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DISCUSSION PAPER SERIES

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# ABSTRACT

# Trusted from Home: Managerial Beliefs and Workers' Spatial Autonomy*

A key difference between on-site and remote work is the reduction in direct managerial oversight when tasks are performed outside traditional office settings. We use survey data on manager trust—measured by the question "...do you think that most people would try to take advantage of you if they got the chance?"—and relate the answers to employees' work-from-home intensities. Our results show that the remote work intensity is higher in countries, regions, and regions-by-industries where managers have higher levels of trust. This association remains robust after controlling for other dimensions of societal trust and confounding factors such as occupation types, broadband access, and digital skills. Manager trust was strongly related to work-from-home levels before the pandemic, and the association became even stronger for occupations in the middle of the remote work distribution following the pandemic surge in work from home. Overall, our findings suggest that manager trust is a crucial prerequisite for high sustained levels of remote work.

**JEL Classification:** J32, M54, D83

**Keywords:** work from home, remote work, management, trust, shirking

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# 1 Introduction

Since the COVID-19 pandemic, most countries have experienced a surge in the incidence of work from home (WFH). Recent evidence suggest that the change is persistent – many workplaces continued to let their workers perform some of their duties from other locations even after the pandemic. A large number of studies have shown that workers value the option of working from home, suggesting that firms can benefit through smoother recruitment processes, higher retention rates, and lower wage costs (Aksoy et al. 2022; Bloom, Han, and Liang 2024; Lewandowski, Lipowska, and Smoter 2022). On the other hand, WFH poses a number of challenges for supervising managers, one of the most salient being the loss of direct oversight when workers and managers are separated in space. Anecdotal evidence suggest that trust issues may be fundamental when managers decide on work-from-home intensities. As an example, 85% of Microsoft's managers reported that the "shift to hybrid work has made it challenging to have confidence that employees are being productive" and 45% were "struggl[ing] to trust their employees to do their best work" (Tsipursky 2022). Despite this, managers, on average, tend to report being more trusting than the general population across most EU countries according to respondents from the European Social Survey (Figure B.1). Surprisingly, the role of manager trust is entirely missing in the very large recent economic literature on work from home.[1] In this paper, we provide a stylized formal model of work from home and trust and show—we believe for the first time—evidence of a very strong empirical association between manager trust and the incidence of work from home.

The widespread increase in WFH during the early pandemic was facilitated by the combination of recent advancements in communication technology and the urgent need to reduce virus transmission (Barrero, Bloom, and Davis 2023; Gill and Skans 2024). The persistence as the pandemic leveled off was likely in part fueled by further technological refinements but the rapid and persistent shift suggest that changing norms, preferences or perceptions may have played an important complementary role. The most recent data indicate that WFH have stabilized at new, higher levels (see Barrero, Bloom, and Davis 2023) suggesting that we have reached a new steady-state with much higher rates of work from home in most countries. But available data also indicate large variations in the incidence of work from home both before, during, and after the pandemic. In this paper, we argue that differences in manager trust may be one important determinant of this variation. Trust is a likely pre-requisite for hybrid work in some jobs and, as we show, managers' perceptions about how much people can be trusted vary substantially across countries, regions, and industries.

Our idea is intuitive. Many jobs that, in a technical sense, can be performed from home involve tasks that are difficult to monitor from a distance. This makes monitoring imperfect if either the worker or the manager is working from home. Workers could then, in principle, choose not to perform their tasks at all (e.g., playing

1. We surveyed NBER and IZA working papers mentioning WFH/remote work in the abstract or title that were published after the pandemic (January 2023-August 2024). Only 3 out of 83 of these mention trust somewhere in the draft. None of the papers consider trust as a primary factor.

golf instead), or to perform them with low levels of attention (e.g., watching golf during zoom meetings). Managers who believe that their workers will shirk unless directly monitored may not allow workers to work from home unless task completion or output can be monitored. This means that less trusting managers will be more reluctant to extend WFH opportunities to jobs and tasks that are difficult to monitor at a distance.[2] Furthermore, imperfect monitoring together with adverse selection can make it more costly to offer work from home unless this is the market norm. In this setting, technological improvements that make WFH possible and desirable can remain underutilized.

To formalize this intuition, we develop a stylized theoretical model where firms endogenously choose to either force their employees to work on site, or to trust them with the WFH amenity. The model, and our empirical approach, treats aggregate managerial trust as fixed across time, an assumption which is supported by our data (see Figure B.2). Work from home can be achieved at a lower wage cost, but at the risk that the workers shirk. Some "dutiful" workers will perform their tasks regardless of whether they are monitored or not, others will shirk unless monitored.[3] The prospect of shirking reduces expected profits when employees work from home in settings where managers lack trust in their workers.

If shirking is heterogeneous across workers, the model can also explain how issues related to trust may have contributed to inefficiently low levels of WFH before the pandemic. The reason is that shirking workers have incentives to self-select into jobs with low monitoring, if possible. This adverse selection makes it unprofitable to offer WFH jobs if all other firms are monitoring on site, even though WFH is optimal when it is the market norm. This aspect of the model thus highlights that market level managerial trust in workers can influence whether or not a work from home equilibrium is stable. This makes it explicit why a shock, such as the COVID-19 pandemic, can push economies into a new work-from-home equilibrium.

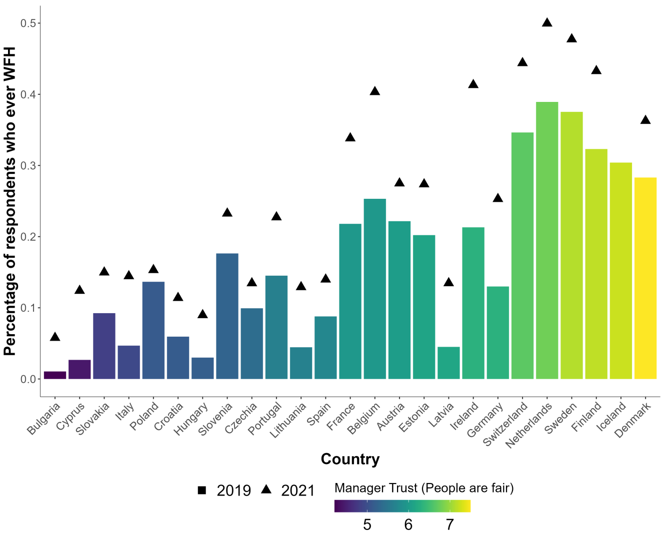
The core of the paper is empirical. To measure manager trust, we use survey data from the European Social Surveys (ESS). From these data, we select respondents who work in managerial positions. As our measure of trust, we use these managers' answers to the question "...do you think that most people would try to take advantage of you if they got the chance, or would they try to be fair?". We pool across survey rounds from 2014 to 2018 and treat the level of trust as fixed. The used question corresponds closely to how we think of trust in our setting – will workers take advantage of the WFH opportunity to shirk, or can they be trusted to do their tasks even if not monitored? To measure work from home, we use individual-level micro data from the European Labor Force Survey (ELFS) which reports work from home intensities for millions of European workers both before and during the pandemic. We associate the measure of manger trust at the country, region, and region-by-industry levels with workers' WFH intensities. The models thus capture macro-level associations, not sorting of workers across firms, while allowing us to control for individual-level confounders related to occupations and demographics.

2. Monitoring WFH tasks is not universally infeasible. In many cases, however, it is more costly and difficult to implement, or it is perceived as intrusive by workers (Thiel et al. 2023).

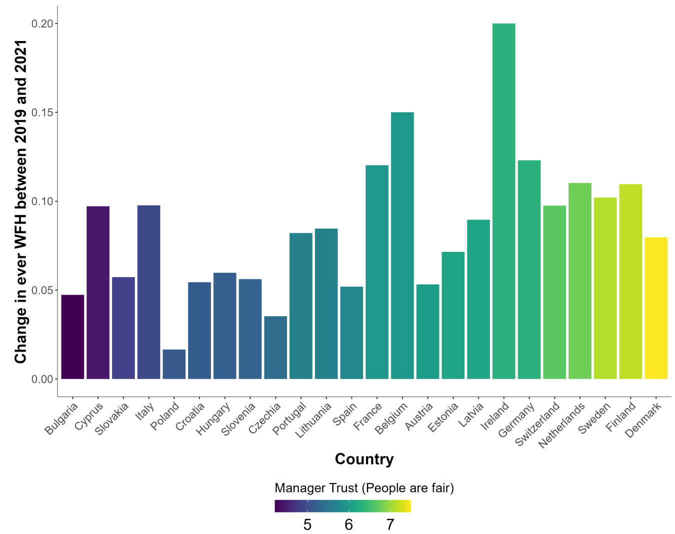
3. See Elingsen and Mohlin (2023) for an extensive discussion of different dimensions of dutifulness and the relationship it has to when and how people take positive actions even without monitoring.

Figure 1: Relationship between WFH and manager trust in Europe

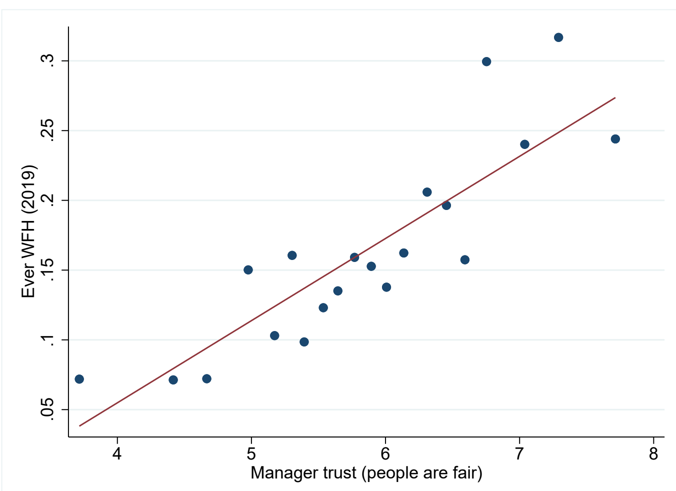
(a) WFH levels in 2019 and 2021 (country level)




(b) Change in WFH from 2019 to 2021 (country level)




(c) Correlation with 2019 WFH percentages (region level)




(d) Correlation with change in WFH from 2019 to 2021 (region level)


*Notes:* Panels (a) and (b) report country-level relationships. In Panel (a), WFH levels represent the percentage of respondents who have ever had WFH for 2019 (bars) and 2021 (triangles). "Ever" WFH = "usually" WFH + "sometimes" WFH. In Panel (b), WFH levels represent the difference of "ever" WFH (2021-2019). For Panels (a) and (b), the colors of the bars reflect the average manager trust within the country and countries are sorted by manager trust levels. Panels (c) and (d) describe relationships at the region level, where "region" is defined as the smallest NUTS level that exist in both the ESS and ELFS surveys (see Appendix C.1 for region breakdown). In Panel (c), WFH levels represent the percentage of respondents who have ever had it for 2019. In Panel (d), we show the relationship with changes in "ever" WFH between 2019 and 2021. The full scatter plots that correspond to Panels (c) and (d) can be found in Figure B.4. For all panels, manager trust uses the "people are fair" definition of trust (average of managers across the 2014, 2016, and 2018 ESS surveys) and uses a broad definition of manager.

A key aspect of our data is that trust, as reported by the mangers, varies substantially between settings. Focusing on cross-country differences, levels of trust are notably higher in the Nordic countries, Switzerland and the Netherlands as compared to countries in Eastern and Southern Europe as illustrated in (Panel (a) of Figure 1). As shown in the same graph, the cross-country correlations between work-from-home and manager trust (colors) are extremely strong both before (bars) and during (triangles) the pandemic. Even with these high aggregate levels of WFH, countries with higher trust also saw larger shifts in WFH during the pandemic (Panel (b) of Figure 1), suggesting that these high trust countries were not just functioning near their peak WFH capacities. Strikingly, we find similar relationships at the region level as well (Panels (c) and (d) of Figure 1). These associations, although extremely strong, could in principle be related to other country-specific factors such as the occupational composition, technical infrastructure, or digital preparedness. In the paper, we therefore exploit conditional associations at different levels of aggregation. We separately analyze the association between trust and WFH in the pre-pandemic period, in the peri-pandemic period, and in terms of changes in WFH during the pandemic. The third set of models implicitly rely on COVID-19 as an exogenous shock, treating managerial trust as an indicator of exposure to this "treatment". Our rich individual-level data allow us to control for a wide set of possible confounders at the aggregate and individual level, including aspects capturing occupations, demographics, the technological infrastructure, and digital preparedness.

These specifications return large, positive, and statistically significant relationships between managerial trust and WFH. Countries, regions, and regions-by-industry where managers generally believe that people can be trusted had higher levels of WFH before the pandemic, and they allowed more of their workers to WFH during the deep COVID years. The associations remain even if we control for managers' trust in legal and political systems, suggesting that the patterns really reflect trust in people, as opposed to institutions. Our estimates are completely robust to controlling for individual occupations. Furthermore, they remain even when we add controls for alternative channels highlighted in the literature including ICT usage, digital preparedness, GDP per capita, and "individualism" (Zarate et al. 2024). Qualitatively, the effects are robust to comparing regions within countries. At the region-by-industry level, an increase of one unit of average managerial trust on a 0-10 scale is estimated to increase WFH levels by 2 percentage points (mean of 16.4 percent). Managers themselves also tend to WFH more often in settings where they have greater trust, suggesting trust is needed to compensate for the reduced monitoring due to managers being at home. We also find that high trust areas had higher WFH during the pandemic. These results arise from a combination of zero effects in occupations with very low or very high WFH potential and a positive effect in the middle range of occupational WFH potential. They thus suggest that the pandemic did not facilitate a "catch-up" among lower trust countries and regions. Overall, we present a collage of evidence suggesting that manager trust is a key determinant of work-from-home levels.

Our paper contributes to a very active literature within economics on the causes and consequences of work from home (see Barrero, Bloom, and Davis (2023) and Gill and Skans (2024) for detailed references). Quite surprisingly, the concept of trust as a determinant of WFH is largely absent from this literature, despite being discussed intensively in the popular debate.[4] While a few papers discuss the role of trust in allowing WFH conceptually (Cascio 2000; Kowalski and Swanson 2005), empirical testing remains scarce. Exceptions include a mostly older set of studies within the management literature, generally relying on small scale data sets in specific industrial and institutional settings (Harrington and Ruppel 1999; Peters, den Dulk, and de Ruitjter 2010; Kaplan et al. 2018). Trust also tend to feature in more indirect terms in recent studies of the productivity consequences of WFH (Stavrova et al. 2023). These studies focus on the consequences of WFH within specific firms, and do not address to what extent variations in manager trust is a *determinant* of WFH intensities in different settings. The concept of trust is closely related to studies on why people take costly actions without apparent self-interest, and thus relates to concepts such as morality and dutifulness (Elingsen and Mohlin 2023). In our setting, trust could be interpreted as expectation of others' dutifulness in a broad sense.

Our paper contributes to the work-from-home literature in two distinct ways. First, we focus explicitly on manager trust as a determinant of WFH, a topic that has received very little attention in the economic literature, in particular since the onset of the pandemic. Second, we provide the first analysis of trust and WFH based on large representative samples of respondents. Our approach allows us to investigate the extent to which manager trust is an important determinant of the heterogeneous use of WFH across countries, regions, and industries. We believe that our results, although not causally identified in a strict sense, are strong enough to motivate a renewed focus on how work from home interacts with manager-worker relationships in different settings.

