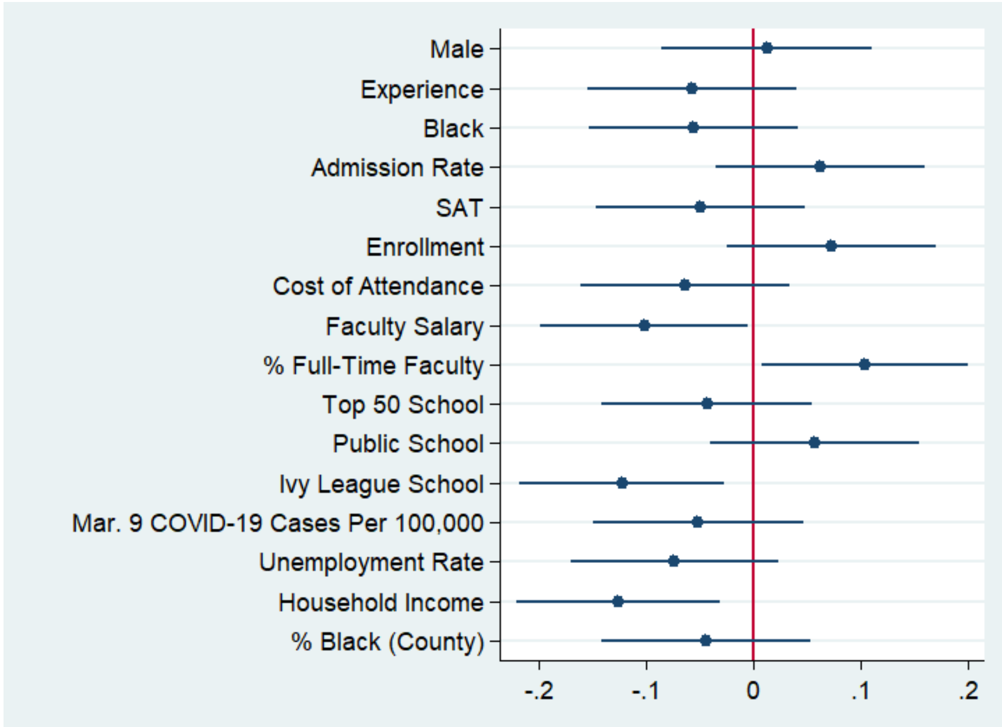
Note: Blue dots (vertical blue lines) represent the point estimates (95% confidence intervals) obtained from the regression of the production of a non-COVID-19-related IZA working paper on week dummies relative a country enforcing university shutdowns for a sample of only women (Eq. (4)). The omitted category is one week before enforcement begins.

Figure 33: Distribution of the Number of Weeks of Remote Instruction - NBER



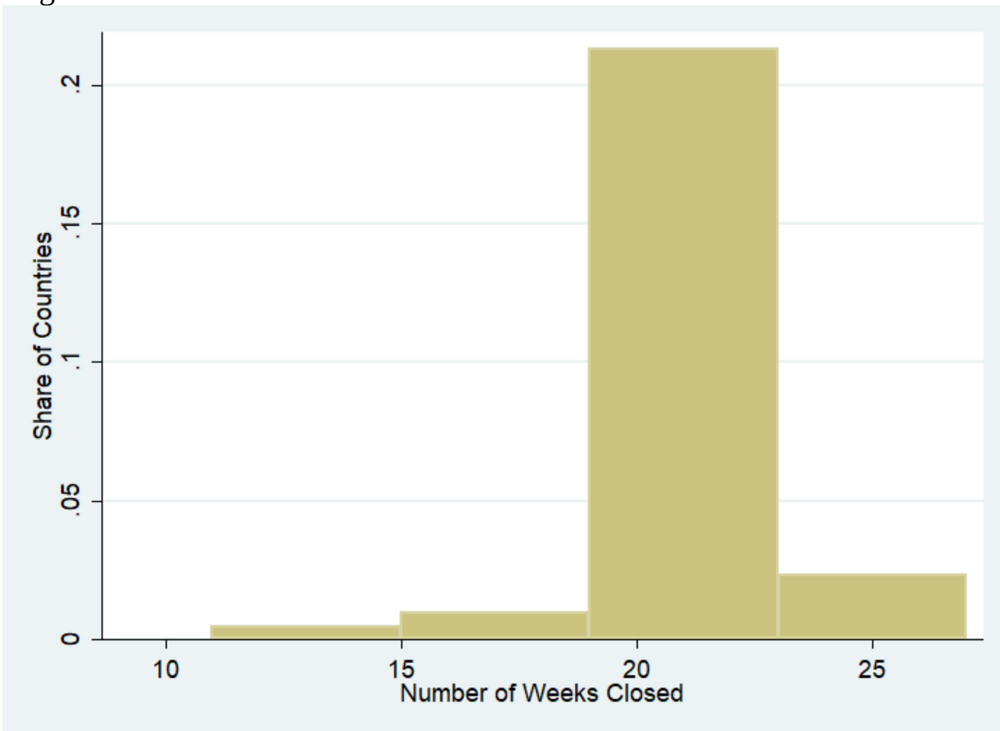
Note: The bars represent the share of the 125 schools with the corresponding number of weeks spent in remote instruction during the Spring Semester. The shortest period of remote instruction is 4 weeks, with the longest being 13 weeks. The graph shows that a majority of schools have 7-8 weeks of remote instruction.

Figure 34: The Correlation between the Number of Weeks Until the First COVID-19 Case and School Characteristics



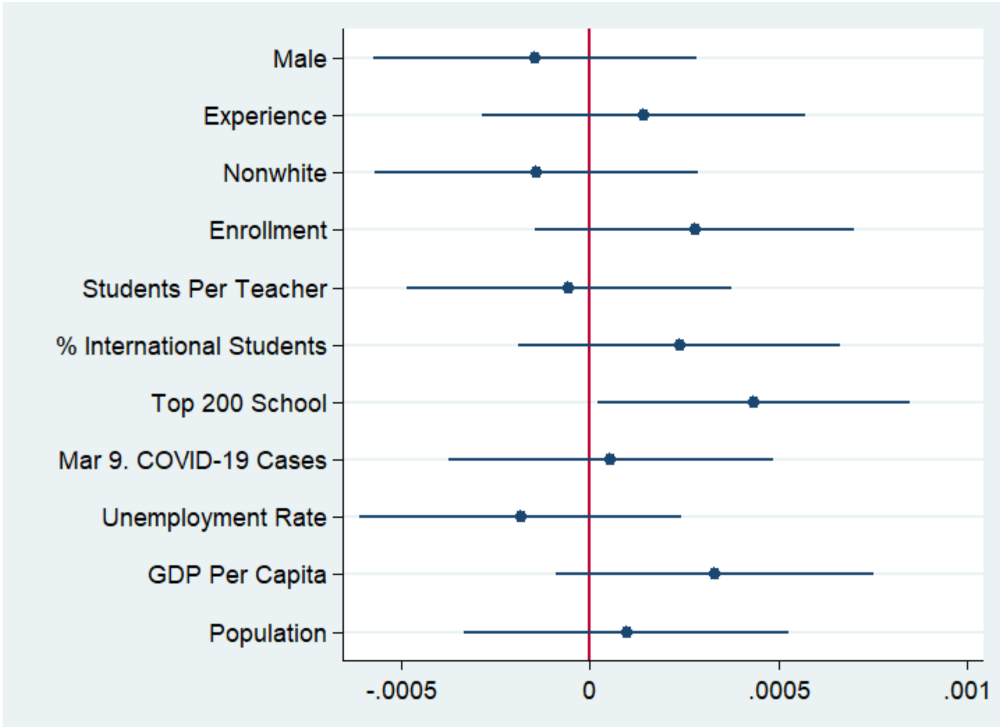
Note: Each blue dot represents point estimates from one regression with horizontal lines representing 95% confidence intervals. The unit of observation is a school. The outcomes are listed to the left of each estimate. The only control variable is the number of weeks until a school has its first COVID-19 case. Before estimating each variable is standardized with sample mean zero. The vertical red line marks zero.

Figure 35: Distribution of the Number of Weeks of Remote Instruction - IZA



Note: The bars represent the share of the 54 countries with the corresponding number of weeks spent enforcing university and college closures during the Spring Semester. The shortest period of closure is 11 weeks, with the longest being 27 weeks. The graph shows that a majority of countries have 20 weeks closed.

Figure 36: The Correlation between the Number of Weeks Until the First COVID-19 Case and School Characteristics for IZA Researchers



Note: Each blue dot represents point estimates from one regression with horizontal lines representing 95% confidence intervals. The unit of observation is a country. The outcomes are listed to the left of each estimate. The only control variable is the number of weeks until a country has over 10 per million COVID-19 cases. Before estimating each variable is standardized with sample mean zero. The vertical red line marks zero.

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Appendix 1: Chapter 1

Appendix Table 1: First Stage for Between Occupations

	(1)	(2)	(3)
	Abstract	Routine	Non-routine Manual
Abstract Instrument	0.1897***	-0.0131***	-0.0105***
	(0.0021)	(0.0018)	(0.0009)
Routine Instrument	-0.0251***	0.1923***	0.0010
	(0.0028)	(0.0031)	(0.0015)
Non-routine Manual Instrument	-0.0208***	-0.0020	0.1948***
	(0.0024)	(0.0021)	(0.0012)
F-Stat Excluded IV	1883.43***	1426.27***	8339.09***
N	22,054	22,054	22,054

Note: This table reports results for the first stage regression of the 2SLS shift-share-instrument on each task. These results are for the estimation of task intensities in column (1) of Table 4. The sample is those who are employed in time t, and under full retirement age in t+1. All regressions include state and year dummies, as well as demographic controls such as age, education level, race/ethnicity, sex, marital status, and job tenure. Robust standard errors in parentheses are clustered at the individual level. * p<0.1 ** p<0.05 *** p<0.01.

Appendix Table 2: First Stage with Occupational Fixed Effects

	(1)	(2)	(3)
	Abstract	Routine	Non-routine Manual
Abstract Instrument	0.1390***	-0.0312***	-0.0225***
	(0.0059)	(0.0054)	(0.0027)
Routine Instrument	-0.0755***	0.1066***	-0.0062**
	(0.0090)	(0.0079)	(0.0031)
Non-routine Manual Instrument	-0.0627***	0.0140*	0.1756***
	(0.0079)	(0.0073)	(0.0034)
F-Stat Excluded IV	938.01***	304.94***	2363.93***
N	22,054	22,054	22,054

Note: This table reports results for the first stage regression of the 2SLS shift-share-instrument on each task. These results are for the estimation of task intensities in column (2) of Table 4. The sample is those who are employed in time t, and under full retirement age in t+1. All regressions include state and year dummies, as well as demographic controls such as age, education level, race/ethnicity, sex, marital status, and job tenure. Robust standard errors in parentheses are clustered at the individual level. * p<0.1 ** p<0.05 *** p<0.01.

Appendix Table 3: First Stage Individual Fixed Effects

	(1)	(2)	(3)
	Abstract	Routine	Non-routine Manual
Abstract Instrument	0.1314***	-0.0317***	-0.0245***
	-0.0054	-0.0042	-0.0024
Routine Instrument	-0.0731***	0.1164***	0.0061*
	-0.0079	-0.0064	-0.0033
Non-routine Manual Instrument	-0.0549***	0.0152**	0.1624***
	-0.0077	-0.0062	-0.0033
F-Stat Excluded IV	698.24	369.47	1826.58
N	22,054	22,054	22,054

Note: This table reports results for the first stage regression of the 2SLS shift-share-instrument on each task. These results are for the estimation of task intensities in column (3) of Table 4. The sample is those who are employed in time t, and under full retirement age in t+1. All regressions include state and year dummies, as well as demographic controls such as age, education level, race/ethnicity, sex, marital status, and job tenure. Robust standard errors in parentheses are clustered at the individual level. * p<0.1 ** p<0.05 *** p<0.01.

Appendix Table 4: Health Outcomes Groups

Cancers and Tumors; Skin Conditions
Cancer--any site or type; leukemia; Hodgkin's disease; melanomas; "tumors" if specified as malignant
Tumors, cysts or growths; “polyps”
Skin conditions--any mention exc. cancer or tumor; dermatitis; eczema; "rashes"; Paget’s disease
Musculoskeletal System and Connective Tissue
Arthritis; rheumatism; bursitis
Back/neck/spine problems: chronic stiffness, deformity or pain; disc problems; scoliosis; spinal bifida; “bad back”
Stiffness, deformity, numbness or chronic pain in foot, leg, arm or hand; “bad knee”/hip problems; hip replacement
Missing legs, feet, arms, hands, or fingers (from amputation or congenital deformity)
Paralysis--any mention (incl. from polio)
Hernias; hiatal hernia
Muscular dystrophy
Other musculoskeletal or connective tissue problems; lupus; osteoporosis; pinched nerve; carpal tunnel syndrome; carpel tunnel syndrome; fibrocitis
Heart, Circulatory and Blood Conditions
Heart problems: heart attack (coronary) or failure; arteriosclerosis; aneurysms; heart deformities; angina; "bad heart"; congestive heart disease
High blood pressure (hypertension)
Stroke; cerebral hemorrhage or accident
Blood disorders: anemia; hemophilia; polycythemia; "bad blood"; toxemia
Other circulatory problems; phlebitis, clots, embolisms; varicose veins; hemorrhoids; low blood pressure
Respiratory System Conditions
Allergies; hayfever; sinusitis; tonsillitis
Asthma
Bronchitis; pneumonia; “acute upper respiratory problems”
Emphysema
Other respiratory problems; tuberculosis

Endocrine, Metabolic and Nutritional Conditions
Diabetes
Thyroid trouble; goiter
Cystic fibrosis
Nutritional problems; weight problems; eating disorders; high cholesterol
Other endocrine/metabolic problems; pancreatitis; pituitary problems; Addison’s disease
Digestive system (stomach, liver, gallbladder, kidney, bladder)
Stomach and intestinal conditions: ulcers; colitis; gastritis; diverticulosis; appendicitis; Chron's disease; "stomach pains"
Liver conditions: cirrhosis; hepatitis
Kidney conditions: kidney stones; kidney failure (incl. dialysis)
Gallbladder conditions
Bladder conditions; urinary infections
Urinary incontinence; urinary loss/leakage; problems with bladder control
Other digestive system problems
Neurological and sensory conditions
Blindness or vision problems: glaucoma; cataracts; detached retina
Deafness, hearing loss or other ear conditions
Multiple sclerosis; cerebral palsy; epilepsy; Parkinson's; ALS; "seizures"; neuropathy
Speech conditions--any mention: congenital speech defects; stuttering
Mental retardation; learning disabilities; Down syndrome
Other neurological/sensory problems; sciatica; "headaches"; "dizziness"; "blackouts"; "brain damage"-- NFS; meningitis; "memory loss"
Emotional and psychological condition
Alcoholism
Drug abuse, addiction
Other severe psychological conditions: (chronic) depression; schizophrenia; mania; paranoia; autism; psychosis
Other emotional and psychological problems; "mental problems"; "nerves"; "nervous breakdown"
Notes: https://hrs.isr.umich.edu/sites/default/files/meta/2000/core/codebook/h00_mastercode.htm

