Work from Home and the Productivity Gains from Rising Disability Employment

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Abstract

Since the pandemic, the supply of workers with disabilities has risen substantially, a trend largely attributed to the expansion of remote work opportunities. This paper examines how the rise in work from home (WFH) among disabled workers has affected productivity. Leveraging plausibly exogenous industry-level variation in WFH among disabled workers, I find that a one standard deviation increase in WFH is associated with a 4% increase in labor productivity. To confirm the observed relationship, I use the COVID-19 Workplace Closure Stringency Index as an instrumental variable, which introduces industry-level variation in disabled WFH driven by broadly applied state-level public health policies. Beyond productivity, I examine how the rise in remote work among disabled workers has impacted employment across firm age and size groups. I document a reallocation of employment from small and young firms to larger, incumbent firms, likely reflecting the latter's greater capacity to implement remote work at scale. These findings suggest that while WFH among disabled workers has enhanced productivity, it has also contributed to increased labor market concentration, favoring larger and older firms over their smaller and younger counterparts.
KEYWORDS: Work from home, productivity, value added, disability employment
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Any opinions and conclusions expressed herein are those of the author and do not necessarily represent the views of the Board of Governors or its staff. Any errors are my own.

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1 Introduction

Historically, individuals with disabilities have faced persistent barriers to workforce participation, with employment rates that lagged far behind those of non-disabled workers (Ne'eman and Maestas, 2022; Bloom et al., 2024). However, since 2020, disability employment in the U.S. has surged to an all-time time high, a trend primarily driven by rising labor force participation. Unlike previous economic recoveries, where employment gains were concentrated among non-disabled workers, the post-pandemic labor market has seen a reversal of this pattern, with individuals with disabilities entering and remaining in the workforce at historical rates (Kaye, 2010; Ne'eman and Maestas, 2022). This surge in disability employment coincided with the widespread adoption of remote work. In fact, recent work by Bloom et al. (2024) shows that the rise in disabled employment post-pandemic can be almost entirely explained by the rise in remote work opportunities.

For decades, disability advocates have pushed for greater workplace accommodations under the Americans with Disabilities Act (ADA) of 1990, which mandates that employers provide "reasonable accommodations" to ensure that disabled individuals have equal employment opportunities. Yet, prior to the pandemic, these accommodations—including requests for remote work—were often met with resistance, as employers cited large implementation costs, logistical challenges, or concerns over productivity (Acemoglu and Angrist, 2001; Kaye et al., 2011). The Covid pandemic unintentionally altered this dynamic. During the pandemic, as firms restructured their operations and rapidly expanded remote work for *all employees*, they unintentionally granted workers with disabilities the flexibility and accessibility they had long been seeking. This shift was not the result of deliberate policy efforts but rather an exogenous shock that forced firms to reevaluate their approach to work arrangements. The result was a fundamental change in the disabled employment landscape: workers with disabilities, who had been historically excluded from certain jobs due to mobility limitations, health concerns, or the need for workplace modifications, were suddenly able to participate in the labor market on a much larger scale.

In this paper, using U.S. micro-data, I document the magnitude of these disabled employment changes and find that disabled employment increased in occupations that were more amenable to remote work, with some occupations experiencing disabled employment gains of 5-7%. Notably, these employment gains were concentrated in professional, office-based occupations where WFH adoption was highest, while traditionally in-person occupations exhibited declines in employment. While prior research has linked the rise in

WFH to the increase in disability employment, my contribution extends this discussion by: (1) examining how these shifts have impacted industry productivity, and (2) examining how the rise in WFH among disabled workers has impacted employment across firm size and age groups.

Using plausibly exogenous industry-level variation in disabled WFH, I find that a one standard deviation increase in disabled WFH is associated with increases in real output, real output per worker, and real output per hour (labor productivity) of 6.6%, 4.6%, and 4.1%, respectively. For robustness and to address potential endogeneity concerns, I construct an instrumental variable using the COVID-19 Workplace Closure Stringency Index. This instrument provides plausibly exogenous variation in disabled WFH across industries, as state-level workplace closure policies were primarily driven by public health considerations rather than industry-specific economic conditions. In particular, these policies varied significantly across states but were implemented broadly across industries within a state. Indeed, the instrumental variable estimates confirm a robust positive relationship between disabled WFH and the productivity measures. Additionally, I examine the relationship between disabled WFH and real value added, including its per worker and per hour measures, and find that disabled WFH is associated with growth in real value added.

The increase in productivity can be linked to improvements associated with remote work for disabled workers. Specifically, remote work can eliminate commuting challenges and provide access to employment opportunities that might otherwise be inaccessible. Additionally, remote work offers greater control over the workspace—such as flexibility in attire, workspace layout, and ventilation—allowing individuals to optimize their working conditions. Moreover, as Choudhury et al. (2021) highlight, workers who self-select into remote arrangements tend to report higher satisfaction and are more likely to exert productivity-enhancing effort, motivated by the nonpecuniary advantages of working from home.

To conclude the paper, I show that the rise in disabled WFH coincided with a reallocation of labor from small and young firms toward larger, incumbent firms—potentially driven by the latter's greater resources to implement remote work at scale. Taken together, these findings highlight both the productivity-enhancing effects of disabled WFH and its unintended consequences for labor market concentration.

2 Data and Definitions

2.1 Data

Employment information. The Quarterly Workforce Indicators (QWI)— which is sourced from the Longitudinal Employer-Household Dynamics—provides local labor market statistics by industry, worker demographics, and firm age and size groups. For my analysis, I construct the quarterly employment share (normalized to 2019) for the smallest and youngest firms as well as the largest and oldest firms.[1] My sample spans from 2017Q1 through 2023Q3.

Industry productivity. The Bureau of Labor Statistics Industry Productivity (BLS-IP) contains annual measures of labor productivity for the U.S. business sector, nonfarm business sector, nonfinancial corporate sector, and manufacturing sector. I use the BLS-IP to construct a panel of industries with information on real sectoral output, real sectoral output per worker, and real sectoral output per hour (labor productivity) across 286, 4-digit North American Industry Classification System (NAICS) industries from 2017 through 2023.[2]

Value added. Data on real value added and its components—Compensation of employees; Taxes on production and imports less subsidies; and Gross operating surplus—at the industry level is from the U.S. Bureau of Economic Analysis (BEA).[3] The BEA provides this information at the super-sector level.[4] I calculate the logarithm of real value added and its components from 2005 to 2023. Additionally, I compute real value added and its components on a per worker basis by first calculating average industry employment by year from 2005 to 2023 using the Quarterly Census of Employment and Wages (QCEW). I then divide each measure by employment. Similarly, I compute real value added and its components on a per hour basis by using hours worked from the BLS-IP and dividing each measure by total hours worked.

[1] Specifically, I focus on firm age groups: 0-1 Years and 11+ Years, and firm size groups: 0-19 Employees, and 500+ Employees.

[2] As defined by the BLS, sectoral output is the gross output less intra-industry transactions, which avoids the issue of double-counting that occurs when one establishment provides materials used by other establishments in the same industry.

[3] As defined by the BEA, the three components include an industry group's return to domestic labor (compensation of employees), its net return to government (taxes on production and imports less subsidies), and its return to domestic capital (gross operating surplus). The components are provided in nominal terms, so I express them in real terms using the PCE chain-type price index.

[4] The BEA creates their own industry classification system that combines multiple NAICS sectors, see: `https://www.bea.gov/resources/learning-center/what-to-know-industries`. Aside from this, the most consistent level of aggregation is at the NAICS super-sector level.

Work from home and disability. Data on work-from-home is from the American Community Survey (ACS) transportation to work question that asks, "What is your primary means of transportation to work on the most recent day worked?" (Flood et al., 2023). Responses to this question include car, bus, train, walk, bicycle, or *worked from home*. I calculate the fraction of *disabled* workers, aged 18 to 64, who answer "Worked from home" for each year and occupation in 2019 and 2022. In addition, for the industry level analysis in Section 3.4, I calculate an analogous measure of disabled WFH at the super-sector level from 2005 through 2023. Lastly, data used to compute changes in disability employment by month, as shown in Figure 1, come from the Current Population Survey (CPS) (Flood et al., 2023).

2.2 Definition of Disability

The CPS and ACS collect information on a respondent's disability status by using six questions which ask about: (1) hearing difficulty; (2) vision difficulty; (3) ambulatory difficulty; (4) independent living difficulty; (5) self-care difficulty; and (6) cognitive difficulty.[5] Prior to the pandemic, between 2017 to 2019, 8% of respondents in the CPS had a disability that fell into one of the six categories. During the same period, roughly 3.5% of respondents in the CPS had a disability and were working. In the ACS, the population with a disability who are working is slightly higher at 5.8%.

As Bloom et al. (2024) show, the cognitive difficulty category—having serious difficulty concentrating, remembering, or making decisions—expanded substantially after the pandemic, rising from around 6 million people before the pandemic to over 7 million after the pandemic. In Appendix Figure B.1, I plot the percent change in the population when including and excluding cognitive difficulty in the definition of disability. Prior to the pandemic, the population with a disability are similar, regardless of the measure used. However, after the pandemic, there was indeed a large inflow of individuals categorized as having a cognitive disability. These changes likely reflect pandemic-related factors, such as increased mental health challenges or long Covid.