This paper is structured as follows: Section 2 presents our stylized theoretical model and its predictions. Section 3 discusses our data and presents basic descriptive statistics. Section 4 presents our methodologies. Section 5 presents our pre-COVID results and during COVID results for the country, region, and region-by-industry analyses as well as discussions about our trust variable and occupational heterogeneity. Section 6 concludes with a discussion of the implications of our results.

## 2 Theoretical Framework

In this section, we outline a theoretical model of monitoring and work from home. Our model relates to the efficiency-wage literature and discussions of adverse selection in the labor market (see Katz 1986 for one overview). The model is deliberately stylized with the aim of conveying the main intuition of our paper as a prelude to the empirical analysis. With imperfect monitoring and heterogeneous dutifulness (level of shirking) among workers, managers beliefs about worker behavior when not monitored is an important driver of work from home. Furthermore, it may be easier for a single employer to offer work from home if others also offer work from home because of adverse selection.

4. See Sharon K. Parker and Keller (2020); Tsipursky (2022); and Gill and Skans (2024).

## 2.1 Shirking, trust, and work from home

Managers in our model face two types of workers, with a direct correspondence to the measure of trust used in our empirical analysis: *Type 0* people will "try to be fair," and *Type 1* people will "take advantage of you [as a manager] if they can." Type 0 workers can be trusted to remain "dutiful", always work, and produce $R$ regardless of monitoring conditions whereas Type 1 workers will shirk and produce 0 unless monitored on site. A crucial parameter for our model is the share $\alpha \in (0, 1)$ of workers in the economy that (managers perceive to) belong to Type 1. Workers are homogeneous within type.

Firms, indexed by $j$, are ex-ante identical, profit-maximizing, and risk-neutral. Firms can choose to monitor workers on site or to trust workers and offer them WFH, without monitoring, as an amenity. We use $WFH$ as an indicator taking the value 1 for work from home jobs. We further use $WFH$ and $m$ as superscripts to indicate other variables that differ between work from home and on-site monitored jobs respectively. We indicate worker type by $\tau \in \{0, 1\}$ and wages by $w$. Firms hire workers with imperfect information about type, and type $\tau = 1$ do not produce unless monitored on site. Thus, profits are:

$$\pi_j = R(1 - WFH_j \times E[\tau|WFH_j = 1]) - WFH_j w^{WFH} - (1 - WFH_j)w^m \tag{1}$$

The difference in profits between offering and not offering WFH is a balance between the expected production loss due to shirking and the potential wage gains:

$$\pi^{WFH} - \pi^m = -R \times E[\tau|WFH_j = 1]) - (w^{WFH} - w^m) \tag{2}$$

Workers have linear utility functions with three components: they derive disutility from work ($h$), disutility from commuting to the office ($C^c$), and utility from consumption arising from the wage ($w_j$) paid by firm $j$. We implicitly assume that dutiful workers ($\tau = 0$) perceive a prohibitive utility cost of violating a duty to always work if being paid, whereas Type 1 workers do not perceive such a cost.[5] Noting that workers of type $\tau = 1$ do not perform any work under WFH because of the lack of supervision, we have the following (type-specific) indirect utility function:

$$U^\tau(WFH) = -h(1 - \tau WFH_j) - C^c(1 - WFH_j) + w_j \tag{3}$$

We do not specify the exact wage-setting mechanism, but assume that the wage gap between WFH and on-site jobs may, in part, reflect the three components that separate the two types of contracts:

1. removing the disutility of traveling to the office, $C^c$
2. a reduction in production arising from shirking workers $E[\tau|WFH = 1]R$
3. removing the disutility of work among shirking workers $E[\tau|WFH = 1]h$

5. Elingsen and Mohlin (2023) provide a model of several types of duties and discuss how they can affect actions in various settings.

For completeness, we allow each component to be shared with a different parameter denoted by $\beta$, $\phi$ and $\kappa$ respectively, but it can be kept in mind that a reasonable special case is when $\beta = \kappa = (1-\phi)$. For our purposes, these parameters can change with market conditions, as long as they are perceived as constants by the firms for given market conditions. With this notation, the WFH wage gap is:

$$w^{WFH} - w^m = -\beta C^c - \phi E[\tau | WFH = 1]R - \kappa E[\tau | WFH = 1]h.$$

On site profits are deterministic because everyone works if monitored,

$$\pi_j^m = R - w^m, \tag{4}$$

but *ex post* profits for a firm offering WFH will depend on the type of labor the firm attracts. Importantly, this will depend on the choices of *other* firms. Thus, our setting has the potential for multiple equilibria:

**Proposition 1**: it is optimal for firms to post WFH if all other firms also post WFH *iff* the share of shirkers is sufficiently low. Thus, if $\alpha$ is sufficiently low, a full WFH economy is always a possible equilibrium.

*Proof*: If all other firms post WFH then the expected composition of hires reflect the composition in the economy, i.e. $E[\tau | WFH = 1] = \alpha$. Thus, expected profits from offering WFH is:

$$\pi_j^{WFH} = (1-\alpha)R - w^{WFH}$$

and if all other firms post WFH, it is optimal for firm $j$ to post WFH iff:

$$(1-\alpha)R - w^{WFH} > R - w^m.$$

Inserting the wage-sharing rule:

$$\alpha \leq \frac{\beta C^c}{(1-\phi)R - \kappa h} \tag{5}$$

To interpret equation (5), we can first assume that firms cannot push down wages to compensate for utility gains of shirkers, i.e. we set $\kappa = 0$. Under these conditions, we can maintain a full WFH equilibrium as long as the share of shirkers in the population is lower than the ratio between the wage savings due to the removal of disutility associated with travel to work $\beta C^c$ and the share of production losses due to shirking that are absorbed by the firm (i.e. the part not shifted onto wages, $(1-\phi)R$). In the special case where we add the condition $\beta = (1-\phi)$, WFH is an equilibrium if production losses are smaller than the utility gains of not having to travel, which is identical to the perfect competition, zero profit, equilibrium.[6] Allowing for $\kappa > 0$, thus allowing firms to save wage costs on the utility gains from shirking, the threshold value for $\alpha$ is higher, i.e. firms can accept more shirkers if shirker-utility reduces overall wage costs.

6. Note that if we assume perfect competition on the labor market, and free entry such that there is zero profits in equilibrium, then the wage is $(1-\alpha)R$ in full WFH. To attract a Type 0 (Type 1 is even more expensive) worker to on-site work, firms need to offer a wage of $(1-\alpha)R + C^c$. On-site profits at this wage are $R - (1-\alpha)R - C^c$ which are greater than WFH-profits (i.e. 0) iff $\alpha > C^c/R$.

## 2.2 Adverse selection

The model presented above illustrates that work from home is likely to be related to manager trust. Thus far, the model would be isomorphic if the shirking loss was equal across all workers and $\alpha$ instead captured an equal, known production loss for each worker. However, with worker heterogeneity, the model will also exhibit multiple equilibria due to adverse selection. Although we will not be able to explicitly test this aspect in the empirical part of the paper, it illustrates how mechanisms related to trust and monitoring can interact with a large shock such as the pandemic to generate large and persistent movements in the WFH incidence since it can be costly for firms to be the first to offer WFH.

**Proposition 2**: A fully on-site economy is always an equilibrium as long as there are frictions and firms are unable to distinguish between shirkers and dutiful workers.

*Proof*: With frictions, workers apply to jobs where the expected returns are the highest. Let $P(WFH)$ and $P(m)$ indicate the respective probabilities of acceptance if applying to the two types of jobs – both probabilities being independent of worker type by definition. We assume that the probabilities are declining in the ratio of applicants to jobs on each sub-market, but do not have to specify the exact functional form. Workers of type $\tau$ are indifferent between applying to the two types of jobs *iff*:

$$U^{\tau}(WFH) \times P(WFH) = U^{\tau}(m) \times P(m) \tag{6}$$

Shirkers derive higher utility from WFH jobs than dutiful workers, i.e. $U^1(WFH) > U^0(WFH)$, whereas $U^1(m) = U^0(m)$, see equation (3).[7] As a consequence, both types of workers *cannot* satisfy equation (6) at the same time. At least one of the worker types only applies to one type of job, and at least one job-type only attracts one type of applicant (if both job-types coexist). If Type 1 workers are indifferent, Type 0 workers will only apply to on-site jobs (they derive lower utility from WFH than shirkers, but the same utility from on-site work). Thus, if the WFH market is small, posting on that market will only attract shirkers as these workers derive a higher utility from these jobs.[8] Thus, $E[\tau|WFH = 1] = 1$, but posting WFH jobs that only attract Type 1 workers can never be optimal as these workers always shirk, and profits are therefore always negative, $\pi^{WFH} = -w^{WFH} < 0$.

## 2.3 Remarks

The purpose of this stylized model is to set the stage for our empirical work and a few remarks may be useful. *First*, what matters are firms' *beliefs* about $\alpha$, not the true share of workers that can be trusted.

7. Due to shirking $U^1(WFH) = w^{WFH}$ whereas $U^0(WFH) = w^{WFH} - h$. With monitoring and commuting both types face the same utility terms $U^1(m) = U^0(m) = w^m - h - C^c$

8. Note that this reasoning is irrelevant at the other extreme where all other firms post WFH since both worker types are as productive when performing on-site work. If all other firms post WFH jobs, posting an onsite job can only attract dutiful workers. But as both types of workers are equally productive in these jobs, sorting is irrelevant, and the conditions of Proposition 1 therefore remains unchanged in a frictional labor market.

In an adverse-selection equilibrium with zero work from home it is not far-fetched to imagine that these beliefs can be disconnected from the true share because firm-level experimentation may generate upward biased beliefs about population-wide $\alpha$ due to self-selection of Type 1 workers into jobs that deviate from the equilibrium. *Second*, a WFH equilibrium is only sustainable if the *aggregate* beliefs about the share of shirking workers is sufficiently low, i.e. managers *in general* must believe that workers are dutiful for WFH to be sustainable. If trust among other managers dissipates, it is no longer optimal for *any* manager to offer WFH positions regardless of their beliefs. *Third*, in cases with "aggregate experimentation" as during the COVID pandemic, the equilibrium may shift from a no-WFH state into a stable WFH equilibrium if sufficiently many firms move to WFH, and, with a lower (perceived) $\alpha$, it is easier for a new equilibrium to emerge.

# 3 Data

To analyze how manager trust relates to WFH-intensities, we need data on both margins for large representative samples. Ideally, these data should allow us to study the use of WFH before the pandemic, as well as the changes in WFH that occurred when the virus arrived. To do this, we rely on two primary data sources: The European Social Surveys (ESS; European Social Survey 2021) for 2014, 2016, and 2018, which include questions related to trust, and the European Labor Force Surveys (ELFS; Eurostat 2021) for the years 2016-2021, which include questions about work from home. We access micro-data version of these data sets which allows us to determine who is a manager in the ESS and to construct variables capturing individual-level heterogeneity in the ELFS. We link the two data sources at aggregate levels (country, region, and region-by-industry).

## 3.1 Primary Data

From the ESS, we extract respondents who work in managerial positions (ISCO codes 1120 and 1200-1439). Our primary measure of trust is how managers responded to the question, "...do you think that most people would try to take advantage of you if they got the chance, or would they try to be fair?". This question corresponds closely to the concept of trusting workers to perform their tasks without direct supervision. Responses are recorded on a scale from 0 to 10 with 10 being complete trust.

We only use pre-pandemic data on manager trust. To gain precision, we aggregate responses from 2014, 2016, and 2018.[9] This becomes particularly important when we study managers within finer cells such as the region-by-industry level. We show that our overall conclusions would remain robust if we only relied on data from the 2018 ESS survey (Tables A.5 and A.6). In our used (micro) data, we have responses from 7,842 individual managers (2,971 in just the 2018 data). In some of the models, we will delve into segments where we have relatively few respondents, thus raising concerns about measurement errors. In these cases,

9. We use the available years in cases when countries did not participate every year.

we complement the main analysis with responses from workers in general (not just managers) to get a less noisy measure (although less precisely related to what we want to measure).

In the ELFS, we use individual-level data on whether respondents performed tasks from home. In these surveys, respondents that indicate they are employed are asked a question about how much they work from home in their main job and they are given four options: "Person mainly works at home," "Person sometimes works at home," "Person never works at home," and "Not applicable" (with a fifth category in the data of "not stated" indicating they did not complete the question). Based on the nature of the question, we avoid non-WFH responses from unemployed individuals, who are not asked the question, and (ideally) from workers who would not be able to work from home, as they should answer "not applicable." This should help reduce the bias in our results that could be driven by differing employment rates or different occupation structures.

From this question, we interpret the response "mainly" as fully remote, "sometimes" as hybrid, and the union of these as overall ("ever") WFH. We also use workers' occupations to determine who is and who is not a manager to construct WFH measures for managers and employees (non-managers) separately. The data include WFH responses from over 3.3 million individual workers per year (on average), of whom about 23 percent are managers.

We collapse the ESS micro data (trust) to aggregate units and then match it to the ELFS (WFH). When linking the data at the region level, we use the smallest possible NUTS region that is available in both datasets, which varies across countries. The number of regions per country range from 1 (Cyprus, Estonia, Iceland, Latvia, and the Netherlands) to 21 (France). See Appendix C.1 for the number of regions in each country. Our used data span 161 regions across 25 countries in total, however for most regressions, we use data from 19 countries (135 regions) due to missing demogrpahic data from some countries.[10]

The association between managers' trust (i.e. their belief that people are fair) and WFH at the country level was already displayed in Figure 1. As is evident, there is a very strong positive association both in 2019 (pre-pandemic) and in 2021 (during) and in the shift to WFH during the pandemic (2021 levels compared to 2019 levels). The growth in WFH during the pandemic was more than twice as large in countries with the highest levels of managerial trust as in the countries with the lowest levels.

## 3.2 Additional Data

As an alternative measure of manager trust, we use a question in the ESS about "trust in people". The question asks "...would you say that most people can be trusted, or that you can't be too careful in dealing with people?". To analyze if the results reflect differences in more general societal trust, we use separate questions regarding trust in politicians, trust in the legal system, and trust in the police. All variables are

10. We remove Norway due to inconsistent regional classifications and survey changes. The last year for Iceland is 2020. Switzerland is missing data on partner and children and Czechia, Iceland, Ireland, Netherlands, and Slovakia are missing data on age.

reported on a similar 0-10 scale.

We construct proxies for digital skill levels using data from the ESS. Our preferred measure for "digital skill" is based on the question "How often do you use the internet on [list of] devices, whether for work or personal use?". Answers are on a scale from 1 (never) to 5 (everyday) and we treat responses as a continuous variable, but this is not crucial for our results.[11]

We also use a proxy for individualism, the extent to which people feel independent (defined in Hofstede 2011), as a control, which has been found to correlate with WFH (Zarate et al. 2024). We use the ESS question about if it is important to "...make [their] own decisions... [and] to be free and not depend on others" as this proxy. This question is reported on a 1 to 6 scale (with 1 being "very much like me"), but we convert the scale to a 0 to 5 scale where 5 is equivalent to "very much like me" to keep the signs of the estimates consistent.