Appendix Table 5: 2SLS Results for The Effect of Tasks on Health Outcomes

	Cancers	Musculoskeletal	Heart	Respiratory
Abstract	0.0003	0.0041**	0.0001	0.0002
	(0.0004)	(0.0018)	(0.0001)	(0.0004)
Routine	0.0001	0.0001	-0.0002	-0.0004
	(0.0007)	(0.0028)	(0.0001)	(0.0007)
Non-routine Manual	0.0001	-0.0008	0.0001	-0.0001
	(0.0005)	(0.0028)	(0.0002)	(0.0007)
N	22,054	22,054	22,054	22,054

	Digestive	Neurological	Emotional	Endocrine
Abstract	0.0003	-0.0005	-0.0001	-0.0003
	(0.0004)	(0.0004)	(0.0004)	(0.0006)
Routine	0.0009	-0.0004	0.0003	0.0006
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Non-routine Manual	0.0001	-0.001	0.0006	-0.0011
	(0.0006)	(0.0006)	(0.0007)	(0.0007)
N	22,054	22,054	22,054	22,054

Note: This table reports results for the health disability outcomes, it takes a value of 1 when individuals state that they have a given work limiting health disability. in t+1, and 0 otherwise. The sample is those who are employed in time t, and under full retirement age in t+1. All regressions include individual, occupation, state, and year dummies, as well as demographic controls such as age, education level, race/ethnicity, sex, marital status, and job tenure. Robust standard errors in parentheses are clustered on individual. * p<0.1 ** p<0.05 *** p<0.01.

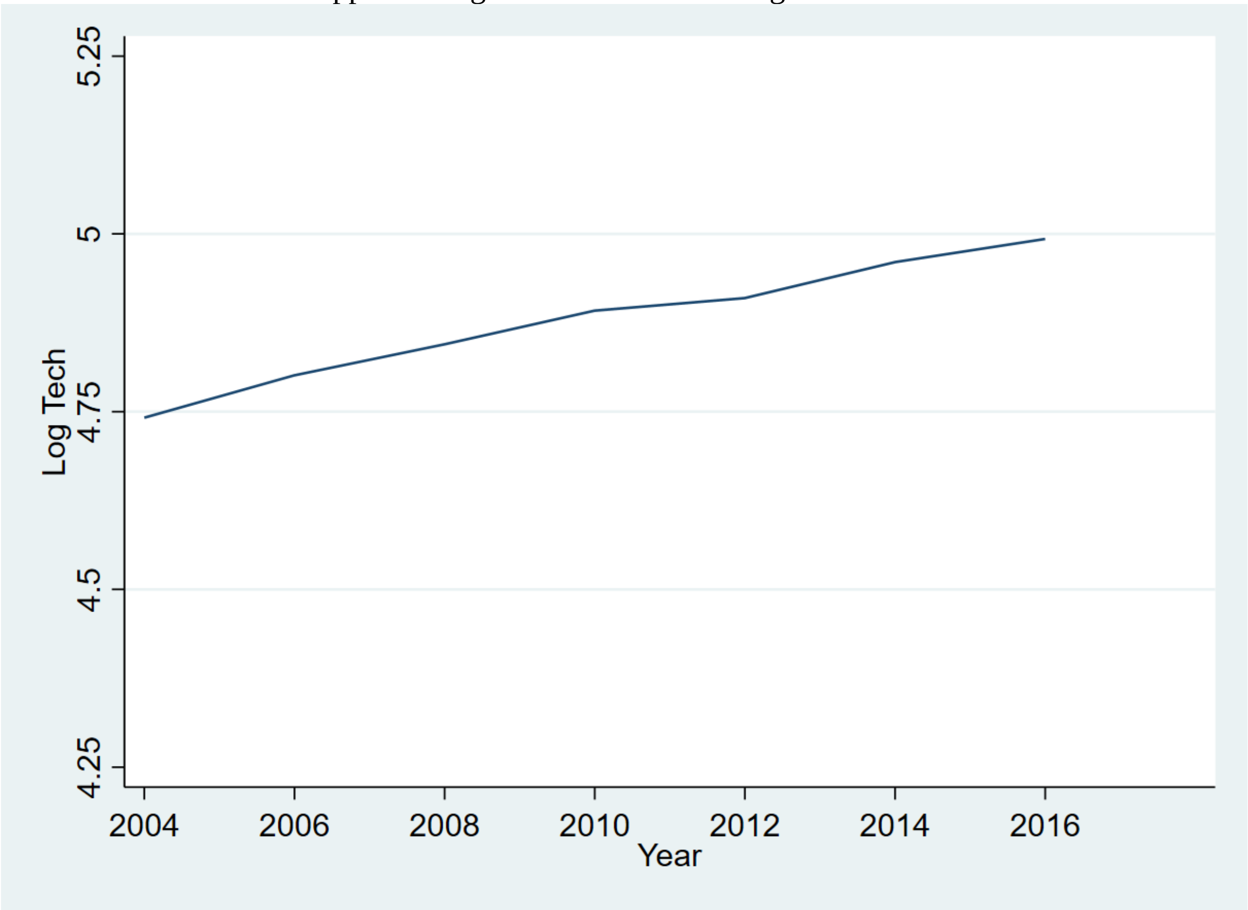
Appendix Table 6: 2SLS Results for The Effect of Tasks on Health Outcomes

	Cancer	Tumors	Skin Conditions	Arthritis	Back Problems	Other Musculoskeletal	Heart Problems
Abstract	0.0003	0.0001	-0.0001	-0.0003	0.0009	0.0042***	0.0002
	(0.0003)	(0.0001)	(0.0001)	(0.001)	(0.0012)	(0.0014)	(0.0004)
Routine	0.0004	0.0000	-0.0003	0.0009	0.0019	-0.0001	0.0004
	(0.0006)	(0.0001)	(0.0002)	(0.0016)	(0.0020)	(0.002)	(0.0007)
Non-routine Manual	-0.0001	0.0002	-0.0001	0.0001	-0.0008	-0.0002	-0.0003
	(0.0004)	(0.0002)	(0.0001)	(0.0014)	(0.002)	(0.002)	(0.0006)
N	22,054	22,054	22,054	22,054	22,054	22,054	22,054

	Blood Disorder	Hypertension	Stroke	Allergies	Asthma	Bronchitis	Emphysema
Abstract	-0.0001	0.0003	-0.0001	0.0001	0.0001	-0.0001	0.0002
	(0.0001)	(0.0002)	(0.0003)	(0.0000)	(0.0003)	(0.0001)	(0.0003)
Routine	-0.0001	-0.0001	-0.0002	0.0001	0.0000	-0.0001	-0.0006
	(0.0002)	(0.0003)	(0.0004)	(0.0001)	(0.0005)	(0.0000)	(0.0005)
Non-routine Manual	0.0001	0.0002	0.0003	-0.0000	-0.0001	0.0002	-0.0001
	(0.0002)	(0.0005)	(0.0005)	(0.0001)	(0.0005)	(0.0001)	(0.0004)
N	22,054	22,054	22,054	22,054	22,054	22,054	22,054

Note: This table reports results for the health disability outcomes, it takes a value of 1 when individuals state that they have a given work limiting health disability. in t+1, and 0 otherwise. The sample is those who are employed in time t, and under full retirement age in t+1. All regressions include individual, occupation, state, and year dummies, as well as demographic controls such as age, education level, race/ethnicity, sex, marital status, and job tenure. Robust standard errors in parentheses are clustered on individual. * p<0.1 ** p<0.05 *** p<0.01.

Appendix Figure 1: Technical Change over Time



Note: The above graph shows the yearly change in technology adoption over time for an occupation that at least one individual in the Health and Retirement Study survey in currently employed.

Appendix 2: Chapter 2

Table A1
Between-Occupation Changes in Task Intensity Over Time by Age Group, Race/Ethnicity, and Gender

	Men												Women											
	White			Black			Asian			Hispanic			White			Black			Asian			Hispanic		
	2005	2019	Δ	2005	2019	Δ	2005	2019	Δ	2005	2019	Δ	2005	2019	Δ	2005	2019	Δ	2005	2019	Δ	2005	2019	Δ
16-24																								
NR COGA	17	18	1	12	8	-4	13	14	1	14	12	-2	11	9	-2	13	9	-4	14	9	-5	14	8	-6
NR COGI	14	15	1	8	6	-2	8	14	6	14	9	-5	16	12	-4	11	9	-2	17	11	-6	12	9	-3
R COG	43	54	11	56	55	-1	58	70	12	51	56	5	52	13	-39	62	23	-39	78	43	-35	66	33	-33
R MAN	93	95	2	92	91	-1	63	70	7	97	95	-2	35	47	12	38	45	7	26	34	8	47	49	2
NR PHYS	90	94	4	85	86	1	60	69	9	96	95	-1	46	51	5	46	47	1	28	44	16	43	49	6
25-34																								
NR COGA	87	80	-8	43	34	-10	98	97	-1	34	41	7	87	79	-8	61	39	-23	98	99	1	30	38	8
NR COGI	80	75	-5	35	33	-2	79	82	3	36	41	5	82	84	3	44	42	-2	89	96	7	28	40	13
R COG	33	38	5	59	71	12	58	72	14	42	50	8	77	59	-18	85	78	-7	94	93	-1	67	75	8
R MAN	66	64	-2	74	78	5	42	37	-5	93	83	-10	12	14	3	23	31	9	23	15	-8	40	31	-9
NR PHYS	68	67	-1	74	76	3	45	40	-6	93	85	-8	12	20	8	15	35	20	7	6	-1	26	29	3
35-44																								
NR COGA	91	91	0	51	57	6	95	99	4	40	50	10	84	85	1	59	59	0	95	96	1	22	27	5
NR COGI	93	92	-2	47	48	1	88	99	11	49	57	8	84	90	7	50	60	10	74	94	20	23	30	8
R COG	25	23	-2	53	62	9	39	45	7	31	30	-1	82	67	-16	83	81	-3	92	84	-8	50	54	4
R MAN	63	57	-6	77	73	-4	45	33	-12	90	88	-2	18	8	-10	27	24	-3	37	14	-23	53	39	-14
NR PHYS	65	60	-5	78	74	-4	53	39	-14	89	89	0	14	12	-3	26	22	-4	23	7	-16	41	31	-10
45-54																								
NR COGA	87	89	2	47	49	2	74	93	19	43	46	3	84	79	-5	54	58	4	76	80	4	21	20	-2
NR COGI	91	92	1	44	49	6	73	88	15	46	54	8	86	79	-7	50	54	5	65	75	10	22	22	-1
R COG	21	16	-5	47	48	1	38	42	4	33	23	-10	88	84	-4	74	78	4	87	84	-3	45	36	-10
R MAN	61	58	-3	80	75	-6	58	52	-6	88	87	-1	18	9	-9	31	22	-9	47	26	-21	50	50	0
NR PHYS	63	63	-1	82	79	-3	58	50	-8	87	90	4	16	9	-8	30	22	-8	39	23	-16	39	37	-2
55-67																								
NR COGA	83	85	2	43	42	-1	66	68	2	34	36	2	65	70	5	31	38	7	68	53	-15	14	15	1
NR COGI	89	82	-7	38	34	-4	59	64	5	40	36	-4	67	71	4	35	36	1	60	48	-12	14	16	2
R COG	13	10	-3	46	48	2	31	35	4	16	23	7	81	91	10	56	72	16	76	74	-2	21	25	4
R MAN	39	54	15	76	77	1	56	64	8	83	86	3	13	11	-2	28	21	-7	45	27	-18	46	43	-3
NR PHYS	54	60	6	82	84	2	55	63	8	82	88	6	9	9	0	35	23	-12	38	24	-14	35	33	-2