One possible concern, as expressed in Bloom et al. (2024), is that these individuals could

[5] Specific question are as follows. Hearing: is anyone deaf or does anyone have serious difficulty hearing? Vision: is anyone blind or does anyone have serious difficulty seeing even when wearing glasses? Ambulatory: does anyone have serious difficulty walking or climbing stairs? Independent living: because of a physical, mental, or emotional condition, does anyone have difficulty doing errands alone such as visiting a doctor's office or shopping? Self-care: does anyone have difficulty dressing or bathing? Cognitive: because of a physical, mental, or emotional condition, does anyone have serious difficulty concentrating, remembering, or making decisions?

have more marginal disabilities and therefore have higher employability. This may bias my estimates as my WFH measure may be contaminated by changes in the population composition. To ensure my analysis isolates the effects of WFH, I focus only on the set of disabilities that do not change drastically pre-post pandemic.[6] This approach reduces potential noise from pandemic-driven compositional changes. For robustness, I repeat my analysis to include the cognitive difficulty in the definition of disability and show my results are not sensitive to its inclusion. From 2017 to 2023, using the definition of disability that does not include cognitive difficulties, henceforth referred to just as "disability" unless otherwise noted, 4.6% and 7% of the population are working in the ACS and CPS, respectively.[7]

3 Results

3.1 Trends in Disabled Employment and Work from Home

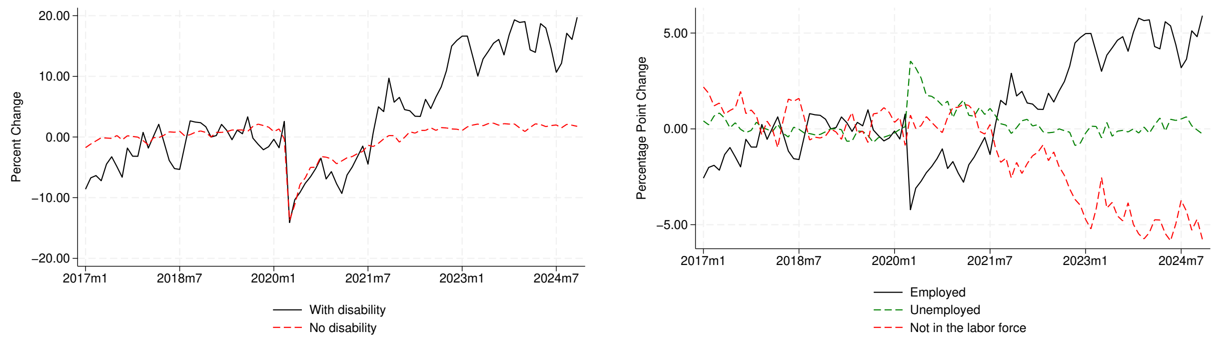
I begin by discussing the overall trends in disabled employment. In Figure 1 left panel, there has been a surge in disability employment in the U.S. since the pandemic. Prior to the pandemic, from 2017 to the end of 2019, employment trends for the disabled follow those for workers without a disability. During the pandemic, both groups exhibited a sharp and temporary decline in employment, a trend also noted by Bloom et al. (2024) and Ne'eman and Maestas (2022). However, post-pandemic, the employment trends begin to diverge. At the end of 2021, disability employment was 6% higher than pre-pandemic levels and continued to rise, as employment was 16% higher at the end of 2022, and nearly 20% at the end of 2024. On the other hand, post-pandemic, employment for the population without a disability remained relatively similar to pre-pandemic trends.

To understand what is driving this increase in employment, Figure 1 right panel decomposes the population with a disability into three groups: employed, unemployed, and not in the labor force. The entire increase in disabled employment in the post-pandemic period comes from a drop in individuals not in the labor force, or in other words a rise in labor force participation for individuals with a disability. In particular, the sharp drop in disabled employment during the onset of the pandemic is mirrored by a sharp increase in unemployment.

[6] Notably, as seen in Appendix Figure B.1, there is a dip in the population with a disability in 2020-2021. This is because the Census Bureau had difficulties in interviewing people during the pandemic.

[7] Prior to the pandemic (from 2017 to 2019), the percent of disabled who are working is 4.4% and 3% in the ACS and CPS, respectively.

FIGURE 1 – The Surge in Disability Employment Post-Pandemic



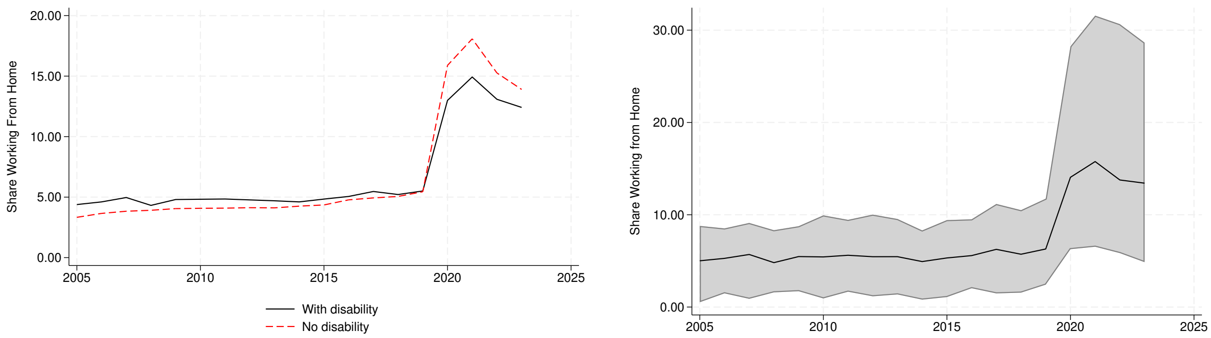
NOTE: Author's calculations from the CPS. The left panel graphs the percent change in the employment rate normalized to 2019 for individuals with and without a non-cognitive disability (18-64 years old). The right panel shows the percentage point change in employment, unemployment, and not in the labor force, normalized to 2019, for individuals with a non-cognitive disability.

However, in the post-pandemic period there are little changes to disabled unemployment, and the post-pandemic surge in employment is mirrored by a drop of disabled individuals not in the labor force.

At the same time of the increasing disability employment there was a concurrent surge in WFH. Figure 2 left panel plots the share of workers with and without a disability who report working from home. From 2005 to 2019, the share working from home remained at or below 5%. However, across both groups, there was a near three fold increase in the WFH share post-pandemic. For workers without a disability the WFH share increased from 6% in 2019 to 18% in 2021. Similarly, for workers with a disability, the WFH share increased from 7% in 2019 to 16% in 2021. Notably, across both groups, the 2023 WFH share is more than double its pre-pandemic value, suggesting that the pandemic led to a permanent shift in working arrangements (Barrero et al., 2023).

Figure 2, right panel, shows substantial variation in the share of disabled workers working from home (WFH) across industries. The figure plots the aggregate share of disabled workers reporting WFH (solid black line) alongside the range of values across industries (shaded area). Notably, the surge in WFH was more pronounced in some industries than others. For instance, industries such as Retail Trade, Utilities, and Education and Health Services had pre-pandemic disabled WFH shares between 2% and 5%, which surged to 7%, 15%, and 14%, respectively, in 2021. Additionally, industries with higher pre-pandemic disabled WFH shares—such as Information, Professional and Business Services, and Financial Activities—reported roughly 10% WFH shares before the pandemic.

FIGURE 2 – The Surge in Work from Home



NOTE: The left panel plots the fraction of people who reported "worked from home" by their disability status using the transportation-to-work question from the ACS. The right figure plots the fraction of disabled individuals who reported "worked from home" for the aggregate (solid black line) and the range of values across industries (shaded area, 5th percentile to 90th percentile).

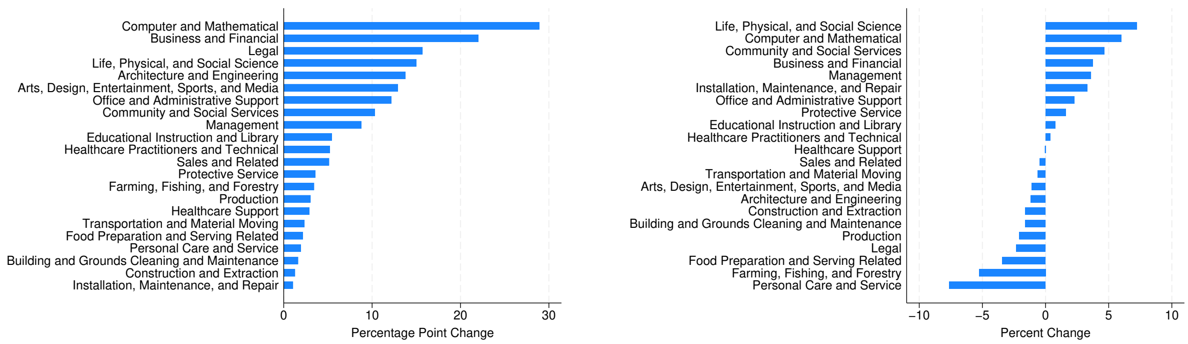
These shares reached all-time highs of 32%, 28%, and 37%, respectively, after the pandemic. As of the latest data vintage, disabled WFH shares across all industries remain well above pre-pandemic levels. In Section 3.4, I will leverage this variation in disabled WFH across industries to estimate its effect on productivity outcomes.

Americans with Disabilities Act (ADA). Taking a step back to understand what policies exist in the U.S. for workers with disabilities, there is the ADA. Title I of the ADA of 1990 requires employers to provide reasonable accommodations, which allows individuals with a disability to have an equal opportunity to get a job and successfully perform their job to the same extent as people without disabilities. These types of accommodations include physical changes, accessible and assistive technologies (such as remote work), and policy enhancements.[8] However, it is not necessary to provide a reasonable accommodation if doing so would cause an undue hardship. Examples of undue hardship include: if the accommodation is costly, extensive, disruptive, or would fundamentally alter the nature or operation of the business.

As a result, employers have been hesitant to implement such accommodations prior to the pandemic (Acemoglu and Angrist, 2001; Kaye et al., 2011; Bloom et al., 2024). However, the pandemic introduced a technology shock where firms restructured production and provided remote work options for all workers. As highlighted by Bloom et al. (2024), this WFH shock unintentionally created new employment opportunities for people with disabilities.

[8]See U.S. EEOC: "Work at Home/Telework as a Reasonable Accommodation"; 2003. EEOCNVTA- 2003-1 https://www.eeoc.gov/laws/guidance/work-hometelework-reasonable-accommodation.

FIGURE 3 – The Disabled WFH Share and Employment Increased the Most in Computer and Office-Focused Occupations



A. WFH Share B. Employment

NOTE: Panel A plots the percentage point change in the disabled WFH share pre-post pandemic across 2-digit occupations from the ACS. Panel B plots the percent change in disability employment pre-post pandemic across 2-digit occupations from the ACS.

As documented in Figure 2, this restructuring towards remote work opportunities led to the WFH share across disabled and non-disabled workers to increase by 3 fold. In addition, as shown in Figure 3, there were meaningful post-Covid employment gains for disabled workers in occupations that be done remotely.