For some of our analysis, we separate between occupations with different levels of WFH potential. We categorize the occupations into quartiles based on pre-COVID levels of "ever" working from home using the 2016-2019 ELFS. Here, we also include data from countries that cannot be matched to the ESS.[12]

Additional control variables are drawn from alternative data sources. We use country-level data for GDP per capita in PPS terms as a measure of the country's overall economic development (Eurostat 2022b). We also use country-level data on the percentage of households that have access to broadband internet as a measure for a country's digital infrastructure (Eurostat 2019). We construct a measure of "excess COVID deaths" using the average of the weekly death from the ninth week of 2020 through the end of 2021 (Eurostat 2022a).[13] After harmonizing the regions, we have COVID excess data for 146 of the 161 regions.[14] We use additional control variables as robustness checks; these data are described in Appendix C.4.

# 4 Econometric Specifications

A key challenge to our analysis is disentangling the effect of "trust" from other factors that may correlate strongly with it. Because of the nature of the variable, we are not able to generate quasi-experimental variation in trust and we instead run a battery of specifications that together paint a broad picture of the relationship between manager trust and WFH.

We begin by looking at the relationship at the country level and then gradually move to more finely defined

11. For alternative measures, we use the question "On a typical day, about how much time do you spend using the internet on a [list of devices], whether for work or personal use?" and a transformation of our original variable into a binary variable (which equals one if the individual reports a 4 or 5), both of which gives us very similar results.

12. This includes ELFS data from Greece, Luxembourg, Malta, Norway, Romania, and the UK, as well as the unmatched regions for countries in our sample (e.g. French Overseas Territories).

13. For Italy, data for the last few weeks of 2021 is missing, so the average excess COVID deaths is taken for only the weeks available.

14. There is no excess COVID deaths data from Switzerland, Ireland, and Iceland and data for Croatia and Slovenia is only at a country-level, not a region level, so they are dropped from the analysis utilizing excess COVID deaths.

units by studying the relationship across regions and region-by-industry combinations. At the country level, we have more precise measures of managerial trust as these are constructed from larger samples. On the other hand, there are obvious omitted-variable concerns. At the more granular level, region-by-industry in particular, we can control for more alternative factors, but the trust measure is likely to be more prone to measurement error. We therefore run our specifications for different levels of analysis, and adjust the controls and fixed effects accordingly.

We utilize two different specifications. In the first model, we study the pre-COVID and during COVID relationships between trust and WFH. Here, we use a repeated-cross-section analysis at the individual level. We hypothesize that individuals in areas with higher manager trust are more likely to work from home relative to similar workers in lower trust areas. Second, we rely on a two-way fixed effects (TWFE) specification where we analyze if the initial level of trust was associated with a larger growth of WFH during the COVID pandemic. This specification is also run at the individual level, but it nets out fixed factors in each country (or region, region-by-industry) and instead studies the shift in WFH by level of trust.

## 4.1 Model 1: Manager Trust and WFH Before/During COVID

To analyze the conditional associations between manager trust and WFH before COVID, we estimate the following model using individual data for the period 2016 to 2019:

$$WFH_{i,k,t} = \beta_0 + \beta_1 Manager\_Trust_k + \boldsymbol{\alpha}\mathbf{X}_{i,k,t} + \boldsymbol{\gamma}\mathbf{\Gamma}_{k,t} + \theta_t + \epsilon_{i,k,t} \tag{7}$$

where $t$ indexes year, $k$ indexes the geographic level (either country, region, or region-by-industry), and $i$ indexes the individual. Manager trust is treated as a fixed attribute for each $k$ and is always measured at the pre-pandemic level. $\mathbf{X}$ is a vector of individual demographic controls, $\mathbf{\Gamma}$ are aggregate controls, and $\theta_t$ denote year dummies.

The $X$-vector, which we keep as fixed across most specifications (except in the raw regressions), include age, sex, partner status, dependent children, level of education, occupation [3 digit], and industry [9 categories].[15] This means that all our specifications, even the crudest ones, control for aspects related to demand side heterogeneity across units in terms of occupations and industries.

We provide variations of the model where we add additional *aggregate* control variables in $\mathbf{\Gamma}$. For the pre-COVID analysis, we add controls for a measure for how "free" people feel in decision making ("Individualism"), a measure of digital use, the percentage of households with broadband access, and GDP per capita in PPS in our main analysis. We also explore specifications controlling for country fixed effects in the region- and region-by-industry level analyses. Given the limited variation we have at the country level in particular, we include these controls one-by-one, but for completeness we also show regressions where we saturate the model with all these controls. Standard errors are clustered at the geographic level (i.e. $k$). We run additional versions of this model as a robustness check, which is detailed in Appendix C.4.

15. For information on the industry categorization, see Appendix C.2. We remove the industry control when studying trust at the region-by-industry level.

In order to study the relationship of WFH levels during COVID and manager trust, we estimate the same model as we do for the pre-COVID analysis (equation 7) except we run it only for the year 2021 but with pre-pandemic levels of manager trust. Because we only use one year, we drop the year fixed effects from the specification, but all the other aspects of the model are the same. For this analysis, we include a specification that controls for excess COVID deaths as well as running a raw regression and a regression controlling for demographic characteristics.

### 4.2 Model 2: Manager Trust and Increased WFH During the Pandemic

To analyze the conditional associations between manager trust and changes in WFH during the COVID-19 pandemic, we estimate the following model using two-way fixed effects for the year and the treatment level (country, region, or region-by-industry) on the individual level data for the period 2016 to 2021. We interact a treatment timing variable ("During") with pre-pandemic manager trust to estimate the differential change in WFH during the pandemic by manager trust:

$$WFH_{i,k,t} = \beta_0 + \beta_1 Manager\_Trust_k * During_t + \gamma_1 During_t + \boldsymbol{\phi}\mathbf{Z}_k * During_t + \boldsymbol{\alpha}\mathbf{X}_{i,k,t} + \theta_t + \theta_k + \epsilon_{i,k,t} \quad (8)$$

where, as in equation 7, $i$ indexes the individual, $t$ indexes year, $k$ indexes the unit of analysis (either country, industry, region, or region-by-industry), $\mathbf{X}$ is a vector of individual demographic controls, and $\theta_t$ indexes the year fixed effects. The variable *During* takes the value one for the years 2020 and 2021. In this model, we include unit fixed effects denoted by $\theta_k$ to isolate *changes* in WFH in response to the exogenous COVID-19 shock. Standard errors are clustered at the unit level (i.e. $k$).

This specification removes any time invariant unobservables, but we need to be concerned about other factors, correlated with trust, that may affect the rise in WFH during the pandemic. In order to assess the robustness of the estimates, we present results from specifications that control for other potential channels interacted with *During*, denoted by $\mathbf{Z}_k$ in equation 8. Here we control for excess COVID deaths in our main analysis, but run robustness regressions on other aggregate controls, detailed in Appendix C.4.

## 5 Results

### 5.1 Different dimensions of trust

Our preferred measure of trust centers on managers' responses to a question that isolates their beliefs about whether people in general "are fair" and can be trusted to do the right thing. This measure closely corresponds to the concept of shirking. As demonstrated in Figure 1, these responses correlate strongly with WFH. However, a key question regarding the robustness of this association is whether it is confounded by other societal factors. To investigate this issue and validate our preferred measure, we conduct a series of simple regressions (including only time fixed effects) where we explain WFH by managerial responses to survey questions related to other dimensions of trust. We begin with our preferred measure, followed by what we consider the closest substitute measure ("don't need caution"), and a set of *institutional* trust measures related to trust in politicians, the police, and the legal system. These measures are intended to capture broader levels of trust but are not directly related to the willingness to offer WFH. Finally, we run a set of regressions where we include all these measures in a joint model. All the measures of trust are based on the pre-pandemic survey responses (2014-2018). The results of these regressions at the country level are presented in Table 1.

Table 1: Manager Trust Measure Comparisons (Country Level Trust)

| | Ever work from home | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Separate regression for each trust | | | | | Alternative trust as controls | | | | |
| **Panel A: Pre-COVID (2016-2019)** | | | | | | | | | | |
| Manager Trust (people are fair) | 0.071*** | — | — | — | — | 0.076** | 0.094*** | 0.105*** | 0.096*** | 0.109*** |
| | (0.024) | | | | | (0.031) | (0.023) | (0.019) | (0.020) | (0.023) |
| Manager Trust (don't need caution) | — | 0.060** | — | — | — | −0.007 | — | — | — | 0.101** |
| | | (0.021) | | | | (0.027) | | | | (0.039) |
| Manager Trust in Politicians | — | — | 0.038* | — | — | — | −0.025 | — | — | −0.079* |
| | | | (0.021) | | | | (0.019) | | | (0.043) |
| Manager Trust in the Police | — | — | — | 0.026 | — | — | — | −0.042** | — | −0.136*** |
| | | | | (0.016) | | | | (0.017) | | (0.047) |
| Manager Trust in the Legal System | — | — | — | — | 0.024* | — | — | — | −0.021 | 0.065 |
| | | | | | (0.014) | | | | (0.015) | (0.048) |
| $N = 4,315,862$ (19 clusters) | | | | | | | | | | |
| **Panel B: During COVID (2021)** | | | | | | | | | | |
| Manager Trust (people are fair) | 0.112*** | — | — | — | — | 0.108*** | 0.133*** | 0.124*** | 0.120*** | 0.131*** |
| | (0.015) | | | | | (0.029) | (0.032) | (0.028) | (0.030) | (0.027) |
| Manager Trust (don't need caution) | — | 0.100*** | — | — | — | 0.006 | — | — | — | 0.075 |
| | | (0.015) | | | | (0.027) | | | | (0.049) |
| Manager Trust in Politicians | — | — | 0.059** | — | — | — | −0.022 | — | — | −0.086** |
| | | | (0.027) | | | | (0.029) | | | (0.040) |
| Manager Trust in the Police | — | — | — | 0.059*** | — | — | — | −0.015 | — | −0.095*** |
| | | | | (0.014) | | | | (0.021) | | (0.032) |
| Manager Trust in the Legal System | — | — | — | — | 0.045*** | — | — | — | −0.007 | 0.071* |
| | | | | | (0.014) | | | | (0.018) | (0.040) |
| $N = 801,758$ (19 clusters) | | | | | | | | | | |

*Note*: In this table, we present the country-level estimates and standard errors to a series of raw regressions showing the relationship of various trust variables and "ever" WFH. Regressions are run at the individual level, but the trust variables are measured at the country level. We do not use any controls other than year fixed effects (in the pre-COVID period) and trust variables (in columns 7-11). These regressions are run both for the pre-COVID period (2016-2019) and the "during COVID" period (2021). Standard errors are clustered at the country level. Full tables that include the region level and region-by-industry level results for the pre-COVID period and the during COVID period can be found in the appendix as Table A.1 and Table A.2, respectively. The sample in this table is restricted to the same sample used in the main analysis (Tables 2 and 3), but results for the full set of countries can be found in Tables A.3 and A.4.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results show that our preferred measure of trust exhibits the strongest association with WFH when included independently. This pattern holds in both the pre-pandemic period (Panel A) and during the pandemic (Panel B). When pairing the preferred measure with alternatives as controls, or when estimating all associations in a joint model, it becomes evident that our preferred measure maintains the strongest association with the outcome—the point estimate for the preferred measure is consistently the largest and remains statistically significant across all specifications. In the appendix, we demonstrate that these relationships persist at the region and region-by-industry levels in both the pre-COVID period (Table A.1) and during the COVID period (Table A.2). Overall, these results suggest that our preferred measure captures a *specific* kind of trust that is strongly related to the intensity of working from home.

## 5.2 Manager trust and work from home before the pandemic

Our main results for the pre-pandemic period, based on the individual-level specification outlined in equation (7), are presented in Table 2. Panel A displays results at the country level. Column (1) shows, in line with results presented above, that the raw (i.e. without controls) association between country-level managerial trust and the individual probability of working from home is positive. In our baseline specification (column 2), where we include controls for demographic characteristics, occupations, and industries, the results become somewhat larger, suggesting that the overall patterns are not driven by the occupational structure or demographic composition of the workforce. The baseline estimate indicates that workers in countries with one point higher average reported manager trust (on a 0-10 scale) are nearly 8 percentage points more likely to work from home, even after accounting for demographic characteristics, occupations, and industries.

These effects also remain positive and significant when we control for a set of aggregate-level confounders. Specifically, we account for individualism (column 3), "digital use" (column 4), broadband access (column 5), and GDP per capita (column 6). In the first three regressions (columns 3-5), the estimates increase relative to the baseline, while in the final regression (column 6, GDP), the estimate remains virtually unchanged relative to the baseline. These patterns suggest that the country-level association between managerial trust and WFH is not driven by any of these aggregate social, technological, and economic factors. In column (8), we include all of these controls together in a saturated regression, which places significant demands on our data that span across 19 different countries. In this regression, we observe a slight loss of precision, but the point estimates remain positive, stable, and marginally significant. Overall, the results presented in Panel A are fully consistent with the hypothesis that managerial trust plays a crucial role in explaining WFH differences across countries.

While the country-level associations are large and stable across specifications, they rely on somewhat limited variation, and it is not inconceivable that other cross-country differences could be confounding our results. To address this, we perform a similar analysis relying on region-level variation in trust. The results are shown in Panel B of Table 2. Although these regional estimates are somewhat smaller in magnitude—possibly due to dilution by measurement errors, as our measure of managerial trust relies on fewer responses per region—they, reassuringly, exhibit a similar qualitative pattern to the country-level regressions, with economically meaningful magnitudes in all specifications. The baseline model (column 2) suggests that a region with one point higher average reported manager trust would be 5 percentage points more likely to have workers engaging in WFH, after controlling for demographic characteristics, occupation, and industry. The results remain reasonably stable when adding additional controls, with estimates ranging from around 0.04 to 0.05 (columns 3 to 6). In the saturated regression (column 8), the estimate is 0.03 and it remains highly significant. To fully eliminate potential country-level effects, we run a specification with country-fixed effects, comparing regions within the same country. This approach reduces the explanatory variation since

Table 2: Pre-COVID analysis (2016-2019)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | |
|---|---|---|---|---|---|---|---|---|---|
| **Panel A: Country level trust** | | | | | | | | | $N = 4,315,862$ (19 clusters) |
| Manager Trust (people are fair) | 0.071*** | 0.078*** | 0.098*** | 0.082** | 0.085*** | 0.076*** | — | 0.072* | |
| | (0.024) | (0.018) | (0.015) | (0.030) | (0.027) | (0.016) | | (0.038) | |
| **Panel B: Region level trust** | | | | | | | | | $N = 4,228,357$ (135 clusters) |
| Manager Trust (people are fair) | 0.051*** | 0.053*** | 0.053*** | 0.040*** | 0.038*** | 0.042*** | 0.013*** | 0.034*** | |
| | (0.007) | (0.006) | (0.006) | (0.011) | (0.009) | (0.008) | (0.004) | (0.010) | |
| **Panel C: Region × Industry level trust** | | | | | | | | | $N = 3,839,135$ (832 clusters) |
| Manager Trust (people are fair) | 0.021*** | 0.019*** | 0.018*** | 0.014*** | 0.009*** | 0.010*** | 0.001 | 0.007*** | |
| | (0.003) | (0.002) | (0.002) | (0.003) | (0.002) | (0.003) | (0.002) | (0.002) | |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | |
| Demographic Characteristics | × | Yes | Yes | Yes | Yes | Yes | Yes | Yes | |
| Individualism | × | × | Yes | × | × | × | × | Yes | |
| Digital Use | × | × | × | Yes | × | × | × | Yes | |
| Household Broadband Access | × | × | × | × | Yes | × | × | Yes | |
| GDP per capita | × | × | × | × | × | Yes | × | Yes | |
| Country Fixed Effects | × | × | × | × | × | × | Yes | × | |

*Note*: Sample size is restricted so it is the same for all regressions in the same panel. Demographic data for some variables is missing for some countries. Switzerland is missing data on partner and children and Czechia, Iceland, Ireland, Netherlands, and Slovakia are missing data on age. Standard errors are clustered at the associated geographic level (country level, region level, or region-by-industry level for Panel A, B, and C, respectively).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

most countries have relatively few regions. Furthermore, it could potentially increase the role of measurement errors as the country dummies will remove much of the true variation in trust. Despite of these caveats, we find a significant estimate of manager trust on WFH of 0.013 (column 7).