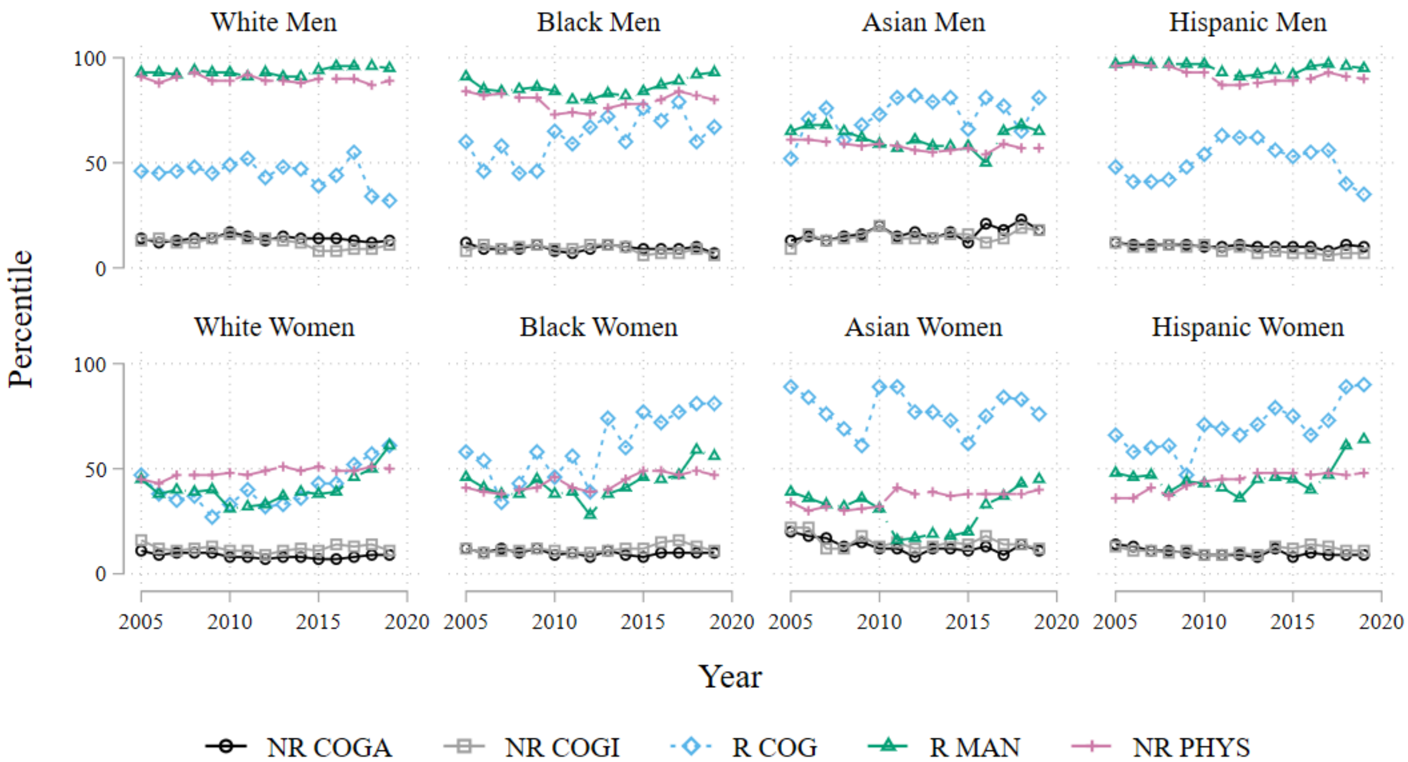
Note: The table presents the median task intensity percentile for each race/ethnicity-gender group from five age ranges (16-24, 25-34, 35-44, 45-54, and 55-67) in 2005 and 2019 as well as the change between the two years. Computing the median task intensity percentiles requires several steps. Using the individual-level ACS-O*NET linked data, we compute employment-weighted means of the task intensity measures for each age-race/ethnicity-gender group in each of the two years. However, the task intensities are not allowed to vary within occupations in these calculations. Instead, we use the values from a base year and assign those to all years. In our case, the base year is 2005. The resulting data set consists of 832 age-race/ethnicity-gender-year observations (=52 age groups × 4 racial/ethnic groups × 2 genders × 2 years). Following these calculations, we then rank and assign the task intensities to percentiles (1—99) for each year. Within each of the five age groupings, we then compute the median task intensity percentiles for each race/ethnicity-gender group in each year.

Table A2
Within and Between Changes in Task Intensity Over Time
by Age Group, Race/Ethnicity, and Gender

	Men												Women											
	White			Black			Asian			Hispanic			White			Black			Asian			Hispanic		
	WI	BW	T	WI	BW	T	WI	BW	T	WI	BW	T	WI	BW	T	WI	BW	T	WI	BW	T	WI	BW	T
16-24																								
NR COGA	-4	1	-3	-1	-4	-5	-1	1	0	-1	-2	-3	-1	-2	-3	0	-4	-4	0	-5	-5	0	-6	-6
NR COGI	-3	1	-2	1	-2	-1	2	6	8	-1	-5	-6	0	-4	-4	3	-2	1	0	-6	-6	2	-3	-1
R COG	-13	11	-2	8	-1	7	13	12	25	-7	5	-2	49	-39	10	59	-39	20	30	-35	-5	51	-33	18
R MAN	-1	2	1	1	-1	0	5	7	12	-1	-2	-3	12	12	24	10	7	17	12	8	20	12	2	14
NR PHYS	-5	4	-1	-5	1	-4	-9	9	0	-4	-1	-5	0	5	5	-1	1	0	-5	16	11	0	6	6
25-34																								
NR COGA	-3	-8	-10	-3	-10	-13	1	-1	1	-2	7	5	-3	-8	-11	-1	-23	-24	-2	1	-1	5	8	13
NR COGI	1	-5	-5	-6	-2	-8	1	3	4	-11	5	-6	-4	3	-1	3	-2	2	-4	7	3	7	13	20
R COG	-22	5	-17	-20	12	-8	-34	14	-20	-20	8	-12	-10	-18	-28	7	-7	0	-29	-1	-30	3	8	10
R MAN	-6	-2	-7	-4	5	1	-22	-5	-26	-1	-10	-11	2	3	5	3	9	11	-13	-8	-20	3	-9	-6
NR PHYS	2	-1	1	-4	3	-1	-10	-6	-16	-1	-8	-9	1	8	8	-2	20	19	-4	-1	-5	1	3	4
35-44																								
NR COGA	-2	0	-2	-5	6	1	0	4	4	-3	10	8	-2	1	-2	-1	0	-1	0	1	1	9	5	14
NR COGI	0	-2	-2	-10	1	-9	-3	11	8	-13	8	-5	-3	7	4	5	10	15	-3	20	18	9	8	17
R COG	-14	-2	-16	-21	9	-12	-22	7	-16	-14	-1	-15	-13	-16	-29	5	-3	3	-28	-8	-36	13	4	17
R MAN	-9	-6	-15	-2	-4	-6	-23	-12	-35	-1	-2	-3	-1	-10	-11	0	-3	-3	-11	-23	-34	5	-14	-9
NR PHYS	3	-5	-2	-1	-4	-5	-4	-14	-18	1	0	1	1	-3	-2	-2	-4	-5	-3	-16	-19	6	-10	-4
45-54																								
NR COGA	-1	2	1	-3	2	-1	0	19	19	0	3	3	-3	-5	-8	2	4	6	0	4	4	7	-2	5
NR COGI	-1	1	1	-6	6	0	-4	15	12	-12	8	-4	-3	-7	-10	7	5	12	0	10	10	9	-1	9
R COG	-8	-5	-13	-15	1	-14	-14	4	-10	-8	-10	-17	-16	-4	-20	10	4	14	-15	-3	-18	23	-10	13
R MAN	-8	-3	-11	-2	-6	-8	-17	-6	-22	1	-1	-1	1	-9	-8	4	-9	-6	-5	-21	-25	9	0	9
NR PHYS	2	-1	1	-2	-3	-5	1	-8	-7	2	4	5	1	-8	-7	-3	-8	-11	-5	-16	-21	6	-2	4
55-67																								
NR COGA	-1	2	1	-8	-1	-9	0	2	2	-3	2	-1	0	5	5	1	7	8	4	-15	-11	4	1	5
NR COGI	4	-7	-3	-7	-4	-11	-7	5	-2	-4	-4	-8	-2	4	2	6	1	7	8	-12	-4	5	2	7
R COG	-5	-3	-8	-9	2	-7	0	4	4	-2	7	5	-11	10	-1	13	16	29	5	-2	3	32	4	36
R MAN	-1	15	14	-1	1	0	-12	8	-4	-2	3	1	4	-2	2	10	-7	3	3	-18	-15	9	-3	6
NR PHYS	7	6	13	-6	2	-4	-5	8	3	0	6	6	2	0	2	0	-12	-12	2	-14	-12	7	-2	5

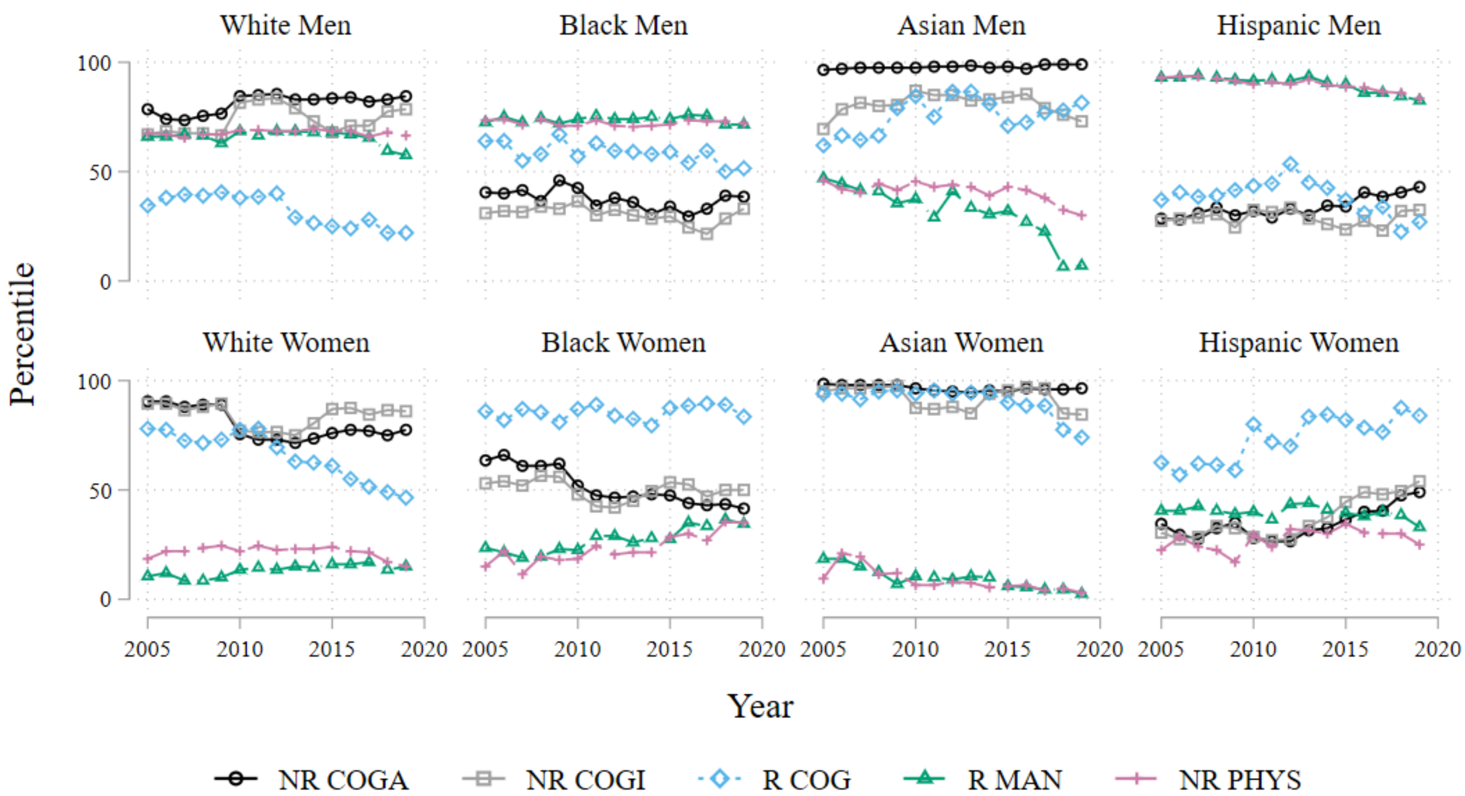
Note: This table decomposes the overall task intensity changes between 2005 and 2019 into “within” and “between” components. The former captures how the occupations themselves have changed over time, and the latter measures changes in task intensities due to workers moving from one occupation to another between the two years. The column headings “WI”, “BW”, and “T” indicate denote the within change, the between change, and the overall or total change. The statistics presented under the “BW” heading are the changes from Appendix Table A1, and those presented under the “T” heading are the changes from Table 2. The “WI” component is computed by subtracting the change in Appendix Table A1 from the change in Table 2. Netting out the between-occupation change leaves the within-occupation change, which is presented under the “WI” heading.

Appendix Figure 1: Changes in Task Intensity Within and Between Occupations Over Time by Race/Ethncitiy, and Gender for 18-24 Year-Olds



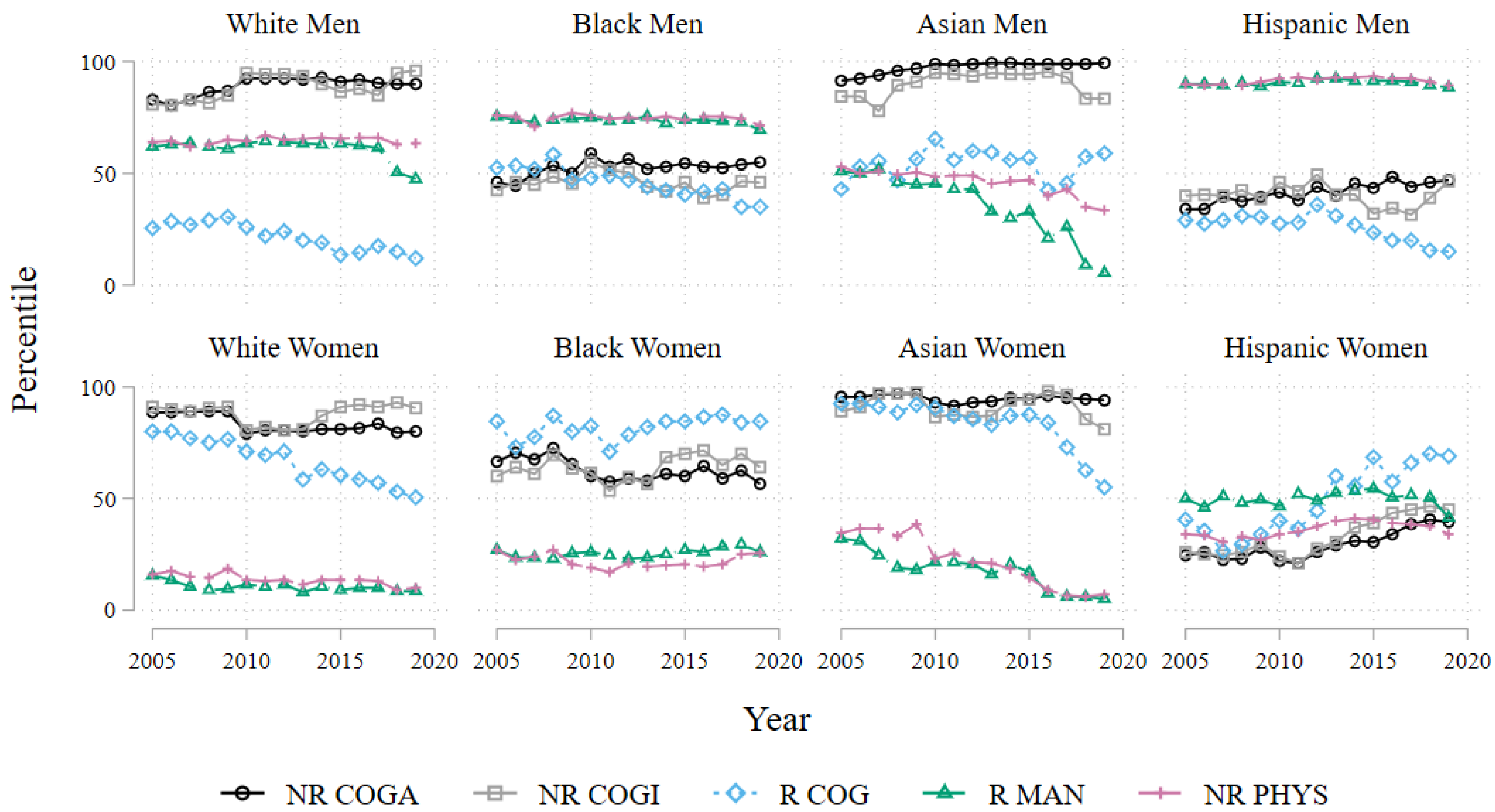
Note: The figure presents time plots from 2005-2019 of the median task intensity percentiles for each race/ethnicity-gender group for 16-24 year-olds. Computing the median task intensity percentiles requires several steps. Using the individual-level ACS-O*NET linked data, we compute employment-weighted means of the task intensity measures for each age-race/ethnicity-gender group in each of the two years. The resulting data set consists of 832 age-race/ethnicity-gender-year observations (=52 age groups × 4 racial/ethnic groups × 2 genders × 2 years). Following these calculations, we then rank and assign the task intensities to percentiles (1—99) for each year. With the 16-24 year-old age group, we then compute the median task intensity percentiles assigned to each race/ethnicity-gender group in each year.