In Figure 3 left panel, the disabled WFH share increased the most for Computer and Mathematical occupations—exhibiting a nearly 30% increase pre-post pandemic. Similarly, Business and Financial, Legal, and Social Science occupations exhibited large increases in the disabled WFH share. On the other hand, occupations with the smallest increases in the disabled WFH share are traditionally in-person such as Instillation and Repair, Construction, and Maintenance. When looking at actual changes in employment for disabled workers, a similar pattern emerges: The largest changes are in computer and office-focused occupations. In particular, Social Science, Computer and Mathematical, Social Service, and Business and Financial had observed increases in disabled employment by roughly 7%, 6%, 5%, and 4.5%, respectively. Occupations with declines in disabled employment include those that can't be performed remotely such as Personal Care and Services, Farming and Fishing, and Food Preparation.

Given these trends, a natural initial question is, "Does the ability to work from home increase employment of individuals with a disability?" Prior work by Bloom et al. (2024) finds that the answer is yes. Using an occupational regression approach, they find that a 1 percentage point increase in WFH is associated with a 1.1% increase in full-time employment for individuals with a disability. In fact, they show that WFH can explain roughly

80% of the rise in disabled employment post-pandemic—the trend that is captured in Figure 1. Put differently, the transformational change in flexible work arrangements unintentionally benefited disabled individuals as they received the accommodation they have been asking for.

Taking the result by Bloom et al. (2024) as given, this paper shifts the attention to understanding the relationship between disabled WFH and industry productivity. To be precise, this paper asks the following question, "How does the rise in disabled work from home affect industry productivity?". In addition, I also examine how the rise in disabled WFH has affected employment across firm age and size groups. In the next section I discuss how I construct the main explanatory variable that leverages variation in disabled WFH across 4-digit NAICS industries.

3.2 Empirical Methodology

The main explanatory variable that will be used in the event study analysis is an exposure instrument of disabled WFH across U.S. industries. I leverage the fact that disabled WFH varies across occupations and that occupations vary in their distribution of industry employment, to create a shift-share variable. The shift-share or "bartik" method was originally proposed by Bartik (1991), and has since taken on different variants.[9] In defining my "shift", I use the ACS transportation to work question to calculate disabled WFH rates in 2019 and 2022 across 3-digit Standard Occupational Classification occupations. I then take the absolute difference between the two years,

$$\Delta \mathrm{WFH}_j^{\mathrm{d}} = \mathrm{WFH}_{j,2022}^{\mathrm{d}} - \mathrm{WFH}_{j,2019}^{\mathrm{d}}.$$

Here, $\mathrm{WFH}_{j,2022}^{d}$ represents the disabled WFH share in three-digit occupation j in 2022, and $\mathrm{WFH}_{j,2019}^{d}$ denotes the disabled WFH share in three-digit occupation j in 2019.[10] For the share component, I use data from the Occupational Employment and Wage Statistics (OEWS), which contains national estimates for cross-industry occupational employment. I use 2019 as my baseline and calculate the employment share of 4-digit industry k in three-digit occupation j. Specifically,

$$\varphi_{j,k} = \frac{E_{j,k}}{E_k}.$$

[9] For example see Autor et al. (2013); Hershbein and Kahn (2018) and Acemoglu and Restrepo (2021).

[10] To see the distribution of the shift component see Appendix Figure B.2. I show the shift when including and excluding cognitive difficulty in the definition of disability.

Here, E_k represents total employment in industry k, and $E_{j,k}$ denotes the total employment of occupation j in industry k.

$$\text{WFH shock}_k = \sum_{k=1}^{K} \varphi_{j,k} * \Delta\text{WFH}_j^{\text{d}}, \quad \Delta\text{WFH}_j^{\text{d}} = \text{WFH}_{j,2022}^{\text{d}} - \text{WFH}_{j,2019}^{\text{d}}. \tag{1}$$

As shown in equation 1, taking the inner product of the shift and share components will give me my main explanatory variable, WFH shock_k. I interpret WFH shock_k as an industries differential exposure to disabled WFH. I am using variation in disabled WFH across industries, as some industries will have high levels of WFH shock_k—indicating that the industry was "hit harder" by disabled WFH—and some industries will have low levels of the WFH shock. In Appendix Figure B.3, I show the distribution of the shift-share.[11] The calculated values range from 0.02 to 0.22. Industries with high exposure to disabled WFH include: Computer Systems Design and Related Services; Software Publishers; and Data Processing, Hosting, and Related Services. On the other hand, industries with low exposure to disabled WFH include: Restaurants and Other Eating Places; Footwear Manufacturing; and Child Day Care Services.

3.3 Threats to Identification

Shift-share variables leverage two sources of variation, and ideally, both components are exogenous (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2025). In my methodology, the first source of variation is the shift in disabled WFH pre-post pandemic (2019 vs 2022). This shift in WFH is plausibly exogenous, as the transition towards remote work was due to an exogenous technology shock stemming from the Covid outbreak. My identifying assumption is that changes in disabled WFH are driven by changes in the supply and demand for non-disabled workers, not for workers with a disability. The basic idea is to isolate the effect of disabled WFH on productivity and employment without confounding from disability-specific labor market dynamics. This may be reasonable given that the disability share of employment was small pre-pandemic at roughly 4%. Hence, if disabled workers did not have much sway in the labor market prior to the pandemic, it is reasonable to assume they do not post-pandemic.

The second source of variation is in the industry-occupation employment shares. The key identification assumption for the shares is that the distribution of occupational em-

[11] In addition, I also contruct a version of the shift-share where the WFH rate—the shift component—includes cognitive difficulty in the definition of disability.

ployment across industries is conditionally exogenous with respect to other determinants of industry-level outcomes. In other words, if the distribution of occupational employment across industries is orthogonal to other determinants of industry-level outcomes, my shift-share variable isolates a source of variation in disabled WFH exposure that can be used to consistently estimate β. In addition, by using 2019 employment shares, I am avoiding Covid specific labor market dynamics or concerns of labor market tightness in the post-pandemic period.

For robustness and to address potential endogeneity concerns with the disabled WFH shock measure, I construct an instrument using the U.S. COVID-19 Workplace Stringency Index (Roser, 2021).[12] The index for workplace closures is calculated at the daily level across all U.S. states and values range from 0 to 3, with higher values indicating more stringent restrictions.[13] I aggregate this index to the industry level as follows:

$$\text{Stringency IV}_k = \sum_{k=1}^{K} \omega_{k,s} * \text{Stringency}_s.$$

Here, $\omega_{s,k}$ represents the 2019 share of employment of 4-digit industry k in state s, and Stringency_s is the average workplace stringency index in that state from March 2020 to the end of 2021. Summing this product across industries yields an industry-level instrument that reflects differential exposure to pandemic-induced workplace restrictions.[14] This approach provides plausibly exogenous variation in disabled WFH adoption across industries, as state-level workplace closure policies were primarily driven by public health considerations rather than industry-specific economic conditions. These policies varied significantly across states but were implemented broadly across industries within a state, reducing concerns that the instrument reflects industry-specific shocks. Additionally, by weighting the index using 2019 employment shares, the instrument captures pre-pandemic industry distributions, minimizing pandemic related labor market conditions. Lastly, by focusing only on workplace closures—rather than broader stringency measures such as school closures or travel restrictions—the instrument isolates variation in disabled WFH that is relevant to industry-level workplace dynamics and minimizes

[12] In general, the overall COVID-19 stringency index uses nine metrics: school closures; workplace closures; cancellation of public events; restrictions on public gatherings; closures of public transport; stay-at-home requirements; public information campaigns; restrictions on internal movements; and international travel controls. I only focus on workplace closures.

[13] For example, on March 28th, the governor of Alaska closed all non-essential business. This is coded as a 3 in the data. See:https://web.archive.org/web/20210412040746/https://gov.alaska.gov/wp-content/uploads/sites/2/03272020-SOA-COVID-19-Health-Mandate-011.pdf.

[14] To see the distribution of the IV see Appendix Figure B.3 Panel B.

correlation with unobserved factors affecting the outcome variable.

3.4 Productivity Results

Disabled WFH and value added. To begin, I examine the raw relationship between changes in disabled WFH and changes in real value added at the industry level. Figure 4 illustrates how changes in disabled WFH are associated with changes in six key outcomes: real value added, real value added per worker, real value added per hour, compensation, compensation per worker, and compensation per hour. Following a similar methodology to Sedlacek and Shi (2024), I calculate changes in these outcomes by comparing the average values at the end of the pre-pandemic period (2018–2019) and the post-pandemic period (2021–2023) to those at the start of the sample (2005–2006).

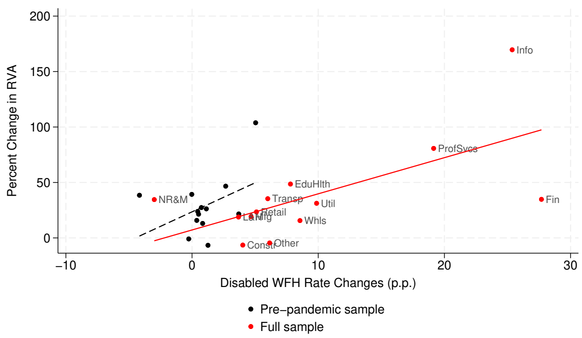
Figure 4 shows that industry level increases in work from home among disabled workers are associated with higher real value added, employee compensation, as well as their per worker and per hour measures. Notably, the correlation between disabled WFH and the measures of interest strengthen post-pandemic. First, real value added rises from 0.42 in the pre-pandemic period to 0.65 in the full sample. The correlation between disabled WFH and real value added per worker increases from 0.51 pre-pandemic to nearly 0.60 in the full sample. Similarly, the correlation between disabled WFH and real value added per hour increased from 0.46 to 0.57. Second, the correlation between disabled WFH and total compensation grows substantially—from near zero (-0.01) pre-pandemic to 0.49 in the full sample. The same pattern holds for compensation per worker, with the correlation rising from 0.50 pre-pandemic to nearly 0.70 post-pandemic; and for compensation per hour, doubling from 0.30 to 0.60. Overall, these results indicate that the raw relationship between disabled WFH and real value added, along with its components, strengthened in the post-pandemic period.