In Panel C of Table 2, we repeat the same approach using region-by-industry variation. Here, we are pushing the data to its limits in terms of granularity, and measurement errors are almost certainly working against us, as we are relying on 7,832 manager responses to characterize 832 region-industry clusters. With this caveat in mind, it is reassuring that the estimates remain significant. We find a baseline estimate of 0.019 (column 2) in the model that controls for industry dummies alongside demographics and occupations. When adding the same controls as in the previous panels, we find significant effects ranging from 0.009 to 0.018 (columns 3 to 6), with a significant effect of 0.007 in the saturated regression (column 8). However, unlike in the region-level specification, the association disappears when we include country fixed effects (column 7). Given the small number of respondents, and the fact that the fixed effects are likely removing a significant part of the true signal, it seems plausible that these estimates are attenuated by measurement errors. Reassuringly, the estimates are more stable if we compute "trust" by averaging across all respondents, i.e. including people in non-managerial positions as well (see Appendix Table A.7).

The main results remain consistent if we restrict the analysis to only using manager trust from the 2018 ESS survey (Table A.5) and if we use trust of all respondents (Table A.7). As a further robustness test, we conducted a full spectrum of regressions incorporating various additional control variables and alternative definitions of trust and managers to assess the consistency of our main results.[16] The detailed results are presented in Appendix Figure B.6, and the overall impression is reassuring. For the country-level regressions, the median estimate is 7.8, and we find positive and significant coefficients in the clear majority

16. A full list and discussion of the regressions can be found in Appendix C.4.

of specifications (99% are positive, and 70% are positive and significant). This pattern extends to the region (Panel (b)) and region-by-industry (Panel (c)) levels as well, with predominantly positive estimates (99% and 98%, respectively) and a large share that are both positive and significant (88% and 83%, respectively). None of the negative results at these levels are significant, and most of the divergent estimates arise when we use an alternative trust measure ("don't need caution", see Table 1).

## 5.3 Manager trust and work from home during the pandemic

In our theory section, we discuss how trust can play a role in shifting equilibria after a shock to WFH. To explore this process, we study if the relationship between manager trust and WFH levels change during the COVID period in columns (1) to (3) of Table 3. The results indicate that these associations not only persisted, but may have became stronger during the pandemic. Both the raw and the baseline control (demographics, occupations, industry) specifications are larger at all level of analysis than the corresponding estimates for the pre-pandemic period. For the cross-country baseline (panel A, column 2) the estimate is 0.102 as compared to 0.078 during the pre-pandemic period (Table 2). The effect decreases somewhat, but remains positive and significant when controlling for differential exposure of the virus, proxied by excess COVID-19 deaths (column 3). As with the pre-COVID results, the estimates remain positive and significant at the region (Panel B) and region-by-industry (Panel C) levels, but with reduced magnitudes.

Table 3: During COVID analysis

| | During COVID (2021) | | | Change due to COVID (DiD) | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | |
| **Panel A: Country level trust** | | | | | | | $N = 801,758$ (19 clusters) |
| Manager Trust (people are fair) | 0.112*** | 0.102*** | 0.084*** | 0.018 | 0.016 | −0.010 | $N = 5,918,465$ |
| | (0.015) | (0.015) | (0.013) | (0.015) | (0.015) | (0.009) | |
| **Panel B: Region level trust** | | | | | | | $N = 742,442$ (131 clusters) |
| Manager Trust (people are fair) | 0.087*** | 0.073*** | 0.058*** | 0.018** | 0.017** | 0.002 | $N = 5,552,009$ |
| | (0.009) | (0.007) | (0.008) | (0.007) | (0.007) | (0.007) | |
| **Panel C: Region × Industry level trust** | | | | | | | $N = 666,976$ (800 clusters) |
| Manager Trust (people are fair) | 0.037*** | 0.029*** | 0.019*** | 0.010*** | 0.010*** | 0.005* | $N = 5,016,481$ |
| | (0.005) | (0.003) | (0.003) | (0.002) | (0.002) | (0.003) | |
| COVID Excess Death | × | × | Yes | × | × | Yes | |
| Demographic Characteristics | × | Yes | Yes | × | Yes | Yes | |
| Time Fixed Effects | × | × | × | Yes | Yes | Yes | |
| Geographic Fixed Effects | × | × | × | Yes | Yes | Yes | |

*Note*: Sample size is restricted so it is the same for all regressions in the same panel for during COVID (columns (1)-(3)) and change due to COVID (columns (4)-(6)). The sample sizes are listed in the last column with the first $N$ in each panel associated with columns (1)-(3) and the second $N$ associated with columns (4)-(6). All six columns have the same number of clusters of each panel. Demographic data for some variables is missing for some countries. Switzerland is missing data on partner and children and Czechia, Iceland, Ireland, Netherlands, and Slovakia are missing data on age. "Geographic F.E." is the fixed effect corresponding to the unit of treatment for that regression and are thus a country-level fixed effect, a region-level fixed effect, and a region-by-industry-level fixed effect for Panels A, B, and C, respectively. Standard errors are clustered at the associated geographic level (country level, region level, or region-by-industry level for Panel A, B, and C, respectively).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

These results indicate that the relationship between managerial trust and WFH became even stronger during the pandemic. This suggests that trust may have played a role in the differential increase in WFH due to the pandemic. To test this directly, we utilize the COVID pandemic as a shock to WFH and examine how differences in managerial trust influenced *changes* in WFH during the pandemic. Since our data consists of repeated cross sections, we rely on the TWFE specification formulated in equation 8. The results are presented in columns (4) to (6) of Table 3. Overall, we find suggestive evidence of a positive effect of higher trust levels on the change in WFH, although these estimates are less robust than our previous findings. Our preferred baseline model suggests a 1 to 2 percentage points additional increase in WFH due to higher levels of managerial trust when demographic controls are included (column 5). However, this effect is not statistically significant in the country-level analysis. When we add controls for differential COVID exposure, most or all of the effect disappears across all three treatment levels (column 6), making it difficult to entirely dismiss alternative channels as potential mechanisms for the baseline change in WFH. Crucially, however, none of our models report any significant *negative* effects on the change in WFH, which we would expect if the COVID pandemic had reduced the role of trust as a determinant of WFH. If this were the case, low-trust settings would have "caught up" during the pandemic, resulting in a negative association between trust and changes in WFH. As with pre-COVID trust, all of these results are consistent with results where we use manager trust only from the 2018 ESS survey (Table A.6), we use trust for all the respondents (Table A.8), we use the WFH measure from the 2020-2022 ESS survey as the outcome (Table A.9), and we look at the extended analysis with additional controls and definitions of the treatment variable (Figure B.6).

In Appendix B, we investigate whether these associations differ between hybrid (responding "sometimes") and fully (responding "mainly") remote work. The results indicate a strong association between managerial trust and the shift to fully remote work at the expense of hybrid work during the pandemic. In this context, our main analysis of overall WFH may mask the fact that managerial trust also increases managers' confidence in allowing workers to transition all their tasks to remote settings during a highly contagious pandemic. Although this extends beyond the scope of our stylized model, it can be easily understood in scenarios where *some* tasks can be effectively monitored even when performed at home but where fully remote work requires trust.

## 5.4 Occupational heterogeneity

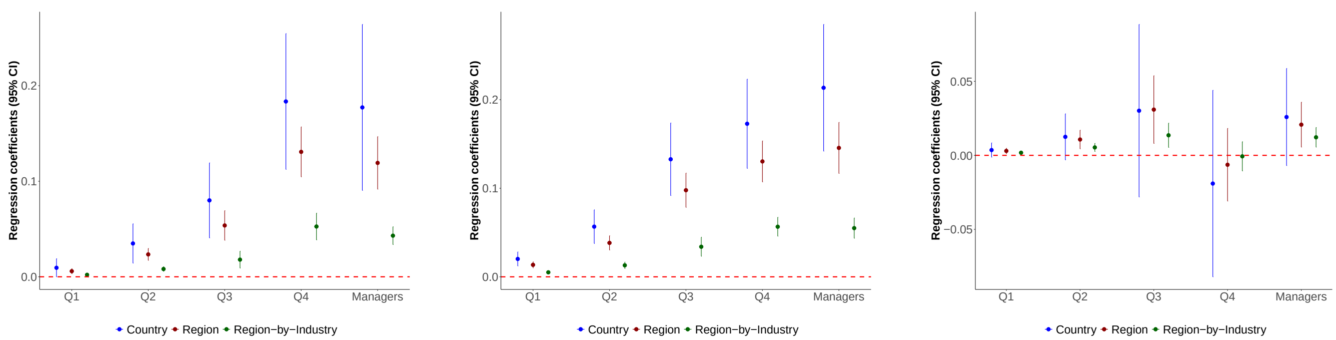
Our main analysis show consistent positive relationships between aggregate manager trust and WFH. However, it seems plausible that these relationships are heterogeneous across occupations as some tasks are easier than others to perform at a distance. In order to analyze this aspect, we split our sample in 5 groups defined by quartile of WFH potential (defined by the pre-COVID share of WFH) among non-manager occupations and treating managerial occupations as a separate category.[17] We then re-estimate our baseline models for these samples and display the results in Figure (2). The results show that trust is positively associated with WFH within all 5 occupational groups both before (Panel A) and during (Panel B) the pandemic. However, the associations are clearly strongest in the occupational quartile with the highest WFH potential (Q4) and

17. A description of example occupations in each quartile can be found in Appendix C.3.

among managers. The estimate in the top quartile is 0.18 (0.05) at the country (region-by-industry) level before the pandemic, and for managers the corresponding estimates are 0.18 and 0.04 respectively. This pattern remains consistent even when adding the various control variables used in the previous analyses, see Appendix A.3 for a full set of estimates.

Figure 2: Relationship of manager trust and "ever" WFH by occupation quartile

(a) Pre-COVID (b) During COVID (c) COVID change




*Notes:* In this figure, we plot the regression coefficients and 95% confidence intervals for our main regressions with demographic controls split by occupation WFH-potential quartile. Panels (a) and (b) are based on specification equation 7, which corresponds to column (2) of Table 2 and column (2) of Table 3, respectively, and Panel (c) is based on specification equation 8, which corresponds to column (5) of Table 3. Separate regressions are run for each occupation group, where the data is subset to only respondents in the relevant occupations. Occupation quartiles are listed as Q1 to Q4, which range from the lowest WFH potential (Q1) to the highest WFH potential (Q4). WFH potential is determined by ranking occupations by the pre-COVID share of WFH within the occupations. Managers are excluded from the ranking and from the occupation quartiles and are instead studied as a separate occupation subset. Each specification is performed at all three treatment levels and plotted from left to right for the country level (blue), region level (red), and region-by-industry level (green).

When examining the association between trust and the *change* in WFH during the pandemic (Panel C), the results paint a slightly different picture. As before, we find no evidence of a reversal (i.e., no significant negative estimates) in any group. However, we do observe consistent positive estimates across various levels of aggregation in the *mid* range (particularly in Q3) and among managers. There are no significant estimates in Q4, and the point estimates are close to zero. This pattern is likely driven by the already high levels of WFH in Q4 occupations prior to the pandemic, which may have saturated these occupations to the extent that low- and high-trust areas exhibited similar changes. Similarly, trust may have had little impact on increasing WFH in Q1 occupations, as these jobs likely involve tasks that are inherently difficult to perform remotely. However, in the mid range of occupations, trust appears to have been positively associated with the growth in WFH, which suggest that these are the jobs where marginal decisions were made and where trust may have played a role. Managers represent an interesting group, as monitoring is one of their core tasks; in order to work from home, even during the pandemic, they must trust their workers not to shirk.

# 6 Conclusion

Work from home has rapidly become an increasingly common form of work in many parts of the world. However, not all countries and regions are adopting these practices at the same rate. While many factors such as technological infrastructure, digital skills, and occupational compositions may contribute to the adoption of work from home, *trust* stands out as an important determinant that has received very little attention in the economic literature. As we argue in this article, many jobs involve tasks that are harder to monitor when performed at a distance. We further argue that the intersection of trust and imperfect monitoring is a theoretically interesting determinant of work from home; coupled with adverse selection it is a plausible source of multiple equilibria.

In our very stylized theoretical model we formalize this intuition. We argue that firms must trust their workers in order to offer them the opportunity to work from home. Furthermore, even high trust managers are disincentivized to offer work from home if few other jobs have this amenity as this would attract less dutiful workers. This suggests that aggregate levels of trust may be an important determinant of the rates of work from home. Our model also predicts that a large shock to WFH may shift a region's equilibrium from on-site work to frequent WFH. Where firm-level experimentation might fail due to adverse selection, a large shock such as the COVID-19 pandemic might move the economy to a stable work-from-home equilibrium.

Empirically, we find patterns that strongly support the notion that manager trust is essential for remote work. We find a robust positive relationship between aggregate manager trust and whether or not workers perform some of their tasks from home. The association is not driven by just any type of trust, instead it arises precisely because of managers' beliefs about others' dutifulness; trust in institutions are, e.g., much less relevant. Importantly, we show that the association between manager trust and work from home is completely robust if we control for worker demographics, occupations, and industries. They remain strong even when we control for likely aggregate confounders such as levels of independence, digital skill levels, internet access, and GDP per capita. The association is present at the cross-country level but also across regions within the same country. Additional evidence suggest that trust continued to be relevant for remote work during the COVID-19 pandemic. Areas that had lower levels of manager trust, and consequently lower levels of remote work pre-pandemic, did not catch up during the pandemic. In contrast, the results indicate that the relationship between managerial trust and work from home became stronger at the onset of the COVID-19 pandemic. This is particularly salient when zooming in on "marginal" occupations in the middle of the remote work distribution, or when focusing on the managers themselves.

Overall, our paper documents the role of trust as a key determinant of why firms in some regions seem more inclined to offer WFH than firms in other regions. The paper also suggests a potential rationale for the apparent untapped potential for remote work before the pandemic. The technology to work from home may have been there, but a large shock causing aggregate changes may have been necessary for firms to take advantage of this technology if monitoring is imperfect and if workers sort across jobs based on their willingness to shirk. At a broader level, our paper aims to push the economic literature on work from home towards incorporating the concepts of trust, shirking, and worker sorting. Our results indicate that these are key processes for work-from-home to remain as a lasting phenomenon, both at the firm and the aggregate level.