Appendix Figure 2: Changes in Task Intensity Within and Between Occupations Over Time by Race/Ethncitiy, and Gender for 25-34 Year-Olds



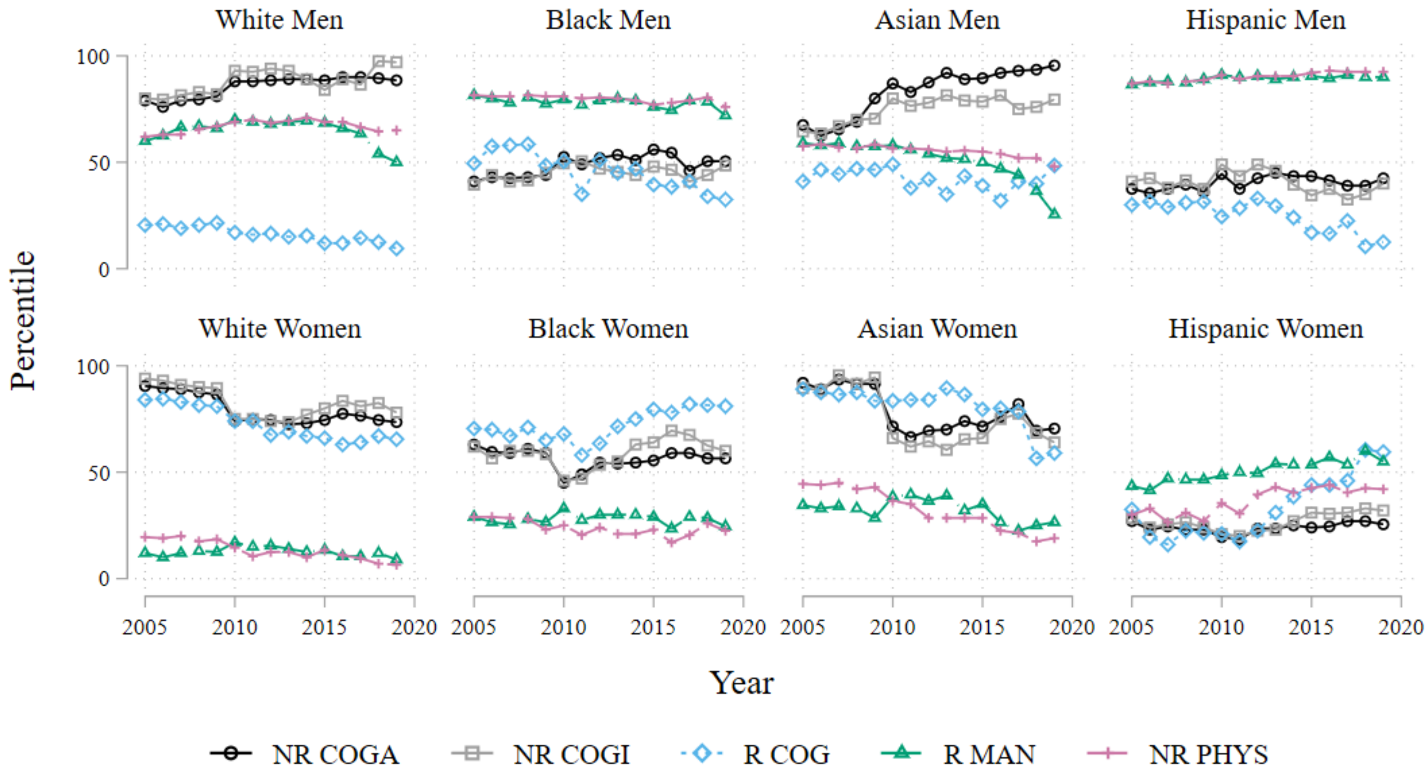
Note: The figure presents time plots from 2005-2019 of the median task intensity percentiles for each race/ethnicity-gender group for 25-34 year-olds. Computing the median task intensity percentiles requires several steps. Using the individual-level ACS-O*NET linked data, we compute employment-weighted means of the task intensity measures for each age-race/ethnicity-gender group in each of the two years. The resulting data set consists of 832 age-race/ethnicity-gender-year observations (=52 age groups × 4 racial/ethnic groups × 2 genders × 2 years). Following these calculations, we then rank and assign the task intensities to percentiles (1—99) for each year. Within the 25-34 year-old age group, we then compute the median task intensity percentiles assigned to each race/ethnicity-gender group in each year.

Appendix Figure 3: Changes in Task Intensity Within and Between Occupations Over Time by Race/Ethncitiy, and Gender for 35-44 Year-Olds



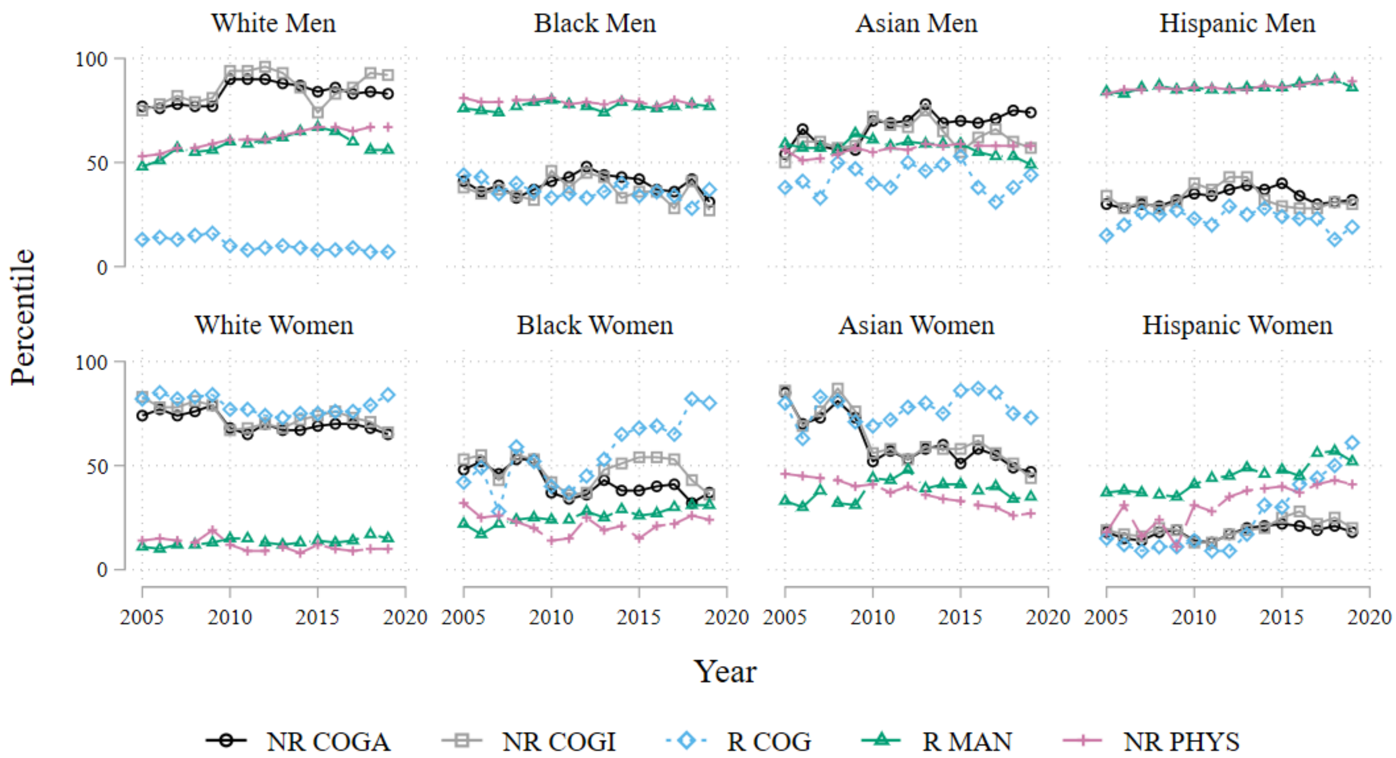
Note: The figure presents time plots from 2005-2019 of the median task intensity percentiles for each race/ethnicity-gender group for 35-44 year-olds. Computing the median task intensity percentiles requires several steps. Using the individual-level ACS-O*NET linked data, we compute employment-weighted means of the task intensity measures for each age-race/ethnicity-gender group in each of the two years. The resulting data set consists of 832 age-race/ethnicity-gender-year observations (=52 age groups × 4 racial/ethnic groups × 2 genders × 2 years). Following these calculations, we then rank and assign the task intensities to percentiles (1—99) for each year. Within the 35-44 year-old age group, we then compute the median task intensity percentiles assigned to each race/ethnicity-gender group in each year.

Appendix Figure 4: Changes in Task Intensity Within and Between Occupations Over Time by Race/Ethncitiy, and Gender for 45-54 Year-Olds



Note: The figure presents time plots from 2005-2019 of the median task intensity percentiles for each race/ethnicity-gender group for 45-54 year-olds. Computing the median task intensity percentiles requires several steps. Using the individual-level ACS-O*NET linked data, we compute employment-weighted means of the task intensity measures for each age-race/ethnicity-gender group in each of the two years. The resulting data set consists of 832 age-race/ethnicity-gender-year observations (=52 age groups × 4 racial/ethnic groups × 2 genders × 2 years). Following these calculations, we then rank and assign the task intensities to percentiles (1—99) for each year. Within the 45-54 year-old age group, we then compute the median task intensity percentiles assigned to each race/ethnicity-gender group in each year.

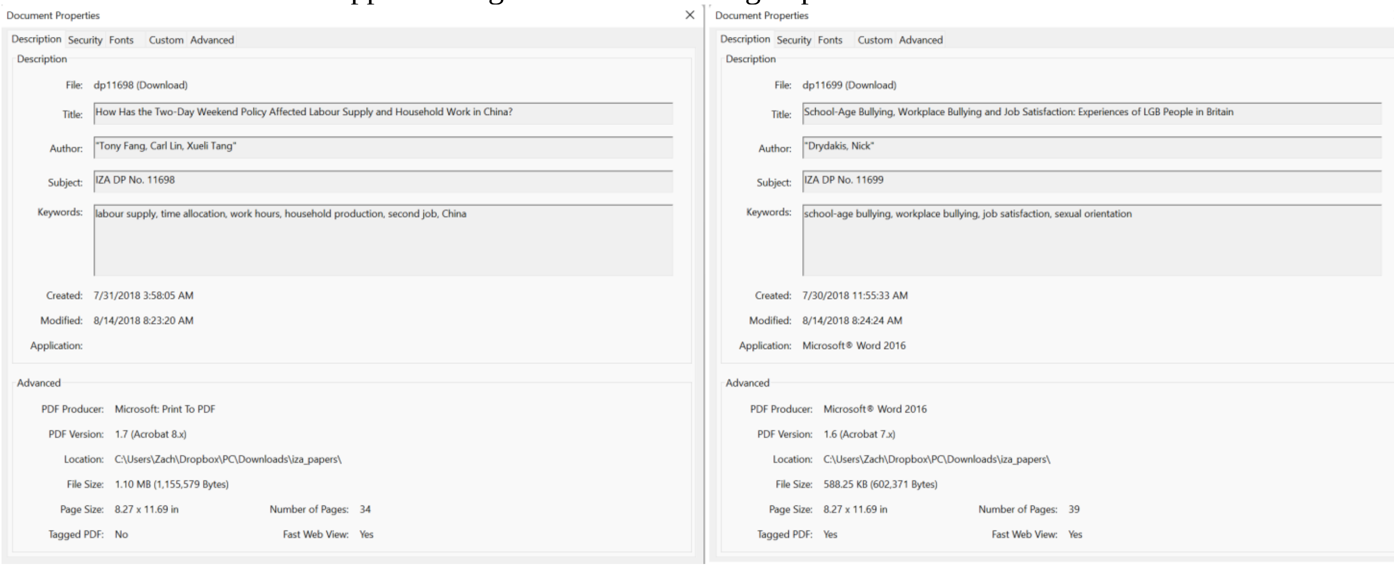
Appendix Figure 5: Changes in Task Intensity Within and Between Occupations Over Time by Race/Ethncitiy, and Gender for 55-67 Year-Olds



Note: The figure presents time plots from 2005-2019 of the median task intensity percentiles for each race/ethnicity-gender group for 55-67 year-olds. Computing the median task intensity percentiles requires several steps. Using the individual-level ACS-O*NET linked data, we compute employment-weighted means of the task intensity measures for each age-race/ethnicity-gender group in each of the two years. The resulting data set consists of 832 age-race/ethnicity-gender-year observations (=52 age groups × 4 racial/ethnic groups × 2 genders × 2 years). Following these calculations, we then rank and assign the task intensities to percentiles (1—99) for each year. Within the 55-67 year-old age group, we then compute the median task intensity percentiles assigned to each race/ethnicity-gender group in each year.

Appendix 3: Chapter 3

Appendix Figure 1: IZA Working Paper Dates



Note: The creation and modified dates can be found in the document properties of PDF files. Above are consecutive papers in the IZA discussion paper series, paper 11698 and 11699. Papers modified dates are similar within two minutes of each other, but paper creation dates significantly differ in comparison.