Next, I will leverage the variation in disabled WFH across industries to estimate the following strongly balanced panel regression:

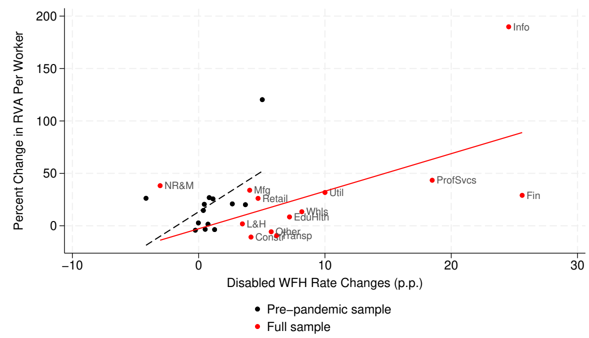
$$\text{outcome}_{k,t} = \delta_k + \delta_t + \beta \text{WFH}^d_{k,t} + \Gamma X_{k,t} + \varepsilon_{k,t}, \tag{2}$$

Here, $\text{outcome}_{k,t}$ is the log of: Real value added; Compensation to employees; Taxes less subsidies; Gross operating surplus; and its per worker and per hour measures in industry k at time t. δ_k and δ_t are industry and time fixed effects, respectively.

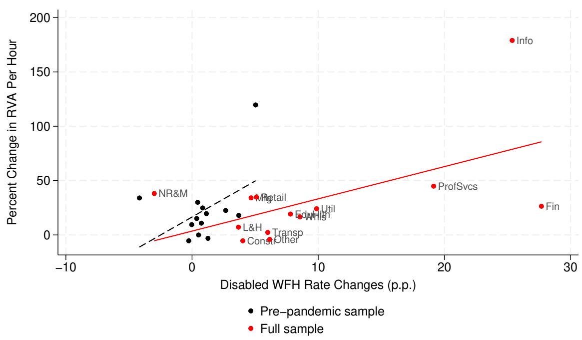
FIGURE 4 – Industry Changes in Disabled Work from Home, Value Added, and Employee Compensation



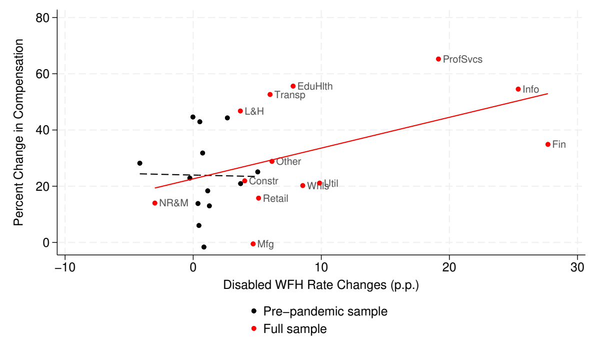
A. RVA



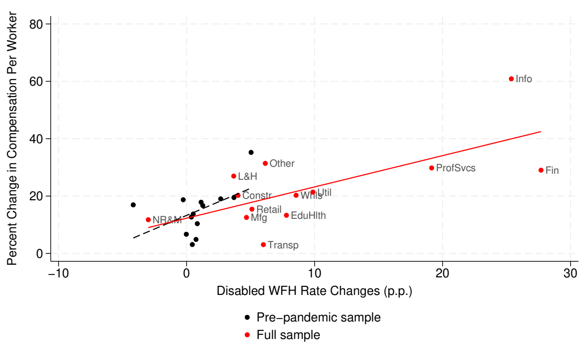
B. RVA per worker



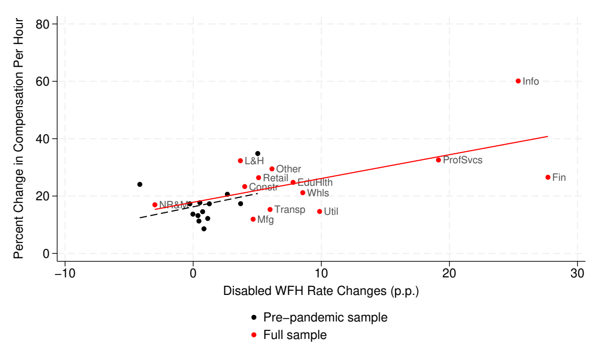
C. RVA per hour



D. Compensation



E. Compensation per worker



F. Compensation per hour

NOTE: Panel A through Panel C plot the relationship between super-sector changes in disabled WFH against changes in real value added, real value added per worker, and real value added per hour, respectively. Panel D through Panel F plot the relationship between super-sector changes in disabled WFH and changes in compensation, compensation per worker, and compensation per hour, respectively. In all panels, the pre-pandemic sample refers to 2005 through 2019 and the full sample refers to 2005 through 2023. WFH is calculated using the transportation-to-work question from the ACS. Data on real value added and compensation of employees is from the BEA.

TABLE 1 – Disabled Work from Home and Real Value Added

Regressor	Dependent Variable: Log of Real Value Added				
	(1)	(2)	(3)	(4)	(5)
A. ***Pre-pandemic (2005-2019)***					
$\text{WFH}^{d}_{k,t}$	0.188^{*}	-0.057	0.143	0.236	0.028
	(0.097)	(0.126)	(0.293)	(0.266)	(0.297)
B. ***Full Sample (2005-2023)***					
$\text{WFH}^{d}_{k,t}$	0.125^{**}	0.019	0.287^{**}	0.371^{***}	0.387^{***}
	(0.056)	(0.080)	(0.110)	(0.123)	(0.128)
Controls		✓	✓	✓	✓
Sector FE			✓	✓	✓
Time FE				✓	✓
Employment Weight					✓

NOTE: The table reports the β's from equation 2. The dependent variable is the log of real value added from the BEA. The independent variable is the disabled work from home (WFH) rate calculated from the ACS. Panel A reports estimates using the pre-pandemic period (2005-2019) only, while Panel B reports results for the entire sample period (2005-2023). Panel A has 182 observations and Panel B has 234 observations. All specifications include 1 lag of the dependent variable. Controls include: male, white, Hispanic, age, education, and a 3rd order polynomial of employment to proxy for labor market tightness. Standard errors are reported in parentheses, * $p < .10$; ** $p < .05$; and *** $p < .01$.

$X_{k,t}$ includes disabled worker characteristics: male, white, Hispanic, age, education, and a 3rd order polynomial of employment to control for labor market tightness.[15] $\varepsilon_{k,t}$ is an error term. The main object of interest is coefficient β, which provides the effect of disabled WFH, $\text{WFH}^{d}_{k,t}$, on real value added and its components.

Table 1 shows that disabled WFH is associated with increases in real value added. Specifically, Panel A of Table 1 examines the relationship between disabled WFH and real value added during the pre-pandemic period (2005–2019). The results indicate no statistically significant or consistent estimates across all specifications. I therefore conclude that there is no detectable effect of disabled WFH on real value added in the pre-pandemic period. Additionally, Appendix Tables A1 and A2 present results for real value added per worker and per hour, which similarly show no detectable effect of disabled WFH during the pre-pandemic period.

[15] In the post-pandemic period, aggregate labor market tightness increased by 60% and may have influenced firms willingness to hire workers with disabilities Bloom et al. (2024). This could confound my analysis if observed changes in real value added and its components are driven by shifts in labor market conditions rather than disabled WFH adoption alone.

TABLE 2 – Disabled WFH and Components of Value Added; Regression Results: 2005-2023

Regressor	Dependent Variable: Log of Compensation to employees	Log of Taxes less subsidies	Log of Gross operating surplus
	Panel A: Level		
$\text{WFH}^d_{k,t}$	0.835^{***}	-0.045	-0.447
	(0.196)	(1.152)	(0.376)
	Panel B: Per worker		
$\text{WFH}^d_{k,t}$	0.718^{***}	-0.162	-0.564
	(0.111)	(1.153)	(0.367)
	Panel C: Per hour		
$\text{WFH}^d_{k,t}$	0.505^{***}	-0.375	-0.777^{**}
	(0.096)	(1.151)	(0.368)

NOTE: The table reports the β's from equation 2. The dependent variable is the log of industry compensation to employees, taxes less subsidies, and gross operating surplus. The independent variable is the disabled work from home (WFH) rate calculated from the ACS. All specifications are weighted by industry size (measured by employment), include industry and year fixed effects, and include the following controls: male, white, Hispanic, age, education, and a 3rd order polynomial of employment to proxy for labor market tightness. N = 247. Dependent variables are expressed in real terms using the PCE chain-type price index. Standard errors are reported in parenthesis, * $p < .10$; ** $p < .05$; and *** $p < .01$.

In contrast, Panel B of Table 1 shows the relationship between disabled WFH and real value added in the full sample (2005–2023). Across all specifications, the results consistently show significant positive effects, suggesting that, post-pandemic, disabled WFH is positively associated with growth in real value added.[16] For example, in the full sample, a 1 percentage point increase in the disabled WFH share increased compensation per hour by 0.51%.

Next, Table 2 shows that the underlying mechanism driving the increase in real value added is higher employee compensation. Specifically, I estimate the effect of disabled WFH on the components of value added—Compensation to Employees, Taxes Less Sub-

[16] Appendix Tables A1 and A2 present similar qualitative results for real value added per worker and per hour.

sidies, and Gross Operating Surplus.[17] The results indicate that, regardless of the measure used—whether the log of levels, per worker, or per hour values—increases in disabled WFH during the post-pandemic period are strongly and statistically significantly associated with higher employee compensation at the 1% level.[18] No detectable effects are found for the other components of value added.

Event study analysis: To examine how the disabled WFH shock affects productivity, I use an event study approach as shown in equation 3.

$$\hat{Y}_{k,t} = \alpha_0 + \sum_{t=-4}^{3} \lambda_t I^t + \sum_{t=-4}^{3} [\alpha_{1,t} I^t \times \text{WFH shock}_k] + \tau_{m,t} + \gamma_k + \varepsilon_{k,t} \tag{3}$$

The left-hand side, $\hat{Y}_{k,t}$, represents the percent change in the level of real output, real output per worker, and real output per hour for industry k at time t, normalized to 2019. The object of interest is α_1, which will explain the relationship between the disabled WFH shock and changes in productivity before, during, and after the Covid pandemic.