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# A Additional Results

## A.1 Additional trust comparisons

Table A.1: Manager Trust Measure Comparisons - Pre-COVID - Main Sample

| | Ever work from home | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Individual regressions | | | | | Alternative trust as controls | | | | |
| **Panel A: Country level trust** | | | | | | | | | | |
| Manager Trust (people are fair) | 0.071*** | — | — | — | — | 0.076** | 0.094*** | 0.105*** | 0.096*** | 0.109*** |
| | (0.024) | | | | | (0.031) | (0.023) | (0.019) | (0.020) | (0.023) |
| Manager Trust (don't need caution) | — | 0.060** | — | — | — | −0.007 | — | — | — | 0.101** |
| | | (0.021) | | | | (0.027) | | | | (0.039) |
| Manager Trust in Politicians | — | — | 0.038* | — | — | — | −0.025 | — | — | −0.079* |
| | | | (0.021) | | | | (0.019) | | | (0.043) |
| Manager Trust in the Police | — | — | — | 0.026 | — | — | — | −0.042** | — | −0.136*** |
| | | | | (0.016) | | | | (0.017) | | (0.047) |
| Manager Trust in the Legal System | — | — | — | — | 0.024* | — | — | — | −0.021 | 0.065 |
| | | | | | (0.014) | | | | (0.015) | (0.048) |
| $N = 4,315,862$ (19 clusters) | | | | | | | | | | |
| **Panel B: Region level trust** | | | | | | | | | | |
| Manager Trust (people are fair) | 0.051*** | — | — | — | — | 0.045*** | 0.051*** | 0.054*** | 0.049*** | 0.045*** |
| | (0.007) | | | | | (0.010) | (0.008) | (0.008) | (0.008) | (0.009) |
| Manager Trust (don't need caution) | — | 0.045*** | — | — | — | 0.010 | — | — | — | 0.017 |
| | | (0.008) | | | | (0.010) | | | | (0.016) |
| Manager Trust in Politicians | — | — | 0.025*** | — | — | — | 0.001 | — | — | −0.007 |
| | | | (0.008) | | | | (0.006) | | | (0.010) |
| Manager Trust in the Police | — | — | — | 0.020*** | — | — | — | −0.005 | — | −0.023* |
| | | | | (0.006) | | | | (0.006) | | (0.012) |
| Manager Trust in the Legal System | — | — | — | — | 0.022*** | — | — | — | 0.003 | 0.016 |
| | | | | | (0.005) | | | | (0.006) | (0.012) |
| $N = 4,228,357$ (135 clusters) | | | | | | | | | | |
| **Panel C: Region-by-industry level trust** | | | | | | | | | | |
| Manager Trust (people are fair) | 0.021*** | — | — | — | — | 0.020*** | 0.019*** | 0.020*** | 0.018*** | 0.018*** |
| | (0.003) | | | | | (0.004) | (0.003) | (0.003) | (0.003) | (0.004) |
| Manager Trust (don't need caution) | — | 0.012*** | — | — | — | 0.003 | — | — | — | −0.000 |
| | | (0.004) | | | | (0.005) | | | | (0.005) |
| Manager Trust in Politicians | — | — | 0.011*** | — | — | — | 0.006** | — | — | 0.001 |
| | | | (0.003) | | | | (0.003) | | | (0.003) |
| Manager Trust in the Police | — | — | — | 0.009** | — | — | — | 0.004 | — | −0.005 |
| | | | | (0.004) | | | | (0.004) | | (0.005) |
| Manager Trust in the Legal System | — | — | — | — | 0.012*** | — | — | — | 0.008** | 0.010** |
| | | | | | (0.003) | | | | (0.003) | (0.004) |
| $N = 3,835,724$ (831 clusters) | | | | | | | | | | |

*Note*: This table presents the expanded results associated with Panel A of Table 1. In this table, we plot the pre-COVID (2016-2019) estimates and standard errors to a series of raw regressions showing the relationship of various trust variables and "ever" WFH. Regressions are run at the individual level, but the trust variables are measured at the country level for Panel A, the region level for Panel B, and the region-by-industry level for Panel C. The sample size is fixed for all regressions at the same level of analysis with the same number of clusters for all regressions within a panel and are set to match the sample used in the main analysis. We do not use any controls other than year fixed effects for all regressions and trust variables in columns 7-11. Standard errors are clustered at the associated geographic level (country level, region level, or region-by-industry level for Panel A, B, and C, respectively).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

## Table A.2: Manager Trust Measure Comparisons - During COVID - Main Sample

| | Ever work from home | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Individual regressions | | | | | Alternative trust as controls | | | | |
| **Panel 1: Country level trust** | | | | | | | | | | |
| Manager Trust (people are fair) | 0.112$^{***}$ | — | — | — | — | 0.108$^{***}$ | 0.133$^{***}$ | 0.124$^{***}$ | 0.120$^{***}$ | 0.131$^{***}$ |
| | (0.015) | | | | | (0.029) | (0.032) | (0.028) | (0.030) | (0.027) |
| Manager Trust (don't need caution) | — | 0.100$^{***}$ | — | — | — | 0.006 | — | — | — | 0.075 |
| | | (0.015) | | | | (0.027) | | | | (0.049) |
| Manager Trust in Politicians | — | — | 0.059$^{**}$ | — | — | — | −0.022 | — | — | −0.086$^{**}$ |
| | | | (0.027) | | | | (0.029) | | | (0.040) |
| Manager Trust in the Police | — | — | — | 0.059$^{***}$ | — | — | — | −0.015 | — | −0.095$^{***}$ |
| | | | | (0.014) | | | | (0.021) | | (0.032) |
| Manager Trust in the Legal System | — | — | — | — | 0.045$^{***}$ | — | — | — | −0.007 | 0.071$^{*}$ |
| | | | | | (0.014) | | | | (0.018) | (0.040) |
| $N = 801,758$ (19 clusters) | | | | | | | | | | |
| **Panel 2: Region level trust** | | | | | | | | | | |
| Manager Trust (people are fair) | 0.087$^{***}$ | — | — | — | — | 0.071$^{***}$ | 0.084$^{***}$ | 0.082$^{***}$ | 0.067$^{***}$ | 0.070$^{***}$ |
| | (0.009) | | | | | (0.014) | (0.013) | (0.011) | (0.011) | (0.013) |
| Manager Trust (don't need caution) | — | 0.081$^{***}$ | — | — | — | 0.024 | — | — | — | 0.016 |
| | | (0.009) | | | | (0.015) | | | | (0.020) |
| Manager Trust in Politicians | — | — | 0.042$^{***}$ | — | — | — | 0.004 | — | — | −0.031$^{***}$ |
| | | | (0.014) | | | | (0.010) | | | (0.012) |
| Manager Trust in the Police | — | — | — | 0.044$^{***}$ | — | — | — | 0.008 | — | −0.036$^{**}$ |
| | | | | (0.009) | | | | (0.009) | | (0.014) |
| Manager Trust in the Legal System | — | — | — | — | 0.052$^{***}$ | — | — | — | 0.024$^{***}$ | 0.060$^{***}$ |
| | | | | | (0.007) | | | | (0.008) | (0.014) |
| $N = 742,442$ (131 clusters) | | | | | | | | | | |
| **Panel 3: Region-by-industry level trust** | | | | | | | | | | |
| Manager Trust (people are fair) | 0.037$^{***}$ | — | — | — | — | 0.031$^{***}$ | 0.033$^{***}$ | 0.032$^{***}$ | 0.027$^{***}$ | 0.028$^{***}$ |
| | (0.005) | | | | | (0.006) | (0.005) | (0.005) | (0.005) | (0.007) |
| Manager Trust (don't need caution) | — | 0.026$^{***}$ | — | — | — | 0.010 | — | — | — | 0.002 |
| | | (0.005) | | | | (0.006) | | | | (0.007) |
| Manager Trust in Politicians | — | — | 0.018$^{***}$ | — | — | — | 0.010$^{**}$ | — | — | −0.009$^{*}$ |
| | | | (0.005) | | | | (0.004) | | | (0.006) |
| Manager Trust in the Police | — | — | — | 0.023$^{***}$ | — | — | — | 0.015$^{***}$ | — | −0.005 |
| | | | | (0.005) | | | | (0.004) | | (0.006) |
| Manager Trust in the Legal System | — | — | — | — | 0.029$^{***}$ | — | — | — | 0.022$^{***}$ | 0.029$^{***}$ |
| | | | | | (0.004) | | | | (0.004) | (0.006) |
| $N = 666,286$ (799 clusters) | | | | | | | | | | |

*Note*: This table presents the expanded results associated with Panel B of Table 1. In this table, we plot the during COVID (2021) estimates and standard errors to a series of raw regressions showing the relationship of various trust variables and "ever" WFH. Regressions are run at the individual level, but the trust variables are measured at the country level for Panel A, the region level for Panel B, and the region-by-industry level for Panel C. The sample size is fixed for all regressions at the same level of analysis with the same number of clusters for all regressions within a panel and are set to match the sample used in the main analysis. The number of clusters at each level differ between the pre˙COVID period and during COVID period because there is no 2021 ELFS data for Iceland (one less country-level cluster, one less region-level cluster, nine less region-by-industry-level clusters). We do not use any controls other than trust variables in columns 7-11. Standard errors are clustered at the associated geographic level (country level, region level, or region-by-industry level for Panel A, B, and C, respectively).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: Manager Trust Measure Comparisons - Pre-COVID - Full Sample

| | Ever work from home | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Individual regressions | | | | | Alternative trust as controls | | | | |
| **Panel A: Country level trust** | | | | | | | | | | |
| Manager Trust (people are fair) | 0.104*** | — | — | — | — | 0.084* | 0.083*** | 0.136*** | 0.120*** | 0.086** |
| | (0.016) | | | | | (0.041) | (0.030) | (0.016) | (0.017) | (0.033) |
| Manager Trust (don't need caution) | — | 0.092*** | — | — | — | 0.021 | — | — | — | 0.051 |
| | | (0.016) | | | | (0.035) | | | | (0.038) |
| Manager Trust in Politicians | — | — | 0.077*** | — | — | — | 0.020 | — | — | 0.019 |
| | | | (0.014) | | | | (0.024) | | | (0.042) |
| Manager Trust in the Police | — | — | — | 0.065*** | — | — | — | −0.046* | — | −0.062 |
| | | | | (0.021) | | | | (0.022) | | (0.039) |
| Manager Trust in the Legal System | — | — | — | — | 0.059*** | — | — | — | −0.014 | −0.006 |
| | | | | | (0.016) | | | | (0.016) | (0.047) |
| $N = 5,970,877$ (25 clusters) | | | | | | | | | | |
| **Panel B: Region level trust** | | | | | | | | | | |
| Manager Trust (people are fair) | 0.080*** | — | — | — | — | 0.052*** | 0.059*** | 0.080*** | 0.064*** | 0.043*** |
| | (0.009) | | | | | (0.012) | (0.009) | (0.011) | (0.009) | (0.010) |
| Manager Trust (don't need caution) | — | 0.074*** | — | — | — | 0.033 | — | — | — | 0.026** |
| | | (0.009) | | | | (0.013) | | | | (0.013) |
| Manager Trust in Politicians | — | — | 0.055*** | — | — | — | 0.024*** | — | — | 0.019* |
| | | | (0.008) | | | | (0.007) | | | (0.011) |
| Manager Trust in the Police | — | — | — | 0.044*** | — | — | — | −0.000 | — | −0.037*** |
| | | | | (0.008) | | | | (0.008) | | (0.014) |
| Manager Trust in the Legal System | — | — | — | — | 0.047*** | — | — | — | 0.016*** | 0.020* |
| | | | | | (0.007) | | | | (0.006) | (0.011) |
| $N = 5,868,631$ (159 clusters) | | | | | | | | | | |
| **Panel C: Region-by-industry level trust** | | | | | | | | | | |
| Manager Trust (people are fair) | 0.044*** | — | — | — | — | 0.033*** | 0.033*** | 0.041*** | 0.032*** | 0.027*** |
| | (0.004) | | | | | (0.005) | (0.004) | (0.004) | (0.004) | (0.005) |
| Manager Trust (don't need caution) | — | 0.034*** | — | — | — | 0.015*** | — | — | — | 0.007 |
| | | (0.005) | | | | (0.005) | | | | (0.005) |
| Manager Trust in Politicians | — | — | 0.032*** | — | — | — | 0.020*** | — | — | 0.011*** |
| | | | (0.004) | | | | (0.004) | | | (0.004) |
| Manager Trust in the Police | — | — | — | 0.021*** | — | — | — | 0.008** | — | −0.015*** |
| | | | | (0.004) | | | | (0.004) | | (0.005) |
| Manager Trust in the Legal System | — | — | — | — | 0.030*** | — | — | — | 0.019*** | 0.020*** |
| | | | | | (0.004) | | | | (0.003) | (0.004) |
| $N = 5,181,461$ (1,011 clusters) | | | | | | | | | | |

*Note*: This table presents the expanded results associated with Panel A of Table 1. In this table, we plot the pre-COVID (2016-2019) estimates and standard errors to a series of raw regressions showing the relationship of various trust variables and "ever" WFH. Regressions are run at the individual level, but the trust variables are measured at the country level for Panel A, the region level for Panel B, and the region-by-industry level for Panel C. The sample size is fixed for all regressions at the same level of analysis with the same number of clusters for all regressions within a panel, but use an extended sample. We do not use any controls other than year fixed effects for all regressions and trust variables in columns 7-11. Standard errors are clustered at the associated geographic level (country level, region level, or region-by-industry level for Panel A, B, and C, respectively).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Manager Trust Measure Comparisons - During COVID - Full Sample

| | Ever work from home | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Individual regressions | | | | | Alternative trust as controls | | | | |
| **Panel 1: Country level trust** | | | | | | | | | | |
| Manager Trust (people are fair) | 0.141*** | — | — | — | — | 0.128*** | 0.113** | 0.167*** | 0.146*** | 0.108** |
| | (0.021) | | | | | (0.033) | (0.043) | (0.032) | (0.032) | (0.051) |
| Manager Trust (don't need caution) | — | 0.124*** | — | — | — | 0.013 | — | — | — | 0.052 |
| | | (0.022) | | | | (0.031) | | | | (0.039) |
| Manager Trust in Politicians | — | — | 0.099*** | — | — | — | 0.025 | — | — | 0.025 |
| | | | (0.013) | | | | (0.032) | | | (0.044) |
| Manager Trust in the Police | — | — | — | 0.100*** | — | — | — | −0.036 | — | −0.061 |
| | | | | (0.016) | | | | (0.026) | | (0.037) |
| Manager Trust in the Legal System | — | — | — | — | 0.081*** | — | — | — | −0.004 | −0.000 |
| | | | | | (0.016) | | | | (0.019) | (0.040) |
| $N = 1,096,315$ (24 clusters) | | | | | | | | | | |
| **Panel 2: Region level trust** | | | | | | | | | | |
| Manager Trust (people are fair) | 0.117*** | — | — | — | — | 0.086*** | 0.092*** | 0.114*** | 0.090*** | 0.070*** |
| | (0.014) | | | | | (0.014) | (0.013) | (0.017) | (0.014) | (0.016) |
| Manager Trust (don't need caution) | — | 0.104*** | — | — | — | 0.034** | — | — | — | 0.023 |
| | | (0.015) | | | | (0.017) | | | | (0.019) |
| Manager Trust in Politicians | — | — | 0.074*** | — | — | — | 0.027** | — | — | 0.011 |
| | | | (0.013) | | | | (0.012) | | | (0.017) |
| Manager Trust in the Police | — | — | — | 0.069*** | — | — | — | 0.004 | — | −0.045** |
| | | | | (0.011) | | | | (0.010) | | (0.018) |
| Manager Trust in the Legal System | — | — | — | — | 0.069*** | — | — | — | 0.026*** | 0.041*** |
| | | | | | (0.010) | | | | (0.007) | (0.015) |
| $N = 1,083,846$ (158 clusters) | | | | | | | | | | |
| **Panel 3: Region-by-industry level trust** | | | | | | | | | | |
| Manager Trust (people are fair) | 0.063*** | — | — | — | — | 0.045*** | 0.048*** | 0.056*** | 0.043*** | 0.037*** |
| | (0.007) | | | | | (0.007) | (0.006) | (0.007) | (0.006) | (0.007) |
| Manager Trust (don't need caution) | — | 0.051*** | — | — | — | 0.025*** | — | — | — | 0.011 |
| | | (0.007) | | | | (0.007) | | | | (0.007) |
| Manager Trust in Politicians | — | — | 0.044*** | — | — | — | 0.028*** | — | — | 0.006 |
| | | | (0.007) | | | | (0.006) | | | (0.006) |
| Manager Trust in the Police | — | — | — | 0.037*** | — | — | — | 0.017*** | — | −0.018** |
| | | | | (0.005) | | | | (0.004) | | (0.007) |
| Manager Trust in the Legal System | — | — | — | — | 0.046*** | — | — | — | 0.033*** | 0.036*** |
| | | | | | (0.005) | | | | (0.004) | (0.006) |
| $N = 918,865$ (1,002 clusters) | | | | | | | | | | |