Appendix Table 2A: Coefficients Presented in Figure 13A

	(1)	(2)	(3)
	Male	Experience	Black
Early Switcher	-0.03	0.86	-0.01
	(0.06)	(1.59)	(0.01)
Late Switcher	-0.12	3.00	0.01
	(0.08)	(2.11)	(0.01)
N	127	127	127

Note: The unit of observation is a school. The only control variables are indicators for whether a school switched to remote instruction earlier or later than the week of March 23rd, 2020. The omitted category is the schools that moved to remote instruction in the week of March 23rd.

Appendix Table 2B: Coefficients Presented in Figure 13B

	(4)	(5)	(6)	(7)
	Admission Rate	SAT	Enrollment	Cost of Attendance
Early Switcher	-0.02	7.29	2642.77	-2443.31
	(0.05)	(23.46)	(2228.90)	(4155.55)
Late Switcher	-0.03	-10.62	-612.23	-3085.60
	(0.07)	(31.22)	(2966.10)	(5529.99)
N	127	127	127	127

	(8)	(9)	(10)	(11)	(12)
	Faculty Salary	% Full-Time Faculty	Public School	Ivy League School	Top 50 School
Early Switcher	702.23	-0.02	0.09	-0.02	0.06
	(553.78)	(0.03)	(0.10)	(0.05)	(0.10)
Late Switcher	2.55	0.01	0.07	0.02	-0.12
	(736.94)	(0.04)	(0.13)	(0.07)	(0.13)
N	127	127	127	127	127

See notes to Appendix Table 2A.

Appendix Table 2C: Coefficients Presented in Figure 13C

	(13)	(14)	(15)	(16)
	COVID-19 Cases per 100,000 (March 9)	Unemployment Rate	Household Income	% Black
Early Switcher	0.00**	0.12	4507.21	-0.04
	(0.00)	(0.16)	(3628.73)	(0.03)
Late Switcher	0.00	0.18	2492.82	0.04
	(0.00)	(0.22)	(4828.93)	(0.04)
N	127	127	127	127

See notes to Appendix Table 2A.

Appendix Table 3A: Coefficients Presented in Figure 16A

	(1)	(2)	(3)
	Male	Experience	Nonwhite
Early Switcher	0.01	-0.69	0.27**
	(0.07)	(1.92)	(0.12)
Late Switcher	0.03	-2.16	0.19
	(0.09)	(2.36)	(0.14)
N	54	54	54

Note: The unit of observation is a country. The only control variables are indicators for whether a country enforced closure earlier or later than the week of March 16th, 2020. The omitted category is the schools that moved to remote instruction in the week of March 16th.

Appendix Table 3B: Coefficients Presented in Figure 16B

	(4)	(5)	(6)	(7)
	Enrollment	Students Per Teacher	% International Students	Top 200 School
Early Switcher	2093.42	2.14	-0.01	0.13
	(2246.24)	(2.11)	(0.02)	(0.09)
Late Switcher	3510.72	-0.34	0.06*	0.44***
	(2752.20)	(2.58)	(0.03)	(0.11)
N	54	54	54	54

See notes to Appendix Table 3A.

Appendix Table 3C: Coefficients Presented in Figure 16C

	(8)	(9)	(10)	(11)
	COVID-19 Cases per Million (March 9)	Unemployment Rate	GDP Per Capita	Population
Early Switcher	-1.48	1.14	-2.61	2795.28***
	(19.29)	(1.42)	(7.27)	(924.31)
Late Switcher	-19.82	1.41	2.25	41.26
	(23.63)	(1.74)	(8.91)	(1132.52)
N	54	54	54	54

See notes to Appendix Table 3A.

Appendix Table 4: Detailed Coefficients Presented in Figure 23 and 24

	All Papers	COVID-19-Related	Non-COVID-19-Related
	(1)	(2)	(3)
6 Weeks or More before Switch	-0.025	-0.002	-0.022
	(0.017)	(0.005)	(0.015)
5 Weeks before Switch	-0.021*	-0.001	-0.019*
	(0.013)	(0.004)	(0.011)
4 Weeks before Switch	-0.018*	-0.001	-0.017*
	(0.010)	(0.003)	(0.009)
3 Weeks before Switch	-0.017**	-0.000	-0.017**
	(0.007)	(0.002)	(0.007)
2 Weeks before Switch	-0.007	0.001	-0.008
	(0.006)	(0.002)	(0.006)
Week of Switch	0.027***	0.004*	0.023***
	(0.009)	(0.002)	(0.008)
1 Week after Switch	0.020**	0.002	0.018*
	(0.009)	(0.004)	(0.009)
2 Week after Switch	0.008	-0.001	0.009
	(0.011)	(0.005)	(0.011)
3 Week after Switch	0.007	0.002	0.005
	(0.013)	(0.008)	(0.013)
4 Week after Switch	0.001	-0.002	0.003
	(0.013)	(0.007)	(0.015)
5 Week after Switch	0.000	-0.003	0.004
	(0.015)	(0.006)	(0.015)
6 or More Weeks after Switch	0.005	-0.004	0.010
	(0.016)	(0.007)	(0.017)
Total COVID Cases in County Per 100,000	0.012**	0.005*	0.007***
	(0.005)	(0.003)	(0.002)
University Closed In-Person	-0.014*	-0.003	-0.012*
	(0.007)	(0.002)	(0.007)
Week of Spring Break	0.007	0.002	0.005
	(0.007)	(0.002)	(0.006)
Week of Spring Break Extension	0.028***	0.003*	0.025***
	(0.008)	(0.002)	(0.008)
Summer Break	-0.012	-0.001	-0.011
	(0.010)	(0.003)	(0.008)
Published in Last 3 Months	-0.048***	-0.004**	-0.044***
	(0.004)	(0.002)	(0.004)
Week F.E.	Yes	Yes	Yes
Individual F.E.	Yes	Yes	Yes
N	43678	43678	43678

Note: Standard errors clustered at the school level. * p<0.1 ** p<0.05 *** p<0.01. The outcome is the number of working papers that a faculty member produces in that week. Week of switch is an indicator equal to one in the week a school switches to remote instruction.

Appendix Table 4: Detailed Coefficients Presented in Figure 25A, 26A, and 27A

	All Papers	COVID-19-Related	Non-COVID-19-Related
	(1)	(2)	(3)
6 Weeks or More before Switch	-0.019	-0.002	-0.018
	(0.017)	(0.005)	(0.015)
5 Weeks before Switch	-0.018	-0.001	-0.017
	(0.012)	(0.004)	(0.011)
4 Weeks before Switch	-0.014	-0.000	-0.014*
	(0.009)	(0.003)	(0.008)
3 Weeks before Switch	-0.016**	0.000	-0.016**
	(0.007)	(0.003)	(0.007)
2 Weeks before Switch	-0.003	0.001	-0.004
	(0.007)	(0.003)	(0.006)
Week of Switch	0.024**	0.005**	0.018**
	(0.009)	(0.003)	(0.008)
1 Week after Switch	0.014	0.002	0.012
	(0.009)	(0.005)	(0.010)
2 Week after Switch	0.001	-0.004	0.005
	(0.011)	(0.007)	(0.011)
3 Week after Switch	-0.006	-0.001	-0.005
	(0.013)	(0.010)	(0.012)
4 Week after Switch	-0.013	-0.007	-0.005
	(0.013)	(0.009)	(0.015)
5 Week after Switch	-0.007	-0.004	-0.002
	(0.015)	(0.009)	(0.014)
6 or More Weeks after Switch	0.001	-0.005	0.007
	(0.015)	(0.010)	(0.016)
Total COVID Cases in County Per 100,000	0.013**	0.005	0.008***
	(0.006)	(0.004)	(0.003)
University Closed In-Person	-0.012	-0.004	-0.008
	(0.008)	(0.003)	(0.007)
Week of Spring Break	0.002	0.003	-0.001
	(0.007)	(0.002)	(0.007)
Week of Spring Break Extension	0.021**	0.004*	0.017*
	(0.010)	(0.002)	(0.009)
Summer Break	-0.012	-0.005	-0.007
	(0.010)	(0.004)	(0.008)
Published in Last 3 Months	-0.050***	-0.006***	-0.044***
	(0.004)	(0.002)	(0.004)
Week F.E.	Yes	Yes	Yes
Individual F.E.	Yes	Yes	Yes
N	33685	33685	33685

Note: Standard errors clustered at the school level. * p<0.1 ** p<0.05 *** p<0.01. The outcome is the number of working papers that a male faculty member produces in that week. Week of switch is an indicator equal to one in the week a school switches to remote instruction.

Appendix Table 5: Detailed Coefficients Presented in Figure 25B, 26B, and 27B

	All Papers	COVID-19-Related	Non-COVID-19-Related
	(1)	(2)	(3)
6 Weeks or More before Switch	-0.044	-0.005	-0.039
	(0.027)	(0.007)	(0.025)
5 Weeks before Switch	-0.031	-0.004	-0.028
	(0.020)	(0.005)	(0.020)
4 Weeks before Switch	-0.030	-0.003	-0.027
	(0.019)	(0.004)	(0.019)
3 Weeks before Switch	-0.022	-0.002	-0.020
	(0.016)	(0.002)	(0.015)
2 Weeks before Switch	-0.021	-0.001	-0.020
	(0.013)	(0.001)	(0.012)
Week of Switch	0.038**	0.001	0.037**
	(0.015)	(0.002)	(0.015)
1 Week after Switch	0.041**	0.001	0.040**
	(0.017)	(0.003)	(0.017)
2 Week after Switch	0.031	0.008	0.022
	(0.021)	(0.005)	(0.020)
3 Week after Switch	0.049**	0.009	0.040**
	(0.023)	(0.009)	(0.020)
4 Week after Switch	0.046*	0.016	0.030
	(0.028)	(0.012)	(0.024)
5 Week after Switch	0.024	-0.001	0.025
	(0.034)	(0.013)	(0.027)
6 or More Weeks after Switch	0.018	-0.002	0.020
	(0.037)	(0.015)	(0.029)
Total COVID Cases in County Per 100,000	0.008*	0.003	0.005
	(0.004)	(0.003)	(0.003)
University Closed In-Person	-0.021	0.001	-0.022
	(0.014)	(0.002)	(0.014)
Week of Spring Break	0.023*	0.000	0.023*
	(0.013)	(0.001)	(0.012)
Week of Spring Break Extension	0.046***	0.001	0.046***
	(0.017)	(0.001)	(0.017)
Summer Break	-0.009	0.011*	-0.021
	(0.016)	(0.006)	(0.015)
Published in Last 3 Months	-0.041***	0.003	-0.043***
	(0.006)	(0.005)	(0.005)
Week F.E.	Yes	Yes	Yes
Individual F.E.	Yes	Yes	Yes
N	9,993	9,993	9,993

Note: Standard errors clustered at the school level. * p<0.1 ** p<0.05 *** p<0.01. The outcome is the number of working papers that a female faculty member produces in that week. Week of switch is an indicator equal to one in the week a school switches to remote instruction.

Appendix Table 6: Detailed Coefficients Presented in Figure 28 and 29

	All Papers	COVID-19-Related	Non-COVID-19-Related
	(1)	(2)	(3)
6 Weeks or More before Switch	-0.004	0.001	-0.005
	(0.008)	(0.002)	(0.007)
5 Weeks before Switch	0.006	0.000	0.005
	(0.010)	(0.002)	(0.009)
4 Weeks before Switch	0.008	0.000	0.008
	(0.012)	(0.001)	(0.011)
3 Weeks before Switch	0.000	-0.000	0.000
	(0.008)	(0.001)	(0.007)
2 Weeks before Switch	0.005	-0.000	0.005
	(0.009)	(0.001)	(0.008)
Week of Switch	0.002	-0.001*	0.004
	(0.009)	(0.001)	(0.008)
1 Week after Switch	-0.001	-0.002**	0.001
	(0.008)	(0.001)	(0.007)
2 Week after Switch	0.014*	0.000	0.014*
	(0.008)	(0.001)	(0.008)
3 Week after Switch	0.002	-0.003***	0.005
	(0.008)	(0.001)	(0.007)
4 Week after Switch	0.013	0.000	0.013*
	(0.008)	(0.002)	(0.007)
5 Week after Switch	0.015***	-0.001	0.016***
	(0.004)	(0.002)	(0.004)
6 or More Weeks after Switch	0.013	0.000	0.013
	(0.008)	(0.002)	(0.008)
Total COVID Cases in Country Per 100,000,000	-0.000***	-0.000	-0.000**
	(0.000)	(0.000)	(0.000)
Published in Last 3 Months	-0.045***	-0.000	-0.045***
	(0.004)	(0.002)	(0.003)
Week F.E.	Yes	Yes	Yes
Individual F.E.	Yes	Yes	Yes
N	38,670	38,670	38,670

Note: Standard errors clustered at the school level. * p<0.1 ** p<0.05 *** p<0.01. The outcome is the number of working papers that a faculty member produces in that week. Week of switch is an indicator equal to one in the week a country enforces closure.

Appendix Table 7: Detailed Coefficients Presented in Figure 30A, 31A, and 32A

	All Papers	COVID-19-Related	Non-COVID-19-Related
	(1)	(2)	(3)
6 Weeks or More before Switch	-0.003	0.000	-0.004
	(0.008)	(0.002)	(0.007)
5 Weeks before Switch	0.008	-0.000	0.008
	(0.009)	(0.002)	(0.008)
4 Weeks before Switch	0.010	-0.000	0.010
	(0.012)	(0.001)	(0.011)
3 Weeks before Switch	-0.001	-0.000	-0.000
	(0.007)	(0.001)	(0.006)
2 Weeks before Switch	0.007	-0.001	0.008
	(0.008)	(0.001)	(0.008)
Week of Switch	0.007	-0.002	0.008
	(0.009)	(0.001)	(0.008)
1 Week after Switch	0.004	-0.002*	0.006
	(0.008)	(0.001)	(0.007)
2 Week after Switch	0.015*	0.001	0.014
	(0.009)	(0.001)	(0.009)
3 Week after Switch	0.000	-0.004**	0.004
	(0.009)	(0.002)	(0.009)
4 Week after Switch	0.010	0.001	0.009
	(0.009)	(0.003)	(0.008)
5 Week after Switch	0.015**	-0.000	0.015**
	(0.007)	(0.002)	(0.007)
6 or More Weeks after Switch	0.008	0.001	0.008
	(0.011)	(0.003)	(0.010)
Total COVID Cases in Country Per 100,000,000	-0.000*	0.000	-0.000**
	(0.000)	(0.000)	(0.000)
Published in Last 3 Months	-0.047***	-0.001	-0.046***
	(0.004)	(0.002)	(0.004)
Week F.E.	Yes	Yes	Yes
Individual F.E.	Yes	Yes	Yes
N	28,020	28,020	28,020

Note: Standard errors clustered at the school level. * p<0.1 ** p<0.05 *** p<0.01. The outcome is the number of working papers that a faculty member produces in that week. Week of switch is an indicator equal to one in the week a country enforces closure.