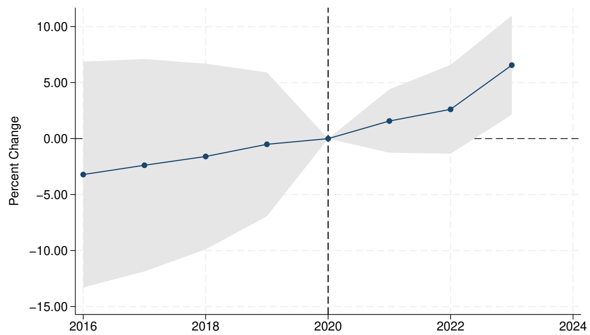
I also include a set of year dummies, I^t, sector by year fixed effects, $\tau_{m,t}$, and industry fixed effects, γ_k. Moreover, I weight the specification by the baseline (2019) employment size for each industry. Using 2019 employment ensures that the weights reflect industry size before any potential distortions caused by the Covid pandemic in 2020, which could bias the estimation if employment changes were driven by temporary shocks rather than underlying industry characteristics. Lastly, $\varepsilon_{k,t}$ is an error term and I cluster standard errors by industry and year.

Figure 5 Panels A through E, plot the point estimates of α_1 from equation 3 and shows the main result of this paper: The rise in disabled WFH is associated with a significant increase in labor productivity post-pandemic. Notably, in Panel D and Panel E, I plot the estimates of α_1 from equation 3, where I am instrumenting for disabled WFH using the COVID-19 Workplace Stringency Index (as described in Section 3.3). In all panels, the pre-trend assumption is valid, as the point estimates before the pandemic are close to zero and not statistically significant, suggesting no systematic differences in trends prior to the rise in disabled WFH.

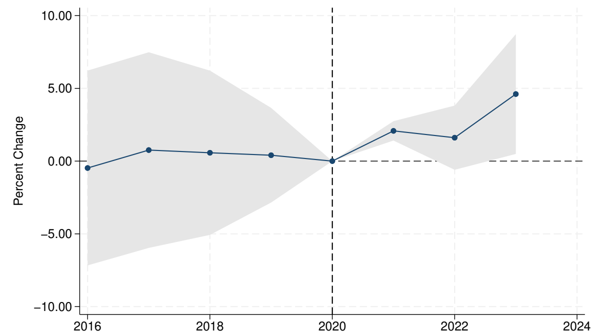
[17] I focus solely on the full sample (2005–2023), as the pre-pandemic period yielded no detectable effects.

[18] As shown in Figure 4, the Information sector is an outlier, exhibiting substantial changes in both disabled WFH and real value added, as well as its components. Excluding this sector from the panel regression analysis yields slightly lower but still statistically significant results. For example, the main estimate for real value added declines from 0.39 to 0.32, while the per worker and per hour measures remain unchanged. Moreover, compensation, compensation per worker, and compensation per hour fall from 0.84 to 0.70, from 0.72 to 0.49, and from 0.51 to 0.30 respectively.

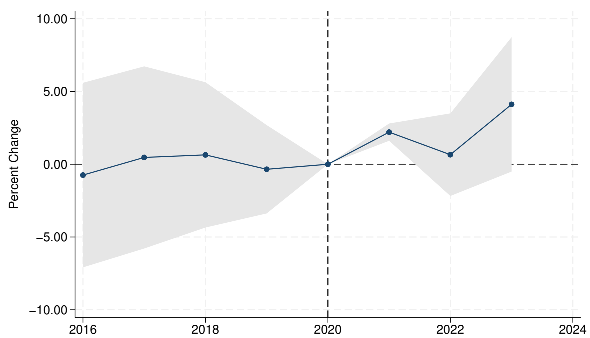
FIGURE 5 – Disabled WFH is Associated with Increases in Productivity



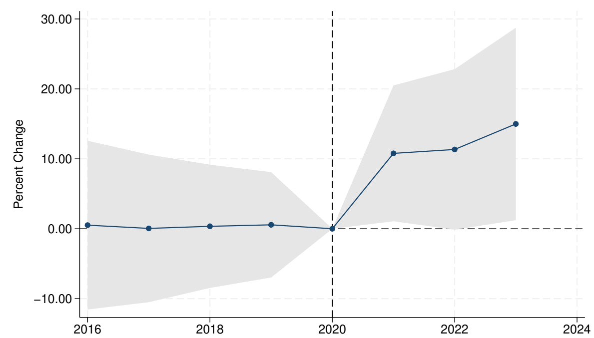
A. Real output



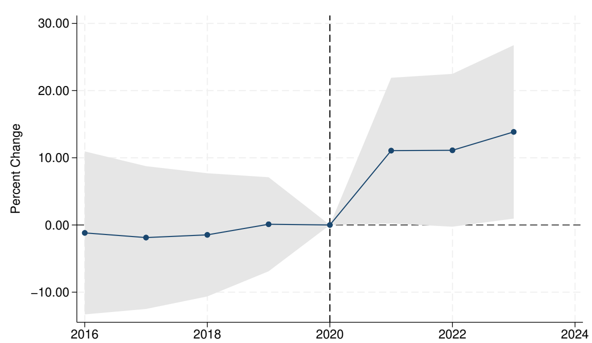
B. Real output per worker



C. Real output per hour



D. Real output per hour: Instrumented



E. Real output per worker: Instrumented

NOTE: The independent variable is a shift-share variable that measures industry exposure to disabled WFH. Panel A to Panel C plot the point estimates of α_1 from equation 3. Panel D and Panel E plot the estimates of α_1 from equation 3, however, the independent variable is instrumented using the COVID-19 Workplace Closure Stringency Index as described in section 3.3 and has a Cragg-Donald Wald F statistic of 24.

In Table 3, I show how the point estimates change when introducing fixed effects and the employment weight.[19] Starting with Table 3 Panel A, in 2021 and 2022, across columns one to four, there is no consistent detectable effect of the disabled WFH shock on changes in the real output level. However, the results in Panel A, row 3 indicate that in 2023, a 1 SD increase in the work from home shock is associated with a statistically significant increase in real output levels across all specifications, with point estimates ranging from 4.1% to 6.7%.

In the baseline model (Column 1), the effect is 4.1% and significant at the 1% level, capturing the raw relationship between disabled WFH and real output without adjusting for structural factors. When sector by year fixed effects are added (Column 2), the estimate increases to 6.7%, suggesting that within-sector changes over time strengthened the relationship. The inclusion of industry fixed effects (Column 3) leads to a slightly lower estimate of 4.8%, indicating that WFH-driven productivity gains persist even after controlling for industry-specific factors. Finally, Weighting by 2019 employment (Column 4) increases the estimate to 6.6%, which suggests that the benefits of disabled WFH were not just driven by small, high-adoption sectors but also meaningfully impacted larger industries that employed most workers in 2019. The result ensures that the estimated effect is representative of the overall economy rather than being skewed by smaller industries with extreme disabled WFH effects.

Similarly, in Table 3 Panel B, the effect of the disabled WFH shock on changes in the real output per worker is consistently detectable in 2023, as the effect of a 1 SD increase in the disabled WFH ranges from 2.7% to 4.6%. The result is robust to the inclusion of sector-year and industry fixed effects as well as weighting by baseline employment levels. In both panels, the effect in 2023 is larger and more robust than in previous years, suggesting that productivity gains from WFH policies for disabled workers strengthened over time.

Panel C of Table 3 examines the effect of the disabled WFH shock on changes in real output per hour—or labor productivity—providing results of productivity at the intensive margin. The results mirror those observed in Panel B, with no consistent detectable effects in 2021 and 2022 across most specifications. However, the relationship becomes statistically significant and robust in 2023, where a 1 SD increase in the disabled WFH shock is associated with an increase in real output per hour ranging from 3.0% to 4.1% across columns one to four.

[19] See Appendix Table A3 for the results when including cognitive difficulty in the definition of disability. The results remain unchanged.

TABLE 3 – The Effect of Disabled Work from Home on Productivity

Regressor	(1)	(2)	(3)	(4)	(5)
Panel A: Dependent Variable: Percent change in real output level					
WFH Shock$_k$ × 2021	0.009	0.029	0.010	0.016	0.098*
	(0.011)	(0.019)	(0.006)	(0.012)	(0.057)
WFH Shock$_k$ × 2022	0.017	0.043*	0.025	0.026	0.122**
	(0.011)	(0.021)	(0.009)	(0.017)	(0.061)
WFH Shock$_k$ × 2023	0.041***	0.067**	0.048***	0.066**	0.152**
	(0.011)	(0.023)	(0.013)	(0.019)	(0.067)
Panel B: Dependent Variable: Percent change in real output per worker					
WFH Shock$_k$ × 2021	−0.021*	−0.005	0.006	0.021***	0.111**
	(0.011)	(0.013)	(0.005)	(0.003)	(0.055)
WFH Shock$_k$ × 2022	0.006	0.014	0.026***	0.016	0.111*
	(0.011)	(0.014)	(0.006)	(0.009)	(0.058)
WFH Shock$_k$ × 2023	0.027**	0.025	0.037**	0.046**	0.139**
	(0.011)	(0.017)	(0.012)	(0.017)	(0.066)
Panel C: Dependent Variable: Percent change in real output per hour					
WFH Shock$_k$ × 2021	−0.017	0.003	0.007	0.022***	0.109**
	(0.012)	(0.012)	(0.006)	(0.003)	(0.050)
WFH Shock$_k$ × 2022	0.001	0.012	0.017**	0.007	0.114*
	(0.012)	(0.014)	(0.006)	(0.012)	(0.059)
WFH Shock$_k$ × 2023	0.019	0.025	0.030**	0.041*	0.151**
	(0.012)	(0.016)	(0.011)	(0.020)	(0.070)
Sector-year FE		✓	✓	✓	✓
Industry FE			✓	✓	✓
Employment Weight				✓	✓
Instrument					✓

NOTE: Reports the point estimates of α_1 from equation 3. The independent variable is a shift-share variable that measures industry exposure to disabled WFH. The instrumental variable used in column five is the COVID-19 Workplace Closure Stringency Index as described in section 3.3. Standard errors are clustered by industry-year and are reported in parenthesis, * $p < .10$; ** $p < .05$; and *** $p < .01$.

In particular, the introduction of industry fixed effects in Column 3 yields a statistically significant 3.0% effect, and when employment weighting is applied in Column 4, the estimate rises to 4.1%. This pattern reinforces the notion that productivity gains from WFH arrangements for disabled workers became more pronounced over time.