*Note*: This table presents the expanded results associated with Panel B of Table 1. In this table, we plot the during COVID (2021) estimates and standard errors to a series of raw regressions showing the relationship of various trust variables and "ever" WFH. Regressions are run at the individual level, but the trust variables are measured at the country level for Panel A, the region level for Panel B, and the region-by-industry level for Panel C. The sample size is fixed for all regressions at the same level of analysis with the same number of clusters for all regressions within a panel, but use an extended sample. The number of clusters at each level differ between the pre˙COVID period and during COVID period because there is no 2021 ELFS data for Iceland (one less country-level cluster, one less region-level cluster, nine less region-by-industry-level clusters). We do not use any controls other than trust variables in columns 7-11. Standard errors are clustered at the associated geographic level (country level, region level, or region-by-industry level for Panel A, B, and C, respectively).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

## A.2 Alternative main analyses

Table A.5: Pre-COVID analysis (2016-2019) - Only 2018 manager trust

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | |
|---|---|---|---|---|---|---|---|---|---|
| **Panel A: Country level trust** | | | | | | | | | $N = 4,315,862$ (19 clusters) |
| 2018 Manager Trust (people are fair) | 0.063** | 0.068*** | 0.070*** | 0.076** | 0.081*** | 0.067*** | — | 0.034 | |
| | (0.022) | (0.017) | (0.014) | (0.029) | (0.019) | (0.013) | | (0.033) | |
| **Panel B: Region level trust** | | | | | | | | | $N = 4,190,921$ (125 clusters) |
| 2018 Manager Trust (people are fair) | 0.032*** | 0.032*** | 0.033*** | 0.017** | 0.019*** | 0.023*** | 0.005** | 0.015** | |
| | (0.006) | (0.006) | (0.006) | (0.007) | (0.006) | (0.006) | (0.002) | (0.006) | |
| **Panel C: Region × Industry level trust** | | | | | | | | | $N = 3,145,472$ (571 clusters) |
| 2018 Manager Trust (people are fair) | 0.015*** | 0.014*** | 0.014*** | 0.011*** | 0.008*** | 0.008*** | 0.002 | 0.007*** | |
| | (0.003) | (0.003) | (0.003) | (0.002) | (0.002) | (0.003) | (0.001) | (0.002) | |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | |
| Demographic Characteristics | × | Yes | Yes | Yes | Yes | Yes | Yes | Yes | |
| Individualism | × | × | Yes | × | × | × | × | Yes | |
| Digital Use | × | × | × | Yes | × | × | × | Yes | |
| Household Broadband Access | × | × | × | × | Yes | × | × | Yes | |
| GDP per capita | × | × | × | × | × | Yes | × | Yes | |
| Country Fixed Effects | × | × | × | × | × | × | Yes | × | |

*Note*: This table is similar to our main pre-COVID regression table (Table 2), except the manager trust variable in restricted to only the 2018 version of the ESS survey. Sample size is restricted so it is the same for all regressions in the same panel. Demographic data for some variables is missing for some countries. Switzerland is missing data on partner and children and Czechia, Iceland, Ireland, Netherlands, and Slovakia are missing data on age. Standard errors are clustered at the associated geographic level (country level, region level, or region-by-industry level for Panel A, B, and C, respectively).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: During COVID analysis - Only 2018 manager trust

| | During COVID (2021) | | | Change due to COVID | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | |
| **Panel A: Country level trust** | | | | | | | $N = 801,758$ (19 clusters) |
| 2018 Manager Trust (people are fair) | 0.099*** | 0.088*** | 0.071*** | 0.014 | 0.012 | −0.008 | $N = 5,918,465$ |
| | (0.016) | (0.015) | (0.013) | (0.014) | (0.014) | (0.009) | |
| **Panel B: Region level trust** | | | | | | | $N = 736,285$ (121 clusters) |
| 2018 Manager Trust (people are fair) | 0.047*** | 0.038*** | 0.027*** | 0.008 | 0.007 | −0.001 | $N = 5,502,876$ |
| | (0.010) | (0.007) | (0.008) | (0.006) | (0.006) | (0.006) | |
| **Panel C: Region × Industry level trust** | | | | | | | $N = 539,752$ (538 clusters) |
| 2018 Manager Trust (people are fair) | 0.023*** | 0.019*** | 0.014*** | 0.003 | 0.002 | −0.001 | $N = 4,068,834$ |
| | (0.006) | (0.004) | (0.004) | (0.003) | (0.003) | (0.003) | |
| COVID Excess Death | × | × | Yes | × | × | Yes | |
| Demographic Characteristics | × | Yes | Yes | × | Yes | Yes | |
| Time Fixed Effects | × | × | × | Yes | Yes | Yes | |
| Geographic Fixed Effects | × | × | × | Yes | Yes | Yes | |

*Note*: This table is similar to our main during COVID regression table (Table 3), except the manager trust variable in restricted to only the 2018 version of the ESS survey. Sample size is restricted so it is the same for all regressions in the same panel for during COVID (columns (1)-(3)) and change due to COVID (columns (4)-(6)). The sample sizes are listed in the last column with the first $N$ in each panel associated with columns (1)-(3) and the second $N$ associated with columns (4)-(6). All six columns have the same number of clusters of each panel. Demographic data for some variables is missing for some countries. Switzerland is missing data on partner and children and Czechia, Iceland, Ireland, Netherlands, and Slovakia are missing data on age. "Geographic F.E." is the fixed effect corresponding to the unit of treatment for that regression and are thus a country-level fixed effect, a region-level fixed effect, and a region-by-industry-level fixed effect for Panels A, B, and C, respectively. Standard errors are clustered at the associated geographic level (country level, region level, or region-by-industry level for Panel A, B, and C, respectively).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.7: Pre-COVID analysis (2016-2019) - General population trust

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | |
|---|---|---|---|---|---|---|---|---|---|
| **Panel A: Country level trust** | | | | | | | | | $N = 4,315,862$ (19 clusters) |
| Population Trust (people are fair) | 0.074*** | 0.081*** | 0.105*** | 0.106*** | 0.095*** | 0.096*** | — | 0.082** | |
| | (0.024) | (0.018) | (0.017) | (0.034) | (0.029) | (0.012) | | (0.033) | |
| **Panel B: Region level trust** | | | | | | | | | $N = 4,190,921$ (125 clusters) |
| Population Trust (people are fair) | 0.069*** | 0.074*** | 0.075*** | 0.080*** | 0.076*** | 0.078*** | 0.013*** | 0.082*** | |
| | (0.009) | (0.008) | (0.007) | (0.014) | (0.014) | (0.008) | (0.004) | (0.014) | |
| **Panel C: Region × Industry level trust** | | | | | | | | | $N = 3,145,472$ (571 clusters) |
| Population Trust (people are fair) | 0.068*** | 0.064*** | 0.066*** | 0.061*** | 0.056*** | 0.057*** | 0.011** | 0.056*** | |
| | (0.005) | (0.004) | (0.004) | (0.006) | (0.006) | (0.006) | (0.005) | (0.006) | |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | |
| Demographic Characteristics | × | Yes | Yes | Yes | Yes | Yes | Yes | Yes | |
| Individualism | × | × | Yes | × | × | × | × | Yes | |
| Digital Use | × | × | × | Yes | × | × | × | Yes | |
| Household Broadband Access | × | × | × | × | Yes | × | × | Yes | |
| GDP per capita | × | × | × | × | × | Yes | × | Yes | |
| Country Fixed Effects | × | × | × | × | × | × | Yes | × | |

*Note*: This table is similar to our main pre-COVID regression table (Table 2), except we use general population trust (the trust for all respondents by geographic area in the ESS surveys) as our main variable. Sample size is restricted so it is the same for all regressions in the same panel. Demographic data for some variables is missing for some countries. Switzerland is missing data on partner and children and Czechia, Iceland, Ireland, Netherlands, and Slovakia are missing data on age. Standard errors are clustered at the associated geographic level (country level, region level, or region-by-industry level for Panel A, B, and C, respectively).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.8: During COVID analysis - General population trust

| | During COVID (2021) | | | Change due to COVID | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | |
| **Panel A: Country level trust** | | | | | | | $N = 801,758$ (19 clusters) |
| Population Trust (people are fair) | 0.116*** | 0.106*** | 0.094*** | 0.021 | 0.020 | −0.005 | $N = 5,918,465$ |
| | (0.013) | (0.012) | (0.012) | (0.014) | (0.014) | (0.012) | |
| **Panel B: Region level trust** | | | | | | | $N = 736,285$ (121 clusters) |
| Population Trust (people are fair) | 0.110*** | 0.096*** | 0.085*** | 0.022*** | 0.020*** | 0.003 | $N = 5,502,876$ |
| | (0.009) | (0.006) | (0.006) | (0.007) | (0.007) | (0.006) | |
| **Panel C: Region × Industry level trust** | | | | | | | $N = 539,752$ (538 clusters) |
| Population Trust (people are fair) | 0.108*** | 0.086*** | 0.072*** | 0.025*** | 0.024*** | 0.015** | $N = 4,068,834$ |
| | (0.007) | (0.004) | (0.004) | (0.005) | (0.004) | (0.006) | |
| COVID Excess Death | × | × | Yes | × | × | Yes | |
| Demographic Characteristics | × | Yes | Yes | × | Yes | Yes | |
| Time Fixed Effects | × | × | × | Yes | Yes | Yes | |
| Geographic Fixed Effects | × | × | × | Yes | Yes | Yes | |

*Note*: This table is similar to our main during COVID regression table (Table 3), except we use general population trust (the trust for all respondents by geographic area in the ESS surveys) as our main variable. Sample size is restricted so it is the same for all regressions in the same panel for during COVID (columns (1)-(3)) and change due to COVID (columns (4)-(6)). The sample sizes are listed in the last column with the first $N$ in each panel associated with columns (1)-(3) and the second $N$ associated with columns (4)-(6). All six columns have the same number of clusters of each panel. Demographic data for some variables is missing for some countries. Switzerland is missing data on partner and children and Czechia, Iceland, Ireland, Netherlands, and Slovakia are missing data on age. "Geographic F.E." is the fixed effect corresponding to the unit of treatment for that regression and are thus a country-level fixed effect, a region-level fixed effect, and a region-by-industry-level fixed effect for Panels A, B, and C, respectively. Standard errors are clustered at the associated geographic level (country level, region level, or region-by-industry level for Panel A, B, and C, respectively).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.9: During COVID analysis - ESS measured during COVID WFH and change in WFH

| | During COVID (ESS - 2020 to 2022) | | | Increase in WFH due to COVID - ESS | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | |
| **Panel A: Country level trust** | | | | | | | $N = 13,515$ (22 clusters) |
| Manager Trust (people are fair) | 0.092*** | 0.066*** | 0.099*** | 0.080 | 0.070*** | 0.037 | $N = 6,297$ (22 clusters) |
| | (0.019) | (0.012) | (0.018) | (0.048) | (0.024) | (0.030) | |
| **Panel B: Region level trust** | | | | | | | $N = 12,132$ (217 clusters) |
| Manager Trust (people are fair) | 0.051*** | 0.033*** | 0.028*** | 0.057*** | 0.044*** | 0.025*** | $N = 5,752$ (216 clusters) |
| | (0.008) | (0.006) | (0.007) | (0.014) | (0.008) | (0.010) | |
| **Panel C: Region × Industry level trust** | | | | | | | $N = 9,516$ (897 clusters) |
| Manager Trust (people are fair) | 0.027*** | 0.019*** | 0.015*** | 0.032*** | 0.023*** | 0.011* | $N = 4,654$ (759 clusters) |
| | (0.005) | (0.003) | (0.003) | (0.009) | (0.006) | (0.006) | |
| COVID Excess Death | × | × | Yes | × | × | Yes | |
| Demographic Characteristics | × | Yes | Yes | × | Yes | Yes | |
| Time Fixed Effects | × | × | × | Yes | Yes | Yes | |
| Geographic Fixed Effects | × | × | × | Yes | Yes | Yes | |

*Note*: This table is similar to our main during COVID regression table (Table 3), except the manager trust variable in restricted to only the 2018 version of the ESS survey. Sample size is restricted so it is the same for all regressions in the same panel for during COVID (columns (1)-(3)) and change due to COVID (columns (4)-(6)). The sample sizes are listed in the last column with the first $N$ in each panel associated with columns (1)-(3) and the second $N$ associated with columns (4)-(6). All six columns have the same number of clusters of each panel. Demographic data for some variables is missing for some countries. Switzerland is missing data on partner and children and Czechia, Iceland, Ireland, Netherlands, and Slovakia are missing data on age. "Geographic F.E." is the fixed effect corresponding to the unit of treatment for that regression and are thus a country-level fixed effect, a region-level fixed effect, and a region-by-industry-level fixed effect for Panels A, B, and C, respectively. Standard errors are clustered at the associated geographic level (country level, region level, or region-by-industry level for Panel A, B, and C, respectively).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