Appendix Table 8: Detailed Coefficients Presented in Figure 30B, 31B, and 32B

	All Papers	COVID-19-Related	Non-COVID-19-Related
	(1)	(2)	(3)
6 Weeks or More before Switch	-0.008	0.003	-0.011
	(0.018)	(0.004)	(0.015)
5 Weeks before Switch	0.000	0.002	-0.002
	(0.014)	(0.003)	(0.013)
4 Weeks before Switch	0.001	0.002	-0.000
	(0.013)	(0.002)	(0.012)
3 Weeks before Switch	0.002	0.001	0.001
	(0.010)	(0.001)	(0.010)
2 Weeks before Switch	-0.001	0.001	-0.002
	(0.011)	(0.001)	(0.011)
Week of Switch	-0.010	-0.001	-0.009
	(0.011)	(0.001)	(0.011)
1 Week after Switch	-0.012	-0.001	-0.011
	(0.010)	(0.001)	(0.011)
2 Week after Switch	0.012	-0.001	0.013
	(0.014)	(0.002)	(0.014)
3 Week after Switch	0.005	-0.001	0.006
	(0.013)	(0.002)	(0.013)
4 Week after Switch	0.020	-0.002	0.021
	(0.014)	(0.003)	(0.015)
5 Week after Switch	0.015	-0.002	0.018
	(0.012)	(0.004)	(0.013)
6 or More Weeks after Switch	0.023*	-0.002	0.025**
	(0.012)	(0.005)	(0.012)
Total COVID Cases in Country Per 100,000,000	-0.000**	-0.000*	-0.000*
	(0.000)	(0.000)	(0.000)
Published in Last 3 Months	-0.041***	0.001	-0.041***
	(0.007)	(0.003)	(0.004)
Week F.E.	Yes	Yes	Yes
Individual F.E.	Yes	Yes	Yes
N	10,650	10,650	10,650

Note: Standard errors clustered at the school level. * p<0.1 ** p<0.05 *** p<0.01. The outcome is the number of working papers that a faculty member produces in that week. Week of switch is an indicator equal to one in the week a country enforces closure.

Appendix Table 9: The Effect of Number of Weeks Remote on the Number of NBER Working Papers

	(1)	(2)	(3)
	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Number of Weeks Remote	-0.001	-0.024	0.023
	(0.041)	(0.024)	(0.025)
Researcher Characteristics			
Male	0.203***	0.093***	0.110**
	(0.066)	(0.031)	(0.051)
Experience	-0.008***	-0.003**	-0.006***
	(0.002)	(0.001)	(0.002)
Black	-0.207	-0.059	-0.148
	(0.132)	(0.081)	(0.115)
School Characteristics			
Admission Rate	0.682	0.253	0.428
	(0.455)	(0.184)	(0.376)
SAT	0.000	-0.000	0.000
	(0.001)	(0.001)	(0.001)
Enrollment	-0.007	-0.013	0.006
	(0.049)	(0.036)	(0.036)
Cost of Attendance	-0.010	0.050	-0.060
	(0.059)	(0.032)	(0.040)
Faculty Salary	0.579***	0.304**	0.275*
	(0.217)	(0.145)	(0.146)
% Full-Time Faculty	-0.162	-0.059	-0.103
	(0.209)	(0.121)	(0.148)
Top 50 School	0.019	-0.030	0.049
	(0.134)	(0.067)	(0.097)
Public School	-0.209	0.085	-0.294*
	(0.228)	(0.117)	(0.165)
Ivy League School	-0.112	-0.156**	0.044
	(0.117)	(0.068)	(0.078)
Number of Weeks	0.024	-0.007	0.030
in the Semester	(0.043)	(0.022)	(0.036)
Quarter System School	-0.109	0.106	-0.215
	(0.296)	(0.138)	(0.247)

Appendix Table 9 Panel B Continued			
	(1)	(2)	(3)
	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Unemployment Rate	0.045	0.044	0.001
	(0.055)	(0.033)	(0.040)
Household Income	-0.018	-0.003	-0.016
	(0.028)	(0.016)	(0.017)
% Black	-0.409	-0.210	-0.199
	(0.287)	(0.154)	(0.183)
N	1,513	1,513	1,513

Note: The unit of observation is a faculty member who is affiliated with the NBER. Column (1) uses the outcome of total number of working papers a faculty member publishes during Spring 2020. Column (2) is the coefficient for when the outcome is the number of papers that the NBER classifies as being related to COVID-19 and is published during Spring 2020. Column (3) uses the outcome for number of papers that are not related to COVID-19 published during Spring 2020. Standard errors clustered at the school level. * p<0.1 ** p<0.05 *** p<0.01.

Appendix Table 10: The Effect of Number of Weeks Remote on the Number of NBER Working Papers for Men

	(1)	(2)	(3)
	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Number of Weeks Remote	-0.021	-0.028	0.008
	(0.043)	(0.023)	(0.028)
Researcher Characteristics			
Experience	-0.009***	-0.003**	-0.005***
	(0.002)	(0.001)	(0.002)
Black	-0.147	-0.016	-0.131
	(0.149)	(0.096)	(0.137)
School Characteristics			
Admission Rate	0.095	0.155	-0.060
	(0.599)	(0.204)	(0.524)
SAT	-0.001	0.000	-0.001
	(0.001)	(0.000)	(0.001)
Enrollment	0.013	0.038	-0.025
	(0.056)	(0.027)	(0.050)
Cost of Attendance	0.024	0.077**	-0.053
	(0.077)	(0.035)	(0.061)
Faculty Salary	0.645**	0.243*	0.402**
	(0.254)	(0.128)	(0.199)
% Full-Time Faculty	-0.228	-0.043	-0.185
	(0.243)	(0.139)	(0.190)
Top 50 School	-0.174	-0.150*	-0.024
	(0.176)	(0.078)	(0.140)
Public School	-0.124	0.116	-0.240
	(0.287)	(0.124)	(0.233)
Ivy League School	-0.110	-0.150**	0.040
	(0.138)	(0.070)	(0.103)
Number of Weeks	0.007	-0.019	0.025
in the Semester	(0.048)	(0.023)	(0.045)
Quarter System School	0.150	0.252*	-0.101
	(0.328)	(0.140)	(0.296)

Appendix Table 10 Panel B Continued			
	(1)	(2)	(3)
	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Unemployment Rate	0.027	0.038	-0.011
	(0.070)	(0.036)	(0.058)
Household Income	-0.016	0.002	-0.018
	(0.034)	(0.018)	(0.024)
% Black	-0.230	-0.152	-0.079
	(0.352)	(0.176)	(0.264)
N	1,170	1,170	1,170

Note: The unit of observation is a male faculty member who is affiliated with the NBER. Column (1) uses the outcome of total number of working papers a male faculty member who is affiliated with the NBER publishes during Spring 2020. Column (2) is the coefficient for when the outcome is the number of papers that the NBER classifies as being related to COVID-19 and is published during Spring 2020. Column (3) uses the outcome for number of papers that are not related to COVID-19 published during Spring 2020. Standard errors clustered at the school level. * p<0.1 ** p<0.05 *** p<0.01

Appendix Table 11: The Effect of Number of Weeks Remote on the Number of NBER Working Papers for Women

	(1)	(2)	(3)
	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Number of Weeks Remote	0.089	0.000	0.089**
	(0.063)	(0.037)	(0.041)
Researcher Characteristics			
Experience	-0.006	-0.001	-0.004
	(0.005)	(0.001)	(0.005)
Black	-0.486*	-0.093*	-0.393
	(0.279)	(0.056)	(0.242)
School Characteristics			
Admission Rate	2.901***	0.711*	2.190***
	(0.860)	(0.383)	(0.656)
SAT	0.004	-0.001	0.005***
	(0.002)	(0.002)	(0.001)
Enrollment	-0.053	-0.123	0.070
	(0.118)	(0.086)	(0.060)
Cost of Attendance	-0.121	-0.010	-0.111
	(0.100)	(0.050)	(0.080)
Faculty Salary	0.335	0.404	-0.070
	(0.471)	(0.316)	(0.312)
% Full-Time Faculty	0.120	-0.001	0.121
	(0.375)	(0.190)	(0.295)
Top 50 School	0.573***	0.254**	0.318**
	(0.192)	(0.107)	(0.147)
Public School	-0.545*	0.043	-0.588**
	(0.325)	(0.198)	(0.277)
Ivy League School	-0.166	-0.139	-0.027
	(0.182)	(0.088)	(0.133)
Number of Weeks	0.024	-0.007	0.030
in the Semester	(0.043)	(0.022)	(0.036)
Quarter System School	-0.109	0.106	-0.215
	(0.296)	(0.138)	(0.247)

Appendix Table 11 Panel B Continued			
	(1)	(2)	(3)
	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Unemployment Rate	0.151	0.069	0.082
	(0.096)	(0.047)	(0.073)
Household Income	-0.023	-0.015	-0.008
	(0.037)	(0.016)	(0.029)
% Black	-1.263***	-0.388	-0.875***
	(0.351)	(0.233)	(0.285)
N	347	347	347

Note: The unit of observation is a male faculty member who is affiliated with the NBER. Column (1) uses the outcome of total number of working papers a female faculty member publishes during Spring 2020. Column (2) is the coefficient for when the outcome is the number of papers that the NBER classifies as being related to COVID-19 and is published during Spring 2020. Column (3) uses the outcome for number of papers that are not related to COVID-19 published during Spring 2020. Standard errors clustered at the school level. * p<0.1 ** p<0.05 *** p<0.01

Appendix Table 12: The Effect of Number of Weeks Remote on the Number of IZA Working Papers

	(1)	(2)	(3)
	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Number of Weeks Remote	-0.011	0.005	-0.017
	(0.020)	(0.007)	(0.018)
Researcher Characteristics			
Male	0.214***	0.025	0.189***
	(0.054)	(0.022)	(0.045)
Experience	-0.006***	-0.002***	-0.004**
	(0.002)	(0.001)	(0.002)
Black	-0.027	-0.011	-0.016
	(0.082)	(0.045)	(0.065)
School Characteristics			
Enrollment	0.002	0.000	0.002
	(0.002)	(0.001)	(0.002)
Students Per Teacher	0.002	0.001	0.001
	(0.002)	(0.001)	(0.002)
% International Students	0.055	0.047	0.008
	(0.304)	(0.118)	(0.229)
Top 200 School	-0.059	-0.021	-0.038
	(0.063)	(0.026)	(0.052)
Country Characteristics			
March 9^{th} COVID-19 per Million	0.001*	0.000	0.001*
	(0.001)	(0.000)	(0.000)
Unemployment Rate	0.016	0.003	0.012
	(0.013)	(0.003)	(0.012)
GDP Per Capita	0.004**	0.002*	0.002
	(0.002)	(0.001)	(0.002)
Population	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)
N	1,289	1,289	1,289

Note: The unit of observation is a faculty member who is affiliated with the IZA. Column (1) uses the outcome of total number of working papers a faculty member publishes during Spring 2020. Column (2) is the coefficient for when the outcome is the number of papers that IZA classifies as being related to COVID-19 and is published during Spring 2020. Column (3) uses the outcome for number of papers that are not related to COVID-19 published during Spring 2020. Standard errors clustered at the school level. * p<0.1 ** p<0.05 *** p<0.01.

Appendix Table 13: The Effect of Number of Weeks Remote on the Number of IZA Working Papers for Males

	(1)	(2)	(3)
	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Number of Weeks Remote	-0.013	0.009	-0.022
	(0.022)	(0.008)	(0.019)
Researcher Characteristics			
Experience	-0.008***	-0.003***	-0.005**
	(0.003)	(0.001)	(0.002)
Nonwhite	-0.110	0.014	-0.124
	(0.109)	(0.066)	(0.077)
School Characteristics			
Enrollment	0.004	0.000	0.003
	(0.003)	(0.001)	(0.003)
Students Per Teacher	-0.000	0.000	-0.000
	(0.003)	(0.001)	(0.002)
% International Students	0.112	0.073	0.039
	(0.369)	(0.151)	(0.276)
Top 200 School	-0.027	-0.025	-0.002
	(0.079)	(0.033)	(0.065)
Country Characteristics			
March 9^{th} COVID-19 per Million	0.001	-0.000	0.001
	(0.001)	(0.000)	(0.001)
Unemployment Rate	0.019	0.002	0.017
	(0.017)	(0.004)	(0.016)
GDP Per Capita	0.005**	0.003*	0.002
	(0.002)	(0.001)	(0.002)
Population	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)
N	934	934	934

Note: The unit of observation is a male faculty member who is affiliated with the IZA. Column (1) uses the outcome of total number of working papers a faculty member publishes during Spring 2020. Column (2) is the coefficient for when the outcome is the number of papers that IZA classifies as being related to COVID-19 and is published during Spring 2020. Column (3) uses the outcome for number of papers that are not related to COVID-19 published during Spring 2020. Standard errors clustered at the school level. * p<0.1 ** p<0.05 *** p<0.01.

Appendix Table 14: The Effect of Number of Weeks Remote on the Number of IZA Working Papers for Females

	(1)	(2)	(3)
	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Number of Weeks Remote	-0.005	-0.004	-0.001
	(0.039)	(0.012)	(0.031)
Researcher Characteristics			
Experience	-0.000	0.000	-0.000
	(0.003)	(0.001)	(0.003)
Nonwhite	0.139	-0.065***	0.204*
	(0.107)	(0.022)	(0.112)
School Characteristics			
Enrollment	-0.002	-0.001	-0.001
	(0.003)	(0.001)	(0.002)
Students Per Teacher	0.009**	0.004	0.005*
	(0.004)	(0.003)	(0.003)
% International Students	-0.157	-0.046	-0.111
	(0.424)	(0.118)	(0.366)
Top 200 School	-0.123	-0.009	-0.114
	(0.089)	(0.038)	(0.070)
Country Characteristics			
March 9th COVID-19 per Million	0.001	0.000	0.001
	(0.001)	(0.000)	(0.001)
Unemployment Rate	0.004	0.004	-0.000
	(0.017)	(0.007)	(0.014)
GDP Per Capita	0.002	0.000	0.002
	(0.004)	(0.001)	(0.003)
Population	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)
N	355	355	355

Note: The unit of observation is a female faculty member who is affiliated with the IZA. Column (1) uses the outcome of total number of working papers a faculty member publishes during Spring 2020. Column (2) is the coefficient for when the outcome is the number of papers that IZA classifies as being related to COVID-19 and is published during Spring 2020. Column (3) uses the outcome for number of papers that are not related to COVID-19 published during Spring 2020. Standard errors clustered at the school level. * p<0.1 ** p<0.05 *** p<0.01.