One possible explanation for the lack of a significant effect of the disabled WFH shock before 2023 is the post-pandemic employment trends. As shown in Figure 1, disability employment did not begin to surge until late 2021 and early 2022. It could be that there is a lagged effect of the increase in productivity, as both firms hiring workers with disabilities and disabled workers themselves required time to adapt to remote work environment. Over time, productivity among disabled workers in WFH arrangements improved. This productivity enhancement can be driven by, but is not limited to, disabled workers saving on commute times (or, in some cases, being unable to commute); the ability to control their workspace (e.g., clothing, layout, ventilation); and, as Choudhury et al. (2021) argue, the fact that individuals who self-select into working from home experience greater satisfaction and exert more productivity-enhancing effort in appreciation of the nonpecuniary benefits of WFH.

Lastly, the fifth column of Table 3 reports the estimates of α_1 from equation 3 when instrumenting for disabled WFH by using the COVID-19 Workplace Closure Stringency Index as described in section 3.3. The instrument picks up on a positive and statistically significant effect from 2021 through 2023 for real output, real output per worker, and real output per hour (labor productivity). In Panel A, the estimated coefficient grows larger overtime, predicting a 9.8% increase in output in 2021 to a 15% increase in 2023. In Panel B, the estimated effect of disabled WFH on real output per-worker remains between 11% and 14%. Lastly, in Panel C, the estimated effect of disabled WFH ranges from 11% to 15%. The instrumental variable results provide qualitative robustness to the effect of disabled WFH on all productivity measures.[20]

3.5 Employment Results

$$\hat{Y}_{f,k,t} = \alpha_0 + \sum_{t=-4}^{3} \lambda_t I^t + \sum_{t=-4}^{3} [\alpha_{1,t} I^t \times \text{WFH shock}_k] + \tau_{m,t} + \theta_{s,t} + \gamma_k + \varepsilon_{k,t} \tag{4}$$

Next, to examine how the disabled WFH shock affects employment by firm age and size, I use a similar methodological approach as equation 2. However, now my outcome variable, $\hat{Y}_{f,k,t}$, represents the deviation in the employment share, normalized to 2019, for

[20] In addition, in Appendix Table A4 I estimate the effect of the instrument across all specifications.

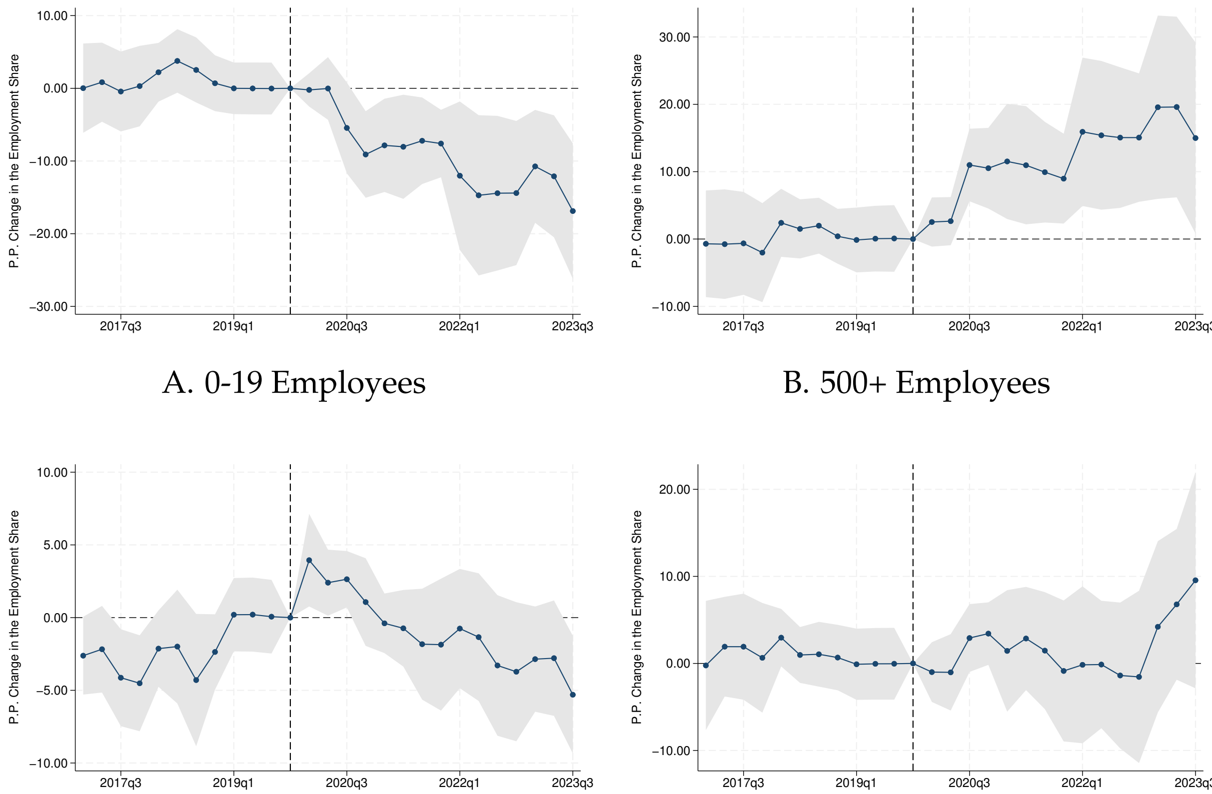
firm size or age group f, in industry k at time t. Again, the object of interest is α_1, which will explain the relationship between the disabled WFH shock and changes in employment before, during, and after the Covid pandemic. I also include a set of year dummies, I^t, sector by quarter fixed effects, $\tau_{m,t}$, state by quarter fixed effects, $\theta_{s,t}$, and industry fixed effects, γ_k. Lastly, $\varepsilon_{k,t}$ is an error term and I cluster standard errors by industry and year.

To begin, I discuss how the disabled WFH shock affects employment along the firm size dimension. In Panels A, B, and D, the pre-trend assumption is valid, as the point estimates before the pandemic are close to zero and not statistically significant, suggesting no systematic differences in trends prior to the rise in disabled WFH. In Figure 6, Panel A, which plots the employment share for small firms (0-19 employees), shows a sharp decline in the employment share following the onset of the pandemic, where a 1 SD increase in the disabled WFH shock leads to declines in employment by nearly 10 percentage point at the end of 2020. The estimates of α_1 suggest that industries more exposed to the disabled WFH shock experienced a steady decline in the employment share among small firms relative to their 2019 baseline.

The downward trend becomes more pronounced in the post-pandemic period, suggesting that small firms struggled to retain or regain employment in industries where WFH became more prevalent. In contrast, in Panel B, for large firms (500+ employees), a 1 SD increase in the disabled WFH shock is associated with a sharp increase in the employment share following the onset of the pandemic. The estimates of α_1 suggest a positive and sustained shift in employment toward large firms, particularly in the later years of the sample. Notably, the decline in employment for small firms is proportional to the increase in employment observed among the largest firms. Hence, the patterns across firm size groups may point towards a reallocation of employment from small to large firms, as large firms were better positioned to adapt to WFH relative to smaller firms.

Turning to the firm age dimension, Panels C and D show how the disabled WFH shock affected the employment share for younger (0-2 years) and older (11+ years) firms. I interpret panel C as purely descriptive since the pre-trends assumption does not hold. In the post-period, young firms showed a notable decline in the employment share for industries more exposed to the disabled WFH shock. For example, a 1 SD increase in the disabled WFH shock decreased the employment share for young firms by roughly 5 percentage points in 2023Q3.

FIGURE 6 – How Disabled WFH Impacts Employment by Firm Size and Age



A. 0-19 Employees

B. 500+ Employees

C. Age 0-2

D. Age 11+

NOTE: The independent variable is a shift-share variable that measures industry exposure to disabled WFH. Panel A and Panel B plot the point estimates of α_1 from equation 4 for small and large firms. Panels C and D plot the estimates of α_1 from equation 4 for young and old firms. All panels are estimated from 2017q1 through 2023Q3.

Conversely, Panel D illustrates that older firms (11+ years) in exposed industries saw a steady rise in employment share post-pandemic. For example, in 2023Q3, a 1 SD increase in the disabled WFH shock led to an increase in the employment share by 10 percentage points.

Taken together, these results suggest that the disabled WFH shock led to a reallocation of employment from small and young firms towards large and incumbent firms. One possibility is that larger and more established firms were able to absorb and benefit from the shift in work arrangements, likely due to having greater flexibility, resources and infrastructure to adopt remote work at scale.

4 Conclusion

The findings of this paper highlight the significant impact of the rise in work from home on both disability employment and productivity. While prior research has linked the post-pandemic surge in disability employment to the concurrent expansion of WFH, I show that the increase in disabled WFH has not only fostered a more inclusive labor market but has also contributed to measurable productivity gains. Specifically a one standard deviation increase in disabled WFH is associated with observed increases in real output, real output per worker, and real output per hour (labor productivity) of 6.6%, 4.6%, and 4.1%, respectively. Instrumental variables confirm the qualitative relationship between disabled WFH and productivity outcomes. The observed productivity gains can be attributed to several factors. These include disabled workers saving time by avoiding commutes (or, in some instances, overcoming commuting barriers altogether); the increased autonomy workers have in tailoring their work environment to their preferences (e.g., clothing choices, workspace layout, ventilation); and, as noted by Choudhury et al. (2021), the greater satisfaction and productivity-enhancing effort exhibited by individuals who self-select into remote work, driven by the appreciation of WFH's nonpecuniary benefits. My analysis also shows an important structural consequence: the rise of disabled WFH has coincided with a reallocation of employment from smaller and younger firms to larger, more established firms. This suggests that while remote work has broadened opportunities for workers with disabilities, it has also contributed to labor market concentration, favoring firms with greater capacity to implement remote work at scale.