## A.3 Occupational heterogeneity analyses

Table A.10: Pre-COVID analysis (2016-2019) - Occupational heterogeneity

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | |
|---|---|---|---|---|---|---|---|---|---|
| **Panel A: Country level trust** | | | | | | | | | |
| *Manager Trust (people are fair)* | | | | | | | | | |
| Quartile 1 (Lowest) | 0.008* | 0.009* | 0.014*** | 0.009* | 0.012** | 0.008** | — | 0.013** | $N = 887,288$ (19 clusters) |
| | (0.004) | (0.005) | (0.003) | (0.005) | (0.004) | (0.003) | | (0.006) | |
| Quartile 2 | 0.028*** | 0.035*** | 0.047*** | 0.039*** | 0.042*** | 0.034*** | — | 0.030* | $N = 1,387,060$ (19 clusters) |
| | (0.010) | (0.010) | (0.008) | (0.013) | (0.013) | (0.008) | | (0.016) | |
| Quartile 3 | 0.050 | 0.080*** | 0.094*** | 0.086** | 0.070** | 0.072*** | — | 0.056** | $N = 944,709$ (19 clusters) |
| | (0.030) | (0.019) | (0.016) | (0.031) | (0.029) | (0.017) | | (0.026) | |
| Quartile 4 (Highest) | 0.156*** | 0.183*** | 0.207*** | 0.214** | 0.206** | 0.182*** | — | 0.240** | $N = 881,949$ (19 clusters) |
| | (0.037) | (0.034) | (0.037) | (0.081) | (0.072) | (0.041) | | (0.108) | |
| Managers | 0.159*** | 0.177*** | 0.219*** | 0.107 | 0.162** | 0.158*** | — | 0.104 | $N = 214,856$ (19 clusters) |
| | (0.045) | (0.041) | (0.044) | (0.064) | (0.058) | (0.039) | | (0.079) | |
| **Panel B: Region level trust** | | | | | | | | | |
| *Manager Trust (people are fair)* | | | | | | | | | |
| Quartile 1 (Lowest) | 0.005*** | 0.006*** | 0.006*** | 0.004** | 0.005*** | 0.004*** | 0.001 | 0.004** | $N = 870,819$ (135 clusters) |
| | (0.001) | (0.001) | (0.001) | (0.002) | (0.001) | (0.001) | (0.001) | (0.002) | |
| Quartile 2 | 0.020*** | 0.023*** | 0.023*** | 0.019*** | 0.018*** | 0.019*** | 0.005** | 0.017*** | $N = 1,363,555$ (135 clusters) |
| | (0.003) | (0.003) | (0.003) | (0.005) | (0.004) | (0.004) | (0.002) | (0.004) | |
| Quartile 3 | 0.032*** | 0.054*** | 0.052*** | 0.040*** | 0.033*** | 0.039*** | 0.018** | 0.029** | $N = 922,556$ (135 clusters) |
| | (0.010) | (0.008) | (0.007) | (0.013) | (0.011) | (0.009) | (0.008) | (0.011) | |
| Quartile 4 (Highest) | 0.115*** | 0.131*** | 0.130*** | 0.102*** | 0.097*** | 0.105*** | 0.026*** | 0.089*** | $N = 861,047$ (135 clusters) |
| | (0.013) | (0.013) | (0.013) | (0.027) | (0.022) | (0.019) | (0.009) | (0.026) | |
| Managers | 0.116*** | 0.119*** | 0.118*** | 0.062*** | 0.083*** | 0.089*** | 0.034*** | 0.054** | $N = 210,380$ (135 clusters) |
| | (0.014) | (0.014) | (0.014) | (0.022) | (0.019) | (0.019) | (0.010) | (0.021) | |
| **Panel C: Region × Industry level trust** | | | | | | | | | |
| *Manager Trust (people are fair)* | | | | | | | | | |
| Quartile 1 (Lowest) | 0.002*** | 0.002*** | 0.002*** | 0.002*** | 0.001** | 0.001 | −0.000 | 0.001 | $N = 791,443$ (831 clusters) |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | |
| Quartile 2 | 0.007*** | 0.008*** | 0.008*** | 0.006*** | 0.004*** | 0.004*** | 0.001 | 0.003** | $N = 1,263,384$ (832 clusters) |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | |
| Quartile 3 | 0.012** | 0.016*** | 0.016*** | 0.013*** | 0.007* | 0.008* | 0.000 | 0.007 | $N = 801,066$ (832 clusters) |
| | (0.005) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.003) | (0.004) | |
| Quartile 4 (Highest) | 0.048*** | 0.052*** | 0.050*** | 0.033*** | 0.023*** | 0.027*** | −0.005 | 0.017** | $N = 786,657$ (832 clusters) |
| | (0.007) | (0.007) | (0.007) | (0.008) | (0.007) | (0.008) | (0.004) | (0.008) | |
| Managers | 0.046*** | 0.043*** | 0.042*** | 0.029*** | 0.023*** | 0.024*** | 0.003 | 0.016*** | $N = 196,585$ (825 clusters) |
| | (0.006) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.003) | (0.005) | |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | |
| Demographic Characteristics | × | Yes | Yes | Yes | Yes | Yes | Yes | Yes | |
| Individualism | × | × | Yes | × | × | × | × | Yes | |
| Digital Use | × | × | × | Yes | × | × | × | Yes | |
| Household Broadband Access | × | × | × | × | Yes | × | × | Yes | |
| GDP per capita | × | × | × | × | × | Yes | × | Yes | |
| Country Fixed Effects | × | × | × | × | × | × | Yes | × | |

*Note*: This table is similar to our main during COVID regression table (Table 2), except the sample is subset into quartiles by WFH potential for non-manager position and results for these quartiles and managers are all presented separately. The quartiles are constructed by ranking occupations by pre-COVID levels of WFH, based on our full set of ELFS data, and then splitting the ranking into fourths, with Quartile 4 having the highest "WFH potential" (highest share of pre-COVID WFH on average) and Quartile 1 having the lowest. Sample size is restricted so it is the same for all regressions in the same panel for each occupation subset. Demographic data for some variables is missing for some countries. Switzerland is missing data on partner and children and Czechia, Iceland, Ireland, Netherlands, and Slovakia are missing data on age. Standard errors are clustered at the associated geographic level (country level, region level, or region-by-industry level for Panel A, B, and C, respectively).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.11: During COVID analysis - Occupational heterogeneity

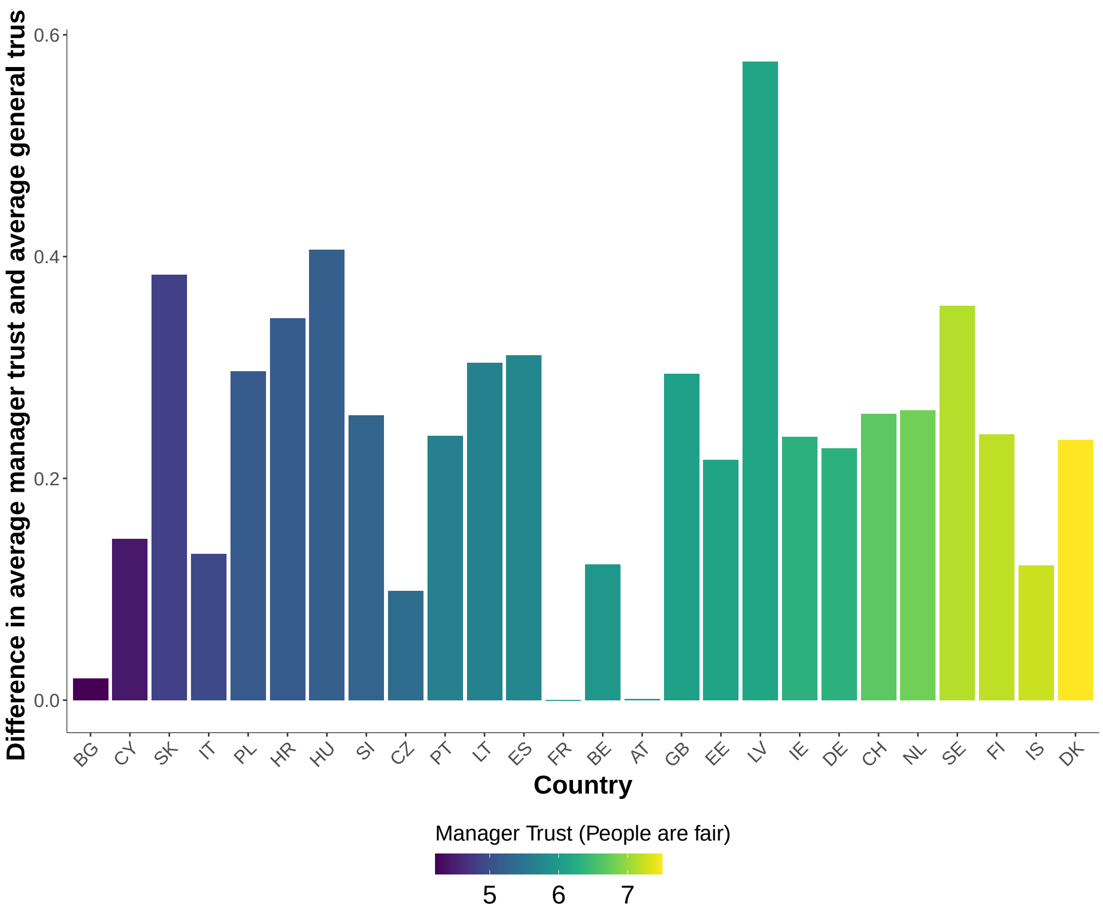
| | During COVID (2021) | | | Change due to COVID | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | |
| **Panel A: Country level trust** | | | | | | | |
| *Manager Trust (people are fair)* | | | | | | | |
| Quartile 1 (Lowest) | 0.015*** | 0.020*** | 0.017*** | 0.004 | 0.004 | 0.002 | $N = 159,213$ / $1,207,907$ |
| | (0.003) | (0.004) | (0.004) | (0.002) | (0.002) | (0.002) | (19 clusters) |
| Quartile 2 | 0.052*** | 0.057*** | 0.055*** | 0.012 | 0.012 | 0.002 | $N = 243,768$ / $1,876,756$ |
| | (0.008) | (0.009) | (0.009) | (0.007) | (0.007) | (0.004) | (19 clusters) |
| Quartile 3 | 0.110*** | 0.133*** | 0.114*** | 0.030 | 0.030 | −0.020 | $N = 174,957$ / $1,293,375$ |
| | (0.018) | (0.020) | (0.018) | (0.029) | (0.028) | (0.017) | (19 clusters) |
| Quartile 4 (Highest) | 0.162*** | 0.173*** | 0.138*** | −0.023 | −0.019 | −0.075*** | $N = 185,763$ / $1,247,832$ |
| | (0.022) | (0.024) | (0.021) | (0.029) | (0.030) | (0.020) | (19 clusters) |
| Managers | 0.229*** | 0.213*** | 0.164*** | 0.026 | 0.026 | −0.002 | $N = 38,057$ / $292,595$ |
| | (0.033) | (0.034) | (0.028) | (0.015) | (0.016) | (0.014) | (19 clusters) |
| **Panel B: Region level trust** | | | | | | | |
| *Manager Trust (people are fair)* | | | | | | | |
| Quartile 1 (Lowest) | 0.011*** | 0.012*** | 0.010*** | 0.003*** | 0.003*** | 0.002** | $N = 144,872$ / $1,117,755$ |
| | (0.001) | (0.002) | (0.002) | (0.001) | (0.001) | (0.001) | (131 clusters) |
| Quartile 2 | 0.038*** | 0.038*** | 0.035*** | 0.011*** | 0.011*** | 0.005* | $N = 229,419$ / $1,783,735$ |
| | (0.004) | (0.004) | (0.005) | (0.003) | (0.003) | (0.003) | (131 clusters) |
| Quartile 3 | 0.087*** | 0.096*** | 0.080*** | 0.031** | 0.030** | −0.000 | $N = 162,006$ / $1,213,485$ |
| | (0.010) | (0.010) | (0.010) | (0.012) | (0.012) | (0.012) | (131 clusters) |
| Quartile 4 (Highest) | 0.131*** | 0.129*** | 0.100*** | −0.011 | −0.008 | −0.036*** | $N = 170,924$ / $1,164,133$ |
| | (0.013) | (0.012) | (0.015) | (0.012) | (0.012) | (0.013) | (131 clusters) |
| Managers | 0.167*** | 0.144*** | 0.104*** | 0.021*** | 0.021*** | 0.004 | $N = 35,221$ / $272,901$ |
| | (0.016) | (0.015) | (0.019) | (0.008) | (0.008) | (0.010) | (131 clusters) |
| **Panel C: Region × Industry level trust** | | | | | | | |
| *Manager Trust (people are fair)* | | | | | | | |
| Quartile 1 (Lowest) | 0.004*** | 0.004*** | 0.003*** | 0.002*** | 0.002*** | 0.001*** | $N = 129,570$ / $1,008,079$ |
| | (0.001) | (0.001) | (0.001) | (0.000) | (0.000) | (0.000) | (784 / 799 clusters) |
| Quartile 2 | 0.015*** | 0.013*** | 0.009*** | 0.006*** | 0.005*** | 0.003* | $N = 210,548$ / $1,646,871$ |
| | (0.002) | (0.002) | (0.002) | (0.001) | (0.001) | (0.002) | (797 / 800 clusters) |
| Quartile 3 | 0.036*** | 0.038*** | 0.027*** | 0.015*** | 0.015*** | 0.008* | $N = 140,023$ / $1,049,895$ |
| | (0.005) | (0.004) | (0.005) | (0.004) | (0.004) | (0.004) | (797 / 799 clusters) |
| Quartile 4 (Highest) | 0.059*** | 0.057*** | 0.037*** | −0.000 | 0.001 | −0.006 | $N = 154,295$ / $1,057,739$ |
| | (0.006) | (0.006) | (0.006) | (0.005) | (0.005) | (0.006) | (794 / 800 clusters) |
| Managers | 0.070*** | 0.055*** | 0.030*** | 0.013*** | 0.013*** | 0.006 | $N = 32,540$ / $253,897$ |
| | (0.008) | (0.006) | (0.006) | (0.004) | (0.003) | (0.003) | (780 / 799 clusters) |
| COVID Excess Death | × | × | Yes | × | × | Yes | |
| Demographic Characteristics | × | Yes | Yes | × | Yes | Yes | |
| Time Fixed Effects | × | × | × | Yes | Yes | Yes | |
| Geographic Fixed Effects | × | × | × | Yes | Yes | Yes | |

*Note*: This table is similar to our main during COVID regression table (Table 3), except the sample is subset into quartiles by WFH potential for non-manager position and results for these quartiles and managers are all presented separately. The quartiles are constructed by ranking occupations by pre-COVID levels of WFH, based on our full set of ELFS data, and then splitting the ranking into fourths, with Quartile 4 having the highest "WFH potential" (highest share of pre-COVID WFH on average) and Quartile 1 having the lowest. Sample size is restricted so it is the same for all regressions in the same panel for each occupation subset for during COVID (columns (1)-(3)) and change due to COVID (columns (4)-(6)). The sample sizes are listed in the last column with the first $N$ in each panel associated with columns (1)-(3) and the second $N$ associated with columns (4)-(6). In Panels A and B, all six columns have the same number of clusters for each regression. In Panel C, the first number of clusters is associated with columns (1)-(3) and the second number of clusters is associated with columns (4)-(6). Demographic data for some variables is missing for some countries. Switzerland is missing data on partner and children and Czechia, Iceland, Ireland, Netherlands, and Slovakia are missing data on age. "Geographic F.E." is the fixed effect corresponding to the unit of treatment for that regression and are thus a country-level fixed effect, a region-level fixed effect, and a region-by-industry-level fixed effect for Panels A, B, and C, respectively. Standard errors are clustered at the associated geographic level (country level, region level, or region-by-industry level for Panel A, B, and C, respectively).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