Appendix Table 15A: Coefficients Presented in Figure 34

	(1)	(2)	(3)
	Male	Experience	Black
Weeks Until First Case	0.01	-0.06	-0.06
	(0.05)	(0.05)	(0.05)
N	123	123	123

Note: The unit of observation is at the school level. The only control variable used is the number of weeks from the start of the semester until the first reported COVID-19 case at a school.

Appendix Table 15B: Coefficients Presented in Figure 34

	(4)	(5)	(6)
	Admission Rate	SAT	Enrollment
Weeks Until First Case	0.06	-0.05	0.07
	(0.05)	(0.05)	(0.05)
N	123	123	123

	(7)	(8)	(9)	(10)	(11)	(12)
	Cost of Attendance	Faculty Salary	% Full-Time Faculty	Public School	Ivy League School	Top 50 School
Weeks Until First Case	-0.06	-0.10**	0.10**	0.06	-0.12**	-0.04
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
N	123	123	123	123	123	123

Appendix Table 15C: Coefficients Presented in Figure 34

	(13)	(14)	(15)	(16)
	COVID-19 Cases per 100,000 (March 9)	Unemployment Rate	Household Income	% Black
Weeks Until First Case	-0.05	-0.07	-0.13**	-0.04
	(0.05)	(0.05)	(0.05)	(0.05)
N	123	123	123	123

Appendix Table 16A: Coefficients Presented in Figure 36

	(1)	(2)	(3)
	Male	Experience	Nonwhite
Weeks Until First Case	-0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)
N	123	123	123

Note: The unit of observation is at the country level. The only control variable used is the number of weeks from the start of the semester until a country has more than 10 COVID-19 cases per million people.

Appendix Table 16B: Coefficients Presented in Figure 36

	(4)	(5)	(6)	(7)
	Enrollment	Students Per Teacher	% International Students	Top 200 School
Weeks Until First Case	0.00	-0.00	0.00	0.00**
	(0.00)	(0.00)	(0.00)	(0.00)
N	54	54	54	54

See note 22A.

Appendix Table 16C: Coefficients Presented in Figure 36

	(8)	(9)	(10)	(11)
	March 9th COVID-19 Cases	Unemployment Rate	GDP Per Capita	Population
Weeks Until First Case	0.00	-0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
N	54	54	54	54

See note 22A.

Appendix Table 17: The Complete List of Estimates in Table 19
Panel A

	(1)	(2)	(3)	(4)
	First Stage		Reduced Form	
	Number of Weeks Remote	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Weeks Until the First Case	-0.179***	-0.039	-0.022	-0.017
	(0.027)	(0.026)	(0.016)	(0.015)
Researcher Characteristics				
Male	0.054	0.204***	0.092***	0.112**
	(0.05)	(0.066)	(0.031)	(0.051)
Experience	0.001	-0.008***	-0.003***	-0.006***
	(0.002)	(0.002)	(0.001)	(0.002)
Black	-0.18	-0.205	-0.051	-0.154
	(0.20)	(0.129)	(0.082)	(0.115)
School Characteristics				
Admission Rate	0.717	0.583	0.180	0.402
	(0.356)	(0.482)	(0.201)	(0.392)
SAT	-0.001	-0.000	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Enrollment	0.112***	-0.012	-0.018	0.006
	(0.044)	(0.049)	(0.039)	(0.038)
Cost of Attendance	-0.021	-0.000	0.058*	-0.058
	(0.050)	(0.060)	(0.034)	(0.041)
Faculty Salary	0.859***	0.516**	0.250**	0.267*
	(0.193)	(0.203)	(0.123)	(0.150)
% Full-Time Faculty	-0.571***	-0.193	-0.070	-0.123
	(0.170)	(0.212)	(0.120)	(0.154)
Top 50 School	0.269***	0.011	-0.040	0.051
	(0.094)	(0.134)	(0.068)	(0.097)
Public School	-0.12	-0.173	0.116	-0.289*
	(0.18)	(0.233)	(0.129)	(0.171)
Ivy League School	0.367***	-0.147	-0.189***	0.042
	(0.076)	(0.118)	(0.068)	(0.079)
Number of Weeks	0.383***	0.041	-0.003	0.044
in the Semester	(0.034)	(0.041)	(0.022)	(0.038)
Quarter System School	2.97***	-0.150	0.004	-0.154
	(0.201)	(0.268)	(0.133)	(0.244)

Appendix Table 17 Panel A Continued				
	(1)	(2)	(3)	(4)
	First Stage	Reduced Form		
	Number of Weeks Remote	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Unemployment Rate	0.170***	0.036	0.033	0.003
	(0.050)	(0.055)	(0.030)	(0.041)
Household Income	0.218	-0.025	-0.013	-0.012
	(0.020)	(0.028)	(0.017)	(0.017)
% Black (County)	0.489	-0.415	-0.229	-0.186
	(0.211)	(0.281)	(0.145)	(0.185)
N	1,513	1,513	1,513	1,513

Note: The unit of observation is a faculty member. The outcome variable in Column (1) is the number of full weeks that a faculty member's school uses remote instruction. Columns (2), (3) and (4) use the number of papers that a faculty member publishes in the Spring of 2020. Estimates are regressed on the number of weeks since the start of the semester to the week that a school reports its first positive COVID-19. Standard errors clustered at the school level. * p<0.1 ** p<0.05 *** p<0.01.

Appendix Table 17: The Complete List of Estimates in Table 19
Panel B

	(1)	(2)	(3)
	2SLS Estimates		
	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Number of Weeks Remote	0.217	0.123	0.094
	(0.214)	(0.135)	(0.106)
Researcher Characteristics			
Male	0.192***	0.085***	0.107**
	(0.065)	(0.032)	(0.051)
Experience	-0.009***	-0.003***	-0.006***
	(0.002)	(0.001)	(0.002)
Black	-0.165	-0.029	-0.136
	(0.121)	(0.084)	(0.110)
School Characteristics			
Admission Rate	0.427	0.092	0.335
	(0.545)	(0.270)	(0.405)
SAT	0.000	-0.000	0.000
	(0.001)	(0.001)	(0.001)
Enrollment	-0.037	-0.032	-0.005
	(0.065)	(0.055)	(0.036)
Cost of Attendance	0.004	0.060	-0.056
	(0.069)	(0.043)	(0.041)
Faculty Salary	0.330	0.144	0.186
	(0.311)	(0.174)	(0.188)
% Full-Time Faculty	-0.069	0.000	-0.069
	(0.251)	(0.163)	(0.154)
Top 50 School	-0.047	-0.073	0.026
	(0.159)	(0.082)	(0.106)
Public School	-0.146	0.131	-0.277*
	(0.250)	(0.162)	(0.162)
Ivy League School	-0.227	-0.234**	0.007
	(0.191)	(0.115)	(0.104)
Number of Weeks	-0.042	-0.050	0.008
in the Semester	(0.081)	(0.046)	(0.048)
Quarter System School	-0.794	-0.362	-0.432
	(0.687)	(0.467)	(0.393)

Appendix Table 17 Panel B Continued			
	(1)	(2)	(3)
	2SLS Estimates		
	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Unemployment Rate	-0.001	0.012	-0.013
	(0.083)	(0.049)	(0.049)
Household Income	-0.073	-0.040	-0.033
	(0.074)	(0.047)	(0.034)
% Black (County)	-0.521*	-0.289*	-0.232
	(0.292)	(0.160)	(0.187)
N	1,513	1,513	1,513

Note: The unit of observation is a faculty member. Column (1) show results for all working papers published in the Spring of 2020. Results that use COVID-19 related working papers and papers with no relation to COVID-19 can be found in columns (2) and (3), respectively.

Appendix Table 18: The Complete List of Estimates in Table 20
Panel A

	(1)	(2)	(3)	(4)
	First Stage		Reduced Form	
	Number of Weeks Remote	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Weeks Until the First Case	-0.163***	-0.019	-0.009	-0.010
	(0.029)	(0.030)	(0.016)	(0.021)
Researcher Characteristics				
Experience	0.001	-0.009***	-0.003**	-0.006***
	(0.002)	(0.002)	(0.001)	(0.002)
Black	-0.24	-0.146	-0.008	-0.138
	(0.24)	(0.144)	(0.095)	(0.136)
School Characteristics				
Admission Rate	1.099***	-0.052	0.095	-0.147
	(0.390)	(0.632)	(0.217)	(0.547)
SAT	-0.0004	-0.001	0.000	-0.001
	(0.001)	(0.001)	(0.000)	(0.001)
Enrollment	0.088*	0.004	0.033	-0.029
	(0.053)	(0.055)	(0.029)	(0.051)
Cost of Attendance	-0.029	0.027	0.082**	-0.055
	(0.058)	(0.077)	(0.036)	(0.061)
Faculty Salary	0.719***	0.590**	0.209*	0.380*
	(0.221)	(0.246)	(0.112)	(0.200)
% Full-Time Faculty	-0.611***	-0.234	-0.038	-0.196
	(0.191)	(0.256)	(0.142)	(0.201)
Top 50 School	0.383***	-0.197	-0.164**	-0.033
	(0.107)	(0.175)	(0.082)	(0.137)
Public School	-0.112	-0.112	0.137	-0.249
	(0.203)	(0.288)	(0.131)	(0.236)
Ivy League School	0.442***	-0.141	-0.176***	0.035
	(0.086)	(0.140)	(0.067)	(0.103)
Number of Weeks	0.376***	0.009	-0.022	0.031
in the Semester	(0.038)	(0.049)	(0.023)	(0.049)
Quarter System School	3.03***	0.066	0.145	-0.079
	(0.23)	(0.309)	(0.141)	(0.301)

Appendix Table 18 Panel A Continued				
	(1)	(2)	(3)	(4)
	First Stage	Reduced Form		
	Number of Weeks Remote	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Unemployment Rate	0.222***	0.015	0.027	-0.012
	(0.056)	(0.073)	(0.036)	(0.059)
Household Income	0.247***	-0.025	-0.008	-0.017
	(0.023)	(0.035)	(0.020)	(0.023)
% Black (County)	0.569**	-0.232	-0.172	-0.061
	(0.242)	(0.341)	(0.164)	(0.262)
N	1167	1167	1167	1167

Note: The unit of observation is a male faculty member who is affiliated with the NBER. The outcome variable in Column (1) is the number of full weeks that a faculty member's school uses remote instruction. Columns (2), (3) and (4) use the number of papers that a faculty member publishes in the Spring of 2020. Estimates are regressed on the number of weeks since the start of the semester to the week that a school reports its first positive COVID-19. Standard errors clustered at the school level. * p<0.1 ** p<0.05 *** p<0.01.

Appendix Table 18: The Complete List of Estimates in Table 20
Panel B

	(1)	(2)	(3)
	2SLS Estimates		
	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Number of Weeks Remote	0.117	0.054	0.062
	(0.213)	(0.113)	(0.136)
Researcher Characteristics			
Experience	-0.009***	-0.003***	-0.006***
	(0.002)	(0.001)	(0.002)
Black	-0.118	0.006	-0.123
	(0.142)	(0.100)	(0.134)
School Characteristics			
Admission Rate	-0.180	0.036	-0.216
	(0.725)	(0.262)	(0.605)
SAT	-0.001	0.000	-0.001
	(0.001)	(0.001)	(0.001)
Enrollment	-0.006	0.029	-0.034
	(0.059)	(0.035)	(0.052)
Cost of Attendance	0.030	0.083**	-0.053
	(0.078)	(0.039)	(0.059)
Faculty Salary	0.506*	0.170	0.335
	(0.302)	(0.139)	(0.234)
% Full-Time Faculty	-0.163	-0.005	-0.158
	(0.256)	(0.164)	(0.191)
Top 50 School	-0.242	-0.185**	-0.057
	(0.199)	(0.086)	(0.157)
Public School	-0.099	0.143	-0.242
	(0.287)	(0.143)	(0.229)
Ivy League School	-0.192	-0.200**	0.008
	(0.197)	(0.096)	(0.132)
Number of Weeks	-0.035	-0.042	0.007
in the Semester	(0.075)	(0.038)	(0.053)
Quarter System School	-0.288	-0.020	-0.269
	(0.753)	(0.405)	(0.556)

Appendix Table 18 Panel B Continued			
	(1)	(2)	(3)
	2SLS Estimates		
	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Unemployment Rate	-0.011	0.015	-0.026
	(0.104)	(0.050)	(0.076)
Household Income	-0.053	-0.021	-0.032
	(0.079)	(0.043)	(0.047)
% Black (County)	-0.299	-0.203	-0.096
	(0.338)	(0.157)	(0.262)
N	1167	1167	1167

Note: The unit of observation is a male faculty member who is affiliated with the NBER. Column (1) show results for all working papers published in the Spring of 2020. Results that use COVID-19 related working papers and papers with no relation to COVID-19 can be found in columns (2) and (3), respectively.