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Work-from-Home and the Productivity Gains from Rising Disability Employment

Online Appendix

Octavio M. Aguilar

A Appendix: Tables

TABLE A1 – Disabled Work From Home and Real Value Added Per Worker

	Dependent Variable: Log of RVA Per Worker				
Regressor	(1)	(2)	(3)	(4)	(5)
A. ***Pre-pandemic (2005-2019)***					
$\text{WFH}^{d}_{k,t}$	0.058	-0.095	0.178	0.198	0.434
	(0.101)	(0.125)	(0.281)	(0.293)	(0.299)
B. ***Full Sample (2005-2023)***					
$\text{WFH}^{d}_{k,t}$	0.047	0.058	0.228^{**}	0.189	0.357^{***}
	(0.050)	(0.067)	(0.091)	(0.109)	(0.101)
Controls		✓	✓	✓	✓
Sector FE			✓	✓	✓
Time FE				✓	✓
Employment Weight					✓

NOTE: The dependent variable is the log of real value added per-worker. The independent variable is the disabled work from home (WFH) rate calculated from the ACS. Panel A reports estimates using the pre-pandemic period (2005-2019) only, while Panel B reports results for the entire sample period (2005-2023). Panel A has 182 observations and Panel B has 234 observations. All specifications include 1 lag of the dependent variable. Controls include: male, white, Hispanic, age, education, and a 3rd order polynomial of employment to control for labor market tightness. Standard errors are reported in parentheses, * $p < .10$; ** $p < .05$; and *** $p < .01$.

TABLE A2 – Disabled Work From Home and Real Value Added Per Hour

Regressor	Dependent Variable: Log of RVA Per Hour				
	(1)	(2)	(3)	(4)	(5)
A. ***Pre-pandemic (2005-2019)***					
$\text{WFH}^{d}_{k,t}$	0.095	-0.077	-0.092	-0.053	0.266
	(0.090)	(0.122)	(0.287)	(0.303)	(0.298)
B. ***Full Sample (2005-2023)***					
$\text{WFH}^{d}_{k,t}$	0.074	0.042	0.157^{*}	0.135	0.293^{***}
	(0.046)	(0.066)	(0.092)	(0.111)	(0.103)
Controls		✓	✓	✓	✓
Sector FE			✓	✓	✓
Time FE				✓	✓
Employment Weight					✓

NOTE: The dependent variable is the log of real value added per-worker. The independent variable is the disabled work from home (WFH) rate calculated from the ACS. Panel A reports estimates using the pre-pandemic period (2005-2019) only, while Panel B reports results for the entire sample period (2005-2023). Panel A has 182 observations and Panel B has 234 observations. All specifications include 1 lag of the dependent variable. Controls include: male, white, Hispanic, age, education, and a 3rd order polynomial of employment to control for labor market tightness. Standard errors are reported in parentheses, * $p < .10$; ** $p < .05$; and *** $p < .01$.

TABLE A3 – Robustness: The Effect of Work from Home on Productivity Including Cognitive Difficulty in the Definition of Disability

Regressor	(1)	(2)	(3)	(4)	(5)
Panel A: Dependent Variable: Percent change in output level					
WFH Shock$_k$ × 2021	0.010	0.029	0.010	0.016	0.098*
	(0.011)	(0.019)	(0.006)	(0.012)	(0.057)
WFH Shock$_k$ × 2022	0.017	0.044*	0.025**	0.026	0.123**
	(0.011)	(0.021)	(0.010)	(0.017)	(0.061)
WFH Shock$_k$ × 2023	0.042***	0.068**	0.049***	0.065***	0.152**
	(0.011)	(0.023)	(0.013)	(0.019)	(0.067)
Panel B: Dependent Variable: Percent change in output per worker					
WFH Shock$_k$ × 2021	−0.021*	−0.007	0.006	0.020***	0.111**
	(0.011)	(0.013)	(0.006)	(0.003)	(0.004)
WFH Shock$_k$ × 2022	0.007	0.012	0.026***	0.015	0.112*
	(0.011)	(0.014)	(0.006)	(0.009)	(0.008)
WFH Shock$_k$ × 2023	0.028**	0.022	0.036**	0.045**	0.139**
	(0.011)	(0.017)	(0.012)	(0.017)	(0.019)
Panel C: Dependent Variable: Percent change in output per hour					
WFH Shock$_k$ × 2021	−0.017	0.001	0.007	0.022***	0.109**
	(0.011)	(0.012)	(0.006)	(0.003)	(0.050)
WFH Shock$_k$ × 2022	0.002	0.010	0.016**	0.006	0.114*
	(0.011)	(0.014)	(0.007)	(0.012)	(0.059)
WFH Shock$_k$ × 2023	0.019	0.022	0.028**	0.040*	0.151**
	(0.012)	(0.016)	(0.012)	(0.020)	(0.070)
Sector-year FE		✓	✓	✓	✓
Industry FE			✓	✓	✓
Employment Weight				✓	✓
Instrument					✓

NOTE: Reports the point estimates of α_1 from equation 3. The independent variable is a shift-share variable that measures industry exposure to disabled WFH—where the shift is constructed using cognitive difficulty in the definition of disability. The instrumental variable used in column five is the COVID-19 Workplace Closure Stringency Index as described in section 3.3. Standard errors are clustered by industry-year and are reported in parenthesis, * $p < .10$; ** $p < .05$; and *** $p < .01$.

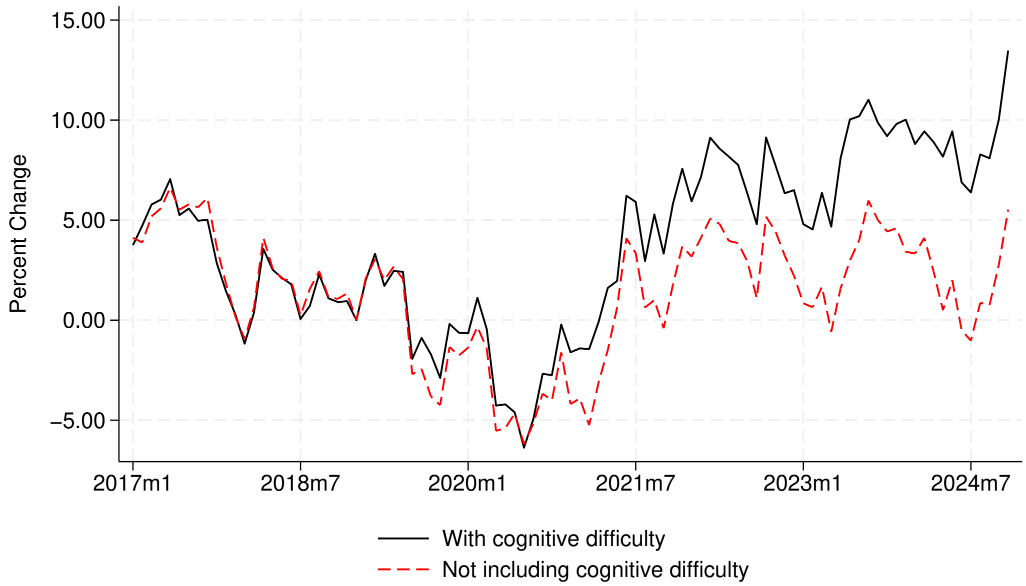
TABLE A4 – The Effect of Disabled Work from Home on Productivity: Instrumental Variable Regressions

Regressor	(1)	(2)	(3)	(4)
Panel A: Dependent Variable: Percent change in real output level				
WFH Shock$_k$ × 2021	0.058**	0.073	0.124	0.098*
	(0.024)	(0.060)	(0.078)	(0.057)
WFH Shock$_k$ × 2022	0.068***	0.106*	0.157*	0.122**
	(0.025)	(0.070)	(0.087)	(0.061)
WFH Shock$_k$ × 2023	0.109***	0.136	0.187**	0.152**
	(0.026)	(0.076)	(0.090)	(0.067)
Panel B: Dependent Variable: Percent change in real output per worker				
WFH Shock$_k$ × 2021	0.085***	0.185**	0.203**	0.111**
	(0.026)	(0.089)	(0.083)	(0.055)
WFH Shock$_k$ × 2022	0.125***	0.205**	0.223**	0.111*
	(0.031)	(0.104)	(0.095)	(0.058)
WFH Shock$_k$ × 2023	0.169***	0.252**	0.270***	0.139**
	(0.035)	(0.115)	(0.104)	(0.066)
Panel C: Dependent Variable: Percent change in real output per hour				
WFH Shock$_k$ × 2021	0.087***	0.204**	0.217**	0.109**
	(0.030)	(0.103)	(0.088)	(0.050)
WFH Shock$_k$ × 2022	0.135***	0.248**	0.260**	0.114*
	(0.034)	(0.125)	(0.108)	(0.059)
WFH Shock$_k$ × 2023	0.171***	0.296**	0.308**	0.151**
	(0.038)	(0.140)	(0.120)	(0.070)
Sector-year FE		✓	✓	✓
Industry FE			✓	✓
Employment Weight				✓

NOTE: Reports the point estimates of α_1 from equation 3, however, the independent variable is instrumented by the COVID-19 Workplace Closure Stringency Index as described in section 3.3. Across all specifications, the Cragg-Donald Wald F statistic ranges from 15 to 32. Standard errors are clustered by industry-year and are reported in parenthesis, * $p < .10$; ** $p < .05$; and *** $p < .01$.

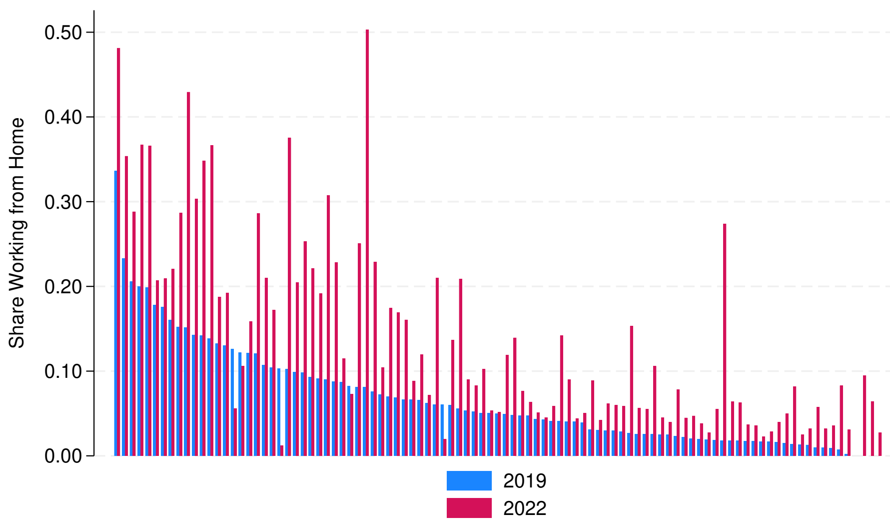
B Appendix: Figures

FIGURE B.1 – Population With a Disability by Month

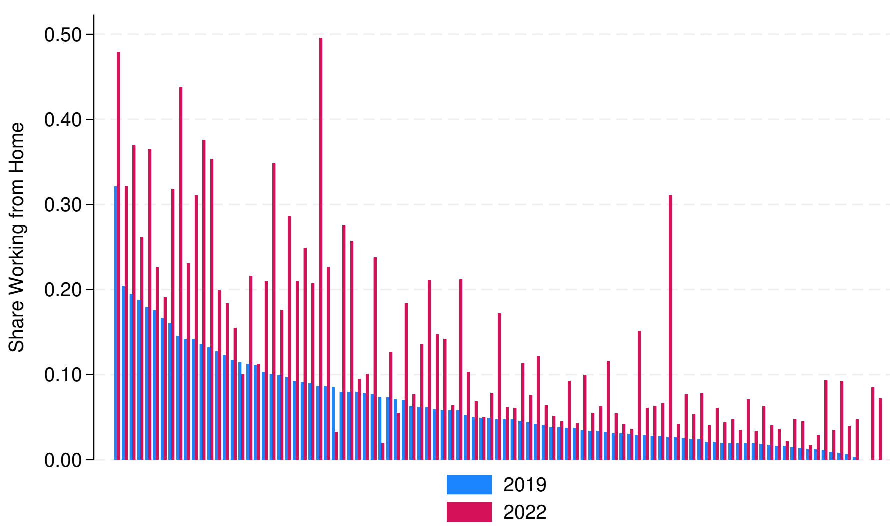


NOTE: Plots percent changes in the population (normalized to 2019m1), when including and not including cognitive difficulty in the definition of disability. Includes CPS sampling weights.

FIGURE B.2 – Work-From-Home Shares



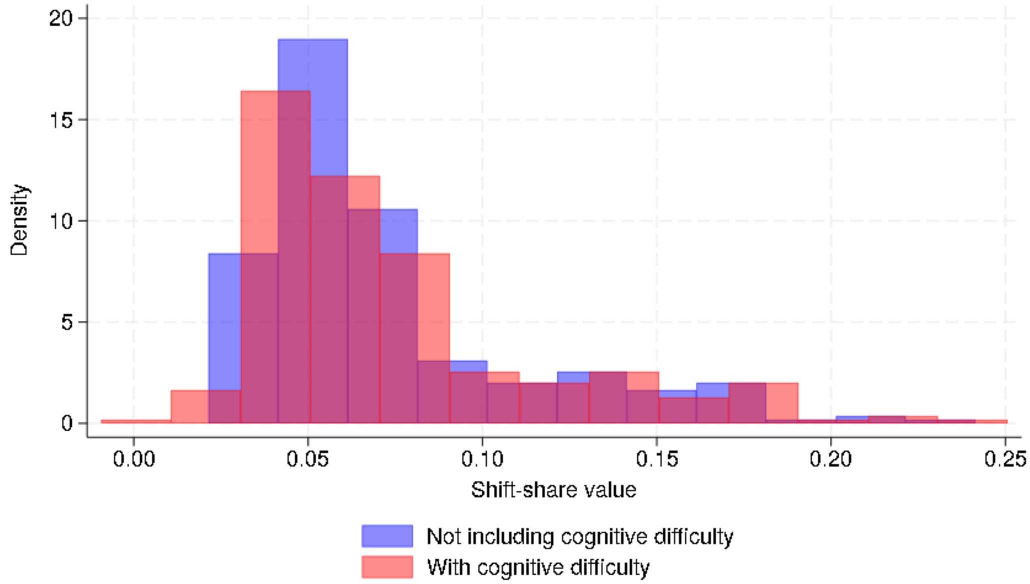
A. Not Including Cognitive Difficulty



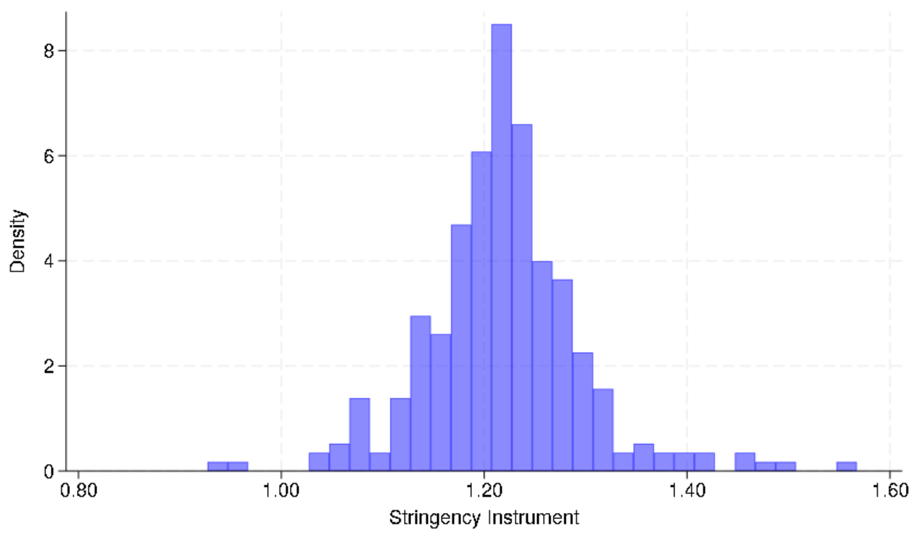
B. With Cognitive Difficulty

NOTE: Panel A plots the share of working from home with a non-cognitive disability by 3-digit occupation in 2019 and 2021 from the ACS. Panel B plots the share of working from home with a cognitive disability by 3-digit occupation in 2019 and 2021 from the ACS. Both panels are sorted by the 2019 values.

FIGURE B.3 – Distribution of the Shift-Share and Covid Stringency Instrument



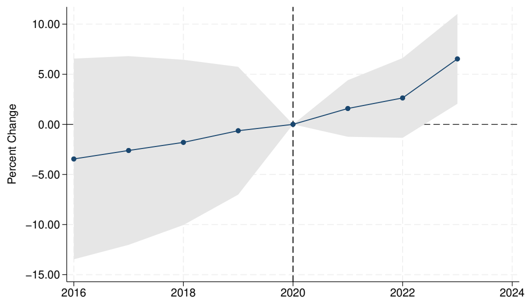
A. Shift-Share



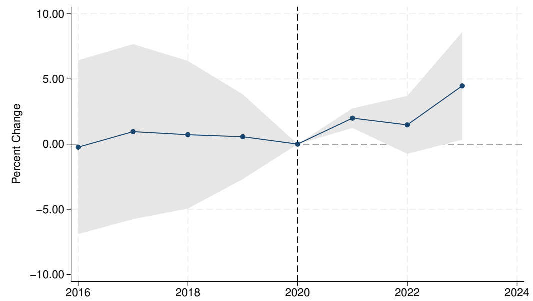
B. Covid Stringency Instrument

NOTE: Panel A plots the distribution of the shift-share variable when excluding and including cognitive difficulty in the definition of disability across 4-digit NAICS industries. Panel B plots the distribution of the Covid Stringency Index instrument (as described in section 3.3) across 4-digit NAICS industries.

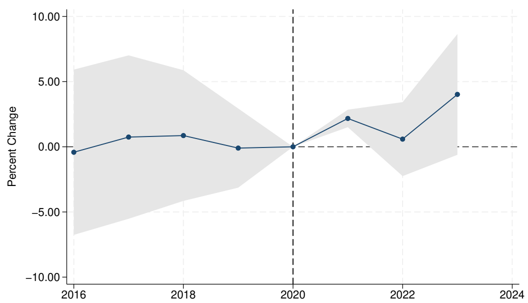
FIGURE B.4 – Robustness: Event Study Including Cognitive Difficulty in the Definition of Disability



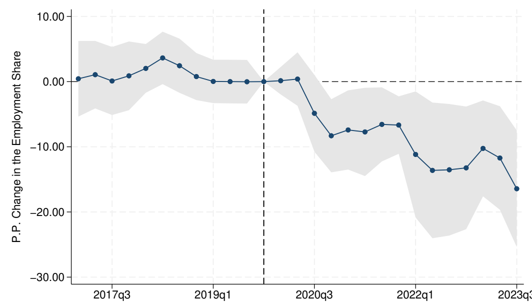
A. Output



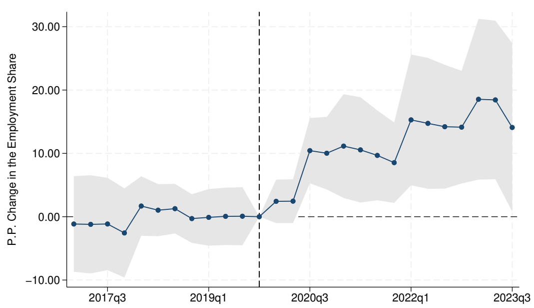
B. Output per worker



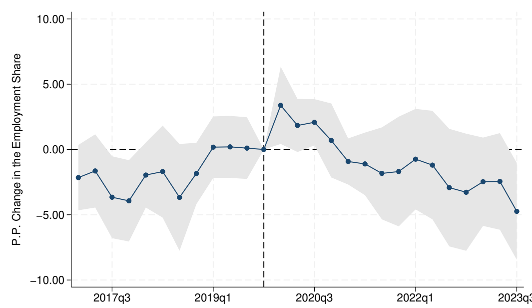
C. Output per hour



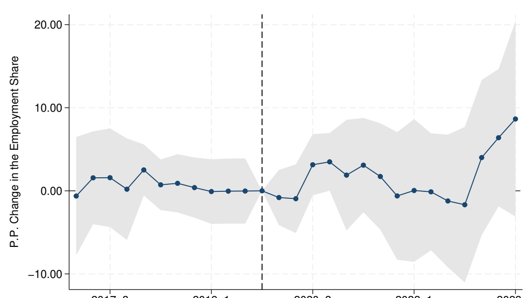
D. 0-19 Employees



E. 500 + Employees



F. Age 0-2



G. Age 11+

NOTE: Reports the point estimates of α_1 from equation 4. The independent variable is a shift-share variable that measures industry exposure to disabled WFH—where the shift is constructed using cognitive difficulty in the definition of disability. All panels are estimated from 2017 through 2023.