Appendix Table 19: The Complete List of Estimates in Table 21
Panel A

	(1)	(2)	(3)	(4)
	First Stage		Reduced Form	
	Number of Weeks Remote	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Weeks Until the First Case	-0.23***	-0.169***	-0.083*	-0.086**
	(0.07)	(0.057)	(0.042)	(0.035)
Researcher Characteristics				
Experience	-0.004	-0.005	-0.001	-0.004
	(0.004)	(0.005)	(0.001)	(0.005)
Black	-0.059	-0.471	-0.083	-0.389
	(0.285)	(0.326)	(0.061)	(0.273)
School Characteristics				
Admission Rate	-.209	2.870***	0.689*	2.181***
	(0.823)	(0.878)	(0.363)	(0.687)
SAT	-0.002	0.004*	-0.001	0.005***
	(0.002)	(0.002)	(0.002)	(0.001)
Enrollment	0.188**	-0.022	-0.115	0.092
	(0.079)	(0.115)	(0.084)	(0.062)
Cost of Attendance	0.01	-0.065	0.022	-0.087
	(0.102)	(0.105)	(0.063)	(0.079)
Faculty Salary	1.21***	0.120	0.231	-0.111
	(0.221)	(0.414)	(0.224)	(0.330)
% Full-Time Faculty	-0.558	0.010	-0.032	0.043
	(0.373)	(0.369)	(0.195)	(0.280)
Top 50 School	0.014	0.588***	0.256**	0.332**
	(0.182)	(0.203)	(0.104)	(0.159)
Public School	-0.149	-0.419	0.126	-0.545**
	(0.385)	(0.327)	(0.243)	(0.266)
Ivy League School	0.167	-0.258	-0.197*	-0.061
	(0.164)	(0.179)	(0.105)	(0.129)
Number of Weeks	0.376***	0.159*	0.043	0.116*
in the Semester	(0.072)	(0.082)	(0.031)	(0.066)
Quarter System School	2.93***	-0.874*	-0.320	-0.554
	(0.42)	(0.522)	(0.201)	(0.414)

Appendix Table 19 Panel A Continued				
	(1)	(2)	(3)	(4)
	First Stage	Reduced Form		
	Number of Weeks Remote	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Unemployment Rate	0.047	0.178**	0.080*	0.097
	(0.11)	(0.089)	(0.045)	(0.070)
Household Income	0.153***	-0.026	-0.024	-0.001
	(0.038)	(0.034)	(0.020)	(0.026)
% Black (County)	0.467	-1.417***	-0.496*	-0.921***
	(0.421)	(0.373)	(0.253)	(0.285)
N	346	346	346	346

Note: The unit of observation is a male faculty member who is affiliated with the NBER. The outcome variable in Column (1) is the number of full weeks that a faculty member's school uses remote instruction. Columns (2), (3) and (4) use the number of papers that a faculty member publishes in the Spring of 2020. Estimates are regressed on the number of weeks since the start of the semester to the week that a school reports its first positive COVID-19. Standard errors clustered at the school level. * p<0.1 ** p<0.05 *** p<0.01.

Appendix Table 19: The Complete List of Estimates in Table 21
Panel B

	(1)	(2)	(3)
	2SLS Estimates		
	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Number of Weeks Remote	0.734	0.360	0.374
	(0.488)	(0.291)	(0.240)
Researcher Characteristics			
Experience	-0.002	0.000	-0.003
	(0.006)	(0.003)	(0.005)
Black	-0.428*	-0.061	-0.367*
	(0.246)	(0.079)	(0.219)
School Characteristics			
Admission Rate	3.024***	0.764	2.260***
	(0.973)	(0.477)	(0.667)
SAT	0.006*	0.000	0.006***
	(0.003)	(0.002)	(0.002)
Enrollment	-0.161	-0.182	0.022
	(0.193)	(0.137)	(0.081)
Cost of Attendance	-0.073	0.018	-0.091
	(0.163)	(0.088)	(0.099)
Faculty Salary	-0.767	-0.204	-0.563
	(0.911)	(0.485)	(0.525)
% Full-Time Faculty	0.420	0.168	0.252
	(0.613)	(0.318)	(0.382)
Top 50 School	0.578***	0.251*	0.327**
	(0.221)	(0.128)	(0.149)
Public School	-0.309	0.180	-0.489
	(0.556)	(0.348)	(0.334)
Ivy League School	-0.380	-0.257	-0.123
	(0.350)	(0.207)	(0.178)
Number of Weeks	-0.117	-0.092	-0.025
in the Semester	(0.182)	(0.104)	(0.096)
Quarter System School	-3.031**	-1.377	-1.654**
	(1.469)	(0.888)	(0.783)

Appendix Table 19 Panel B Continued			
	(1)	(2)	(3)
	2SLS Estimates		
	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Unemployment Rate	0.144	0.064	0.080
	(0.148)	(0.074)	(0.090)
Household Income	-0.138	-0.080	-0.059
	(0.125)	(0.072)	(0.063)
% Black (County)	-1.760***	-0.664*	-1.096***
	(0.680)	(0.403)	(0.392)
N	346	346	346

Note: The unit of observation is a male faculty member who is affiliated with the NBER. Column (1) show results for all working papers published in the Spring of 2020. Results that use COVID-19 related working papers and papers with no relation to COVID-19 can be found in columns (2) and (3), respectively.

Appendix Table 20: The Complete List of Estimates in Table 22
Panel A

	(1)	(2)	(3)	(4)
	First Stage	Reduced Form		
	Number of Weeks Remote	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Weeks Until the First Case	-0.311***	-0.006	-0.002	-0.004
	(0.060)	(0.020)	(0.006)	(0.018)
Researcher Characteristics				
Male	0.073	0.212***	0.025	0.187***
	(0.064)	(0.055)	(0.022)	(0.045)
Experience	0.004	-0.006***	-0.002***	-0.004**
	(0.002)	(0.002)	(0.001)	(0.002)
Nonwhite	0.053	-0.029	-0.011	-0.018
	(0.185)	(0.081)	(0.045)	(0.064)
School Characteristics				
Enrollment	-0.001	0.002	0.000	0.002
	(0.002)	(0.002)	(0.001)	(0.002)
Students Per Teacher	0.024***	0.002	0.001	0.000
	(0.002)	(0.002)	(0.001)	(0.002)
% International Students	-3.37***	0.084	0.028	0.056
	(0.304)	(0.296)	(0.114)	(0.228)
Top 200 School	-0.059	-0.058	-0.022	-0.036
	(0.069)	(0.062)	(0.026)	(0.052)
Country Characteristics				
March 9^{th} COVID-19 Cases	0.005	0.001	0.000	0.001
	(0.001)	(0.001)	(0.000)	(0.001)
Unemployment Rate	0.011	0.016	0.003	0.012
	(0.013)	(0.013)	(0.003)	(0.012)
GDP Per Capita	0.002	0.004**	0.002**	0.002
	(0.004)	(0.002)	(0.001)	(0.002)
Population	0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
N	1,289	1,289	1,289	1,289

Note: The unit of observation is a faculty member. The outcome variable in Column (1) is the number of full weeks that a faculty member's school uses remote instruction. Columns (2), (3) and (4) use the number of papers that a faculty member publishes in the Spring of 2020. Estimates are regressed on the number of weeks since the start of the semester to the week that a school reports its first positive COVID-19. Standard errors clustered at the school level. * p<0.1 ** p<0.05 *** p<0.01.

Appendix Table 20: The Complete List of Estimates in Table 22
Panel B

	(1)	(2)	(3)
	2SLS Estimates		
	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Number of Weeks Remote	0.020	0.008	0.013
	(0.063)	(0.020)	(0.056)
Researcher Characteristics			
Male	0.211***	0.024	0.186***
	(0.055)	(0.022)	(0.045)
Experience	-0.006***	-0.002***	-0.004**
	(0.002)	(0.001)	(0.002)
Nonwhite	-0.030	-0.011	-0.018
	(0.081)	(0.045)	(0.064)
School Characteristics			
Enrollment	0.002	0.000	0.002
	(0.002)	(0.001)	(0.002)
Students Per Teacher	0.001	0.001	-0.000
	(0.003)	(0.001)	(0.002)
% International Students	0.153	0.054	0.099
	(0.316)	(0.126)	(0.250)
Top 200 School	-0.057	-0.021	-0.036
	(0.063)	(0.026)	(0.052)
Country Characteristics			
March 9th COVID-19 Cases	0.001	-0.000	0.001
	(0.001)	(0.000)	(0.001)
Unemployment Rate	0.016	0.003	0.012
	(0.013)	(0.003)	(0.012)
GDP Per Capita	0.004**	0.002**	0.002
	(0.002)	(0.001)	(0.002)
Population	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)
N	1,289	1,289	1,289

Note: The unit of observation is a faculty member. Column (1) show results for all working papers published in the Spring of 2020. Results that use COVID-19 related working papers and papers with no relation to COVID-19 can be found in columns (2) and (3), respectively.

Appendix Table 21: The Complete List of Estimates in Table 23
Panel A

	(1)	(2)	(3)	(4)
	First Stage	Reduced Form		
	Number of Weeks Remote	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Weeks Until the First Case	-0.282***	0.008	-0.004	0.013
	(0.075)	(0.025)	(0.009)	(0.021)
Researcher Characteristics				
Experience	0.004	-0.008***	-0.003**	-0.005**
	(0.002)	(0.003)	(0.001)	(0.002)
Nonwhite	0.007**	-0.109	0.014	-0.123
	(0.249)	(0.108)	(0.066)	(0.076)
School Characteristics				
Enrollment	-0.001	0.004	0.000	0.003
	(0.003)	(0.003)	(0.001)	(0.003)
Students Per Teacher	0.025***	-0.000	0.000	-0.001
	(0.002)	(0.003)	(0.001)	(0.002)
% International Students	-3.04***	0.156	0.044	0.112
	(0.353)	(0.366)	(0.150)	(0.280)
Top 200 School	-0.083	-0.026	-0.025	-0.001
	(0.086)	(0.079)	(0.033)	(0.065)
Country Characteristics				
March 9^{th} COVID-19 Cases	0.006	0.001	-0.000	0.001
	(0.001)	(0.001)	(0.000)	(0.001)
Unemployment Rate	0.011*	0.019	0.003	0.017
	(0.015)	(0.017)	(0.004)	(0.016)
GDP Per Capita	0.001	0.005**	0.003**	0.002
	(0.000)	(0.002)	(0.001)	(0.002)
Population	0.000***	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
N	934	934	934	934

Note: The unit of observation is a male faculty member. The outcome variable in Column (1) is the number of full weeks that a faculty member's school uses remote instruction. Columns (2), (3) and (4) use the number of papers that a faculty member publishes in the Spring of 2020. Estimates are regressed on the number of weeks since the start of the semester to the week that a school reports its first positive COVID-19. Standard errors clustered at the school level. * p<0.1 ** p<0.05 *** p<0.01.

Appendix Table 21: The Complete List of Estimates in Table 23
Panel B

	(1)	(2)	(3)
	2SLS Estimates		
	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Number of Weeks Remote	-0.030	0.016	-0.046
	(0.091)	(0.032)	(0.078)
Researcher Characteristics			
Experience	-0.008***	-0.003***	-0.005**
	(0.003)	(0.001)	(0.002)
Black	-0.109	0.013	-0.123
	(0.109)	(0.066)	(0.078)
School Characteristics			
Enrollment	0.004	0.000	0.003
	(0.003)	(0.001)	(0.003)
Students Per Teacher	0.000	0.000	0.000
	(0.004)	(0.001)	(0.003)
% International Students	0.064	0.092	-0.028
	(0.397)	(0.166)	(0.301)
Top 200 School	-0.028	-0.024	-0.004
	(0.081)	(0.034)	(0.066)
Country Characteristics			
March 9th COVID-19 Cases	0.001	-0.000	0.001
	(0.001)	(0.000)	(0.001)
Unemployment Rate	0.020	0.002	0.017
	(0.017)	(0.003)	(0.016)
GDP Per Capita	0.005**	0.003**	0.002
	(0.002)	(0.001)	(0.002)
Population	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)
N	934	934	934

Note: The unit of observation is a faculty member. Column (1) show results for all working papers published in the Spring of 2020. Results that use COVID-19 related working papers and papers with no relation to COVID-19 can be found in columns (2) and (3), respectively.

Appendix Table 22: The Complete List of Estimates in Table 24
Panel A

	(1)	(2)	(3)	(4)
	First Stage		Reduced Form	
	Number of Weeks Remote	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Weeks Until the First Case	-0.374***	-0.041	0.002	-0.043*
	(0.094)	(0.025)	(0.006)	(0.026)
Researcher Characteristics				
Experience	0.004	0.000	0.000	-0.000
	(0.004)	(0.004)	(0.001)	(0.003)
Nonwhite	0.167	0.141	-0.066***	0.207*
	(0.246)	(0.105)	(0.022)	(0.109)
School Characteristics				
Enrollment	-0.000	-0.002	-0.001	-0.001
	(0.003)	(0.003)	(0.001)	(0.002)
Students Per Teacher	0.022***	0.009**	0.004	0.005*
	(0.004)	(0.004)	(0.003)	(0.003)
% International Students	-4.47***	-0.173	-0.028	-0.145
	(0.658)	(0.350)	(0.088)	(0.324)
Top 200 School	0.010	-0.122	-0.009	-0.113
	(0.115)	(0.088)	(0.038)	(0.069)
Country Characteristics				
March 9th COVID-19 Cases	0.003***	0.001	0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.001)
Unemployment Rate	0.003	0.006	0.004	0.002
	(0.028)	(0.017)	(0.007)	(0.014)
GDP Per Capita	0.002	0.004	0.000	0.003
	(0.010)	(0.003)	(0.001)	(0.003)
Population	0.000***	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
N	355	355	355	355

Note: The unit of observation is a faculty member. The outcome variable in Column (1) is the number of full weeks that a faculty member's school uses remote instruction. Columns (2), (3) and (4) use the number of papers that a faculty member publishes in the Spring of 2020. Estimates are regressed on the number of weeks since the start of the semester to the week that a school reports its first positive COVID-19. Standard errors clustered at the school level. * p<0.1 ** p<0.05 *** p<0.01.

Appendix Table 22: The Complete List of Estimates in Table 24
Panel B

	(1)	(2)	(3)
		2SLS Estimates	
	All WPs	COVID-19-Related WPs	Non-COVID-19-Related WPs
Number of Weeks Remote	0.109	-0.006	0.115
	(0.075)	(0.015)	(0.078)
Researcher Characteristics			
Experience	-0.000	0.000	-0.001
	(0.003)	(0.001)	(0.003)
Nonwhite	0.123	-0.065***	0.188
	(0.110)	(0.022)	(0.115)
School Characteristics			
Enrollment	-0.002	-0.001	-0.001
	(0.003)	(0.001)	(0.002)
Students Per Teacher	0.007*	0.004*	0.002
	(0.004)	(0.003)	(0.003)
% International Students	0.313	-0.057	0.370
	(0.468)	(0.094)	(0.479)
Top 200 School	-0.123	-0.009	-0.114
	(0.089)	(0.038)	(0.072)
Country Characteristics			
March 9th COVID-19 Cases	0.000	0.000	-0.000
	(0.001)	(0.000)	(0.001)
Unemployment Rate	0.005	0.004	0.001
	(0.018)	(0.007)	(0.016)
GDP Per Capita	0.003	0.000	0.003
	(0.004)	(0.001)	(0.003)
Population	-0.000*	0.000	-0.000**
	(0.000)	(0.000)	(0.000)
N	355	355	355

Note: The unit of observation is a faculty member. Column (1) show results for all working papers published in the Spring of 2020. Results that use COVID-19 related working papers and papers with no relation to COVID-19 can be found in columns (2) and (3), respectively.