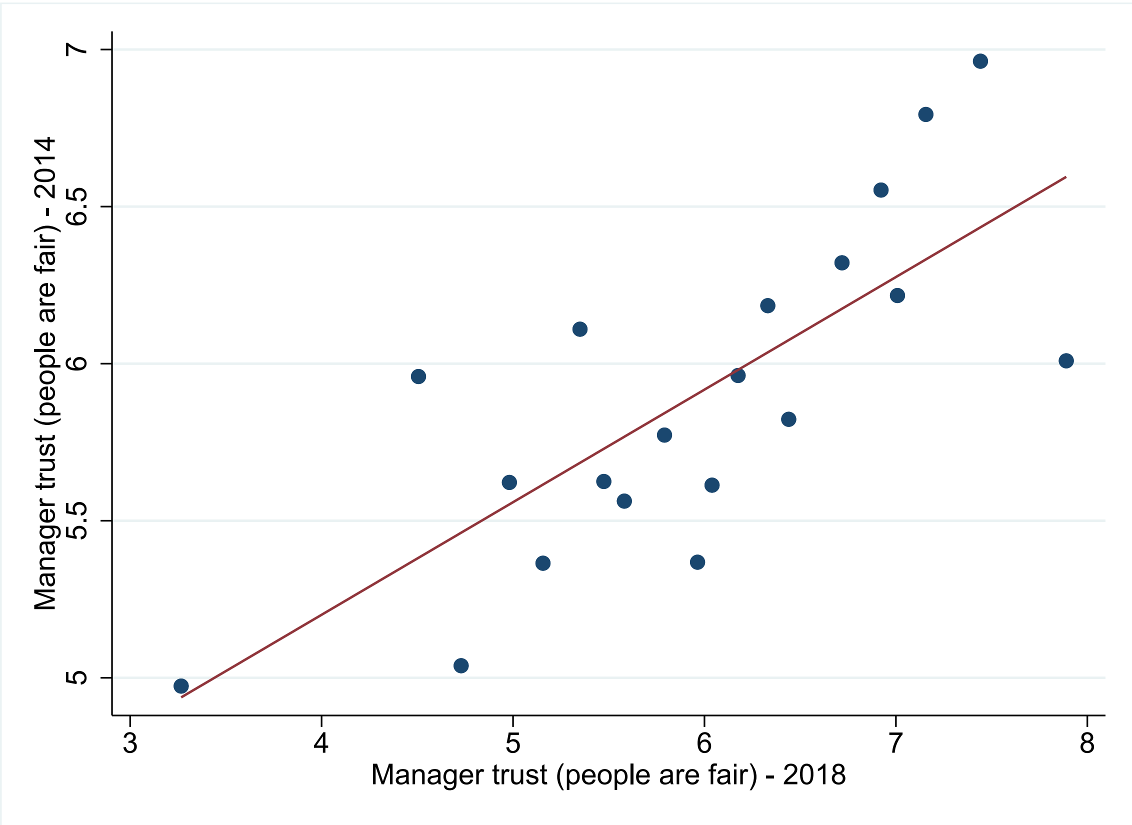
# B Additional Figures

Figure B.1: Difference in manager and general trust



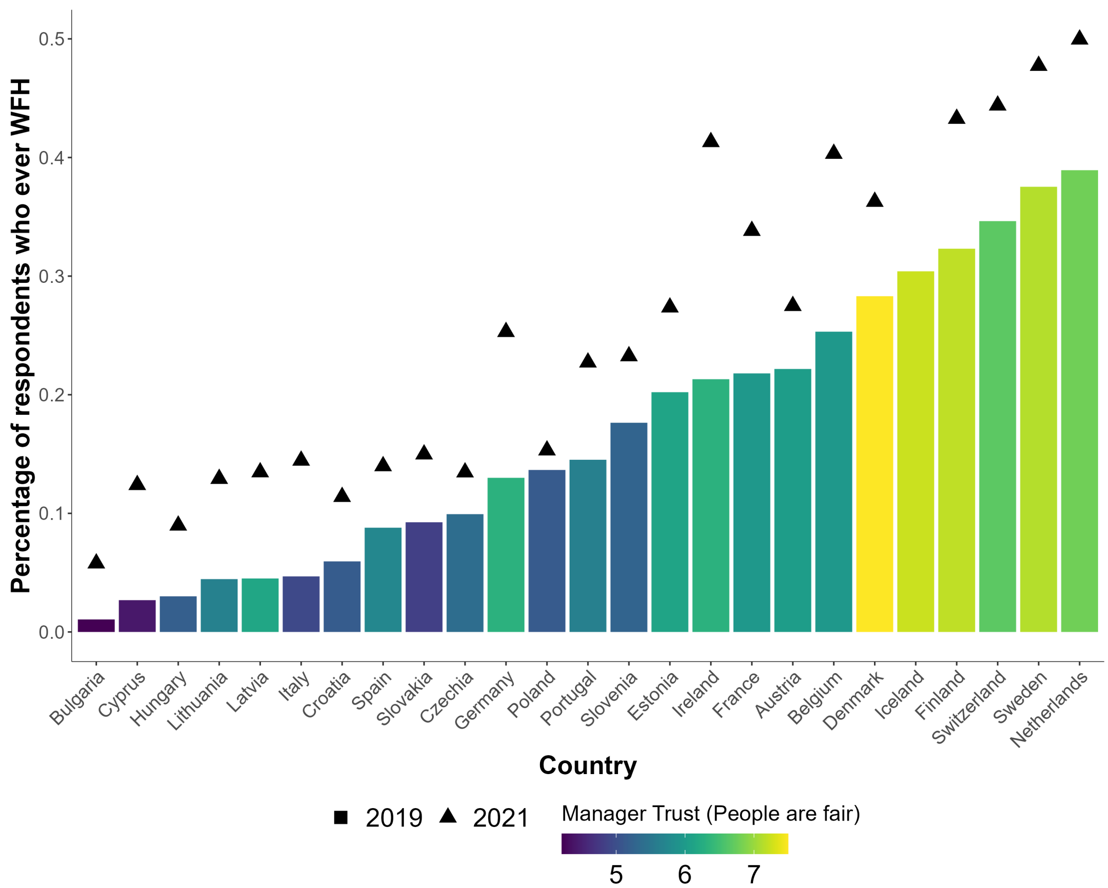

*Notes:* This figure plots the difference in average manager trust (people fair) and average general trust (people fair) across the 2014, 2016, and 2018 waves of the ESS survey by country. Countries are sorted by their average levels of manager trust. For all countries except France, the average manager trust is higher than the average trust for the general respondents. However, there is no correlation between manager trust and the difference in trust (Pearson's correlation $= 0.10$, $p = 0.62$).

Figure B.2: Relationship between manager trust in 2018 and 2014




*Notes:* This figure plots the region-level manager trust in 2018 (ESS round 9) against the manager trust in 2014 (ESS round 7). The regions plotted here are all of the regions in our main analysis that have participated in both round 7 and round 9 of the ESS surveys and have at least one manager answering the question about if "people are fair" in each round ($N$ = 115). Observations are grouped into 20 bins and the red line represents the linear relationship of manager trust across these two survey rounds. There is a strong, positive relationship showing that the 2014 region-level manager trust is a strong predictor of 2018 levels, suggesting that relative trust remains fairly stable over the years.

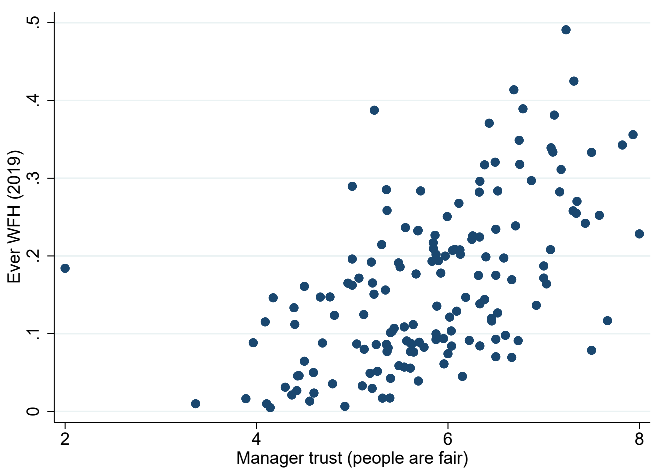
Figure B.3: State of WFH in Europe



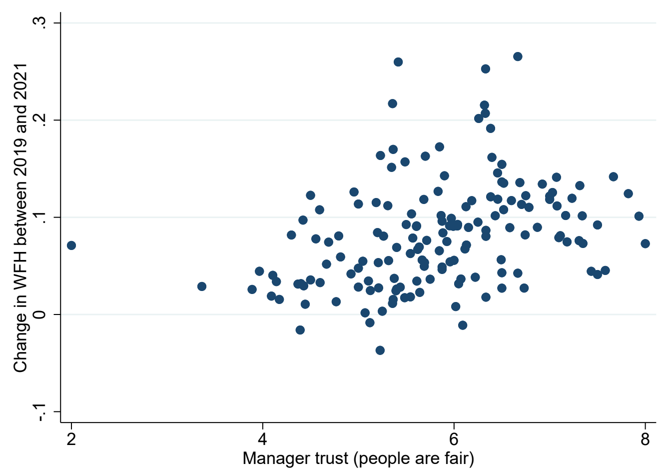

*Notes:* This figure is an alternative plot for Panel (a) of Figure 1 where countries are sorted by 2019 WFH levels. In this figure, the WFH levels represent the percentage of respondents with "ever" WFH for 2019 (bars) and 2021 (triangles) ELFS surveys. "Ever" WFH = "usually" WFH + "sometimes" WFH. Colors of the bars reflect the average trust within the country for respondents with a manager occupation in the 2014, 2016, and 2018 ESS surveys. Manager trust uses the "people are fair" definition of trust and uses a broad definition of manager. Countries are sorted by 2019 WFH levels. WFH data for Iceland is missing for 2021.

Figure B.4: Correlation between WFH and Manager Trust - Full data (Region Level)

(a) WFH levels in 2019



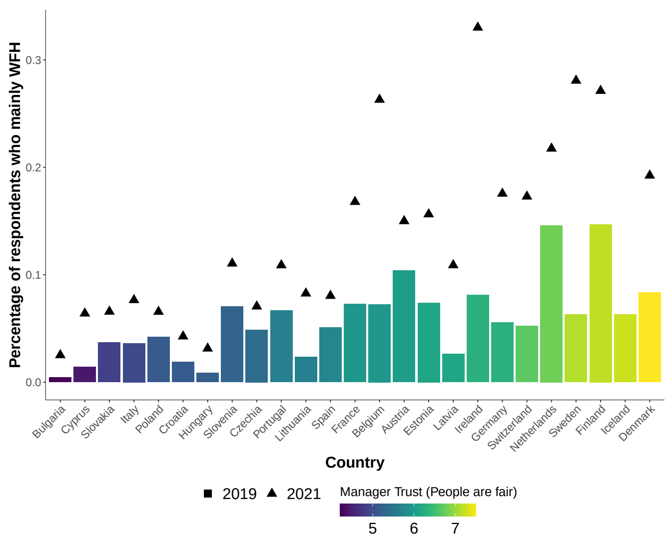

(b) Change in WFH from 2019 to 2021



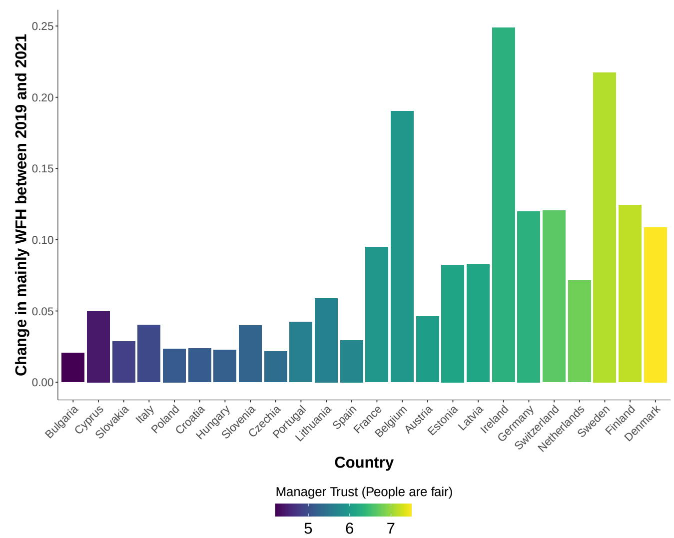

*Notes:* These figures are the full scatterplots that correspond to the binned scatter plots in Panels (c) and (d) of Figure 1. In Panel (a), WFH levels represent the percentage of respondents who have ever had it for 2019. In Panel (b), WFH is the change in "ever" WFH between 2019 and 2021. Manager trust uses the "people are fair" definition of trust and uses the broad definition of manager.

Figure B.5: Relationship between mainly and sometimes WFH and manager trust in Europe

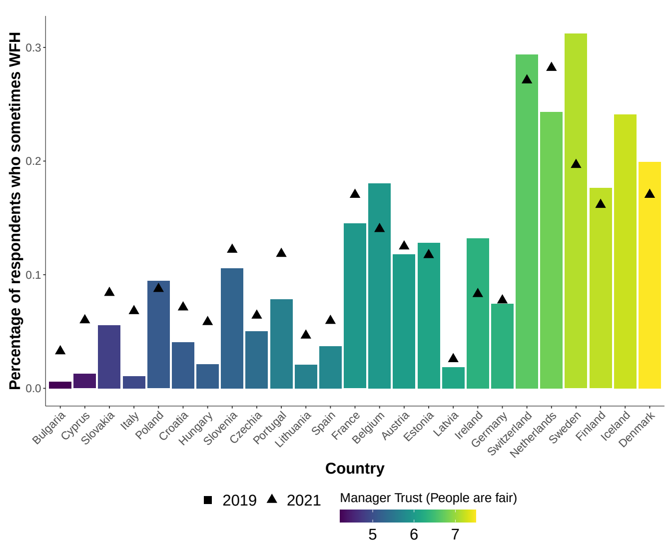
(a) Mainly WFH levels in 2019 and 2021



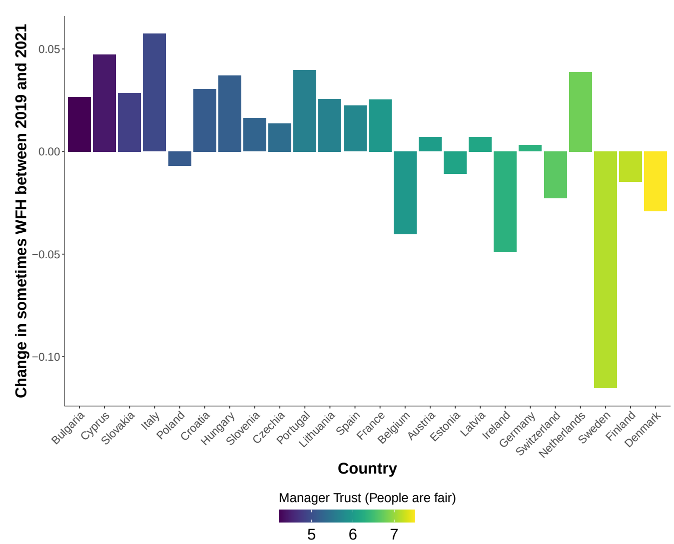

(b) Change in mainly WFH from 2019 to 2021




(c) Sometimes WFH levels in 2019 and 2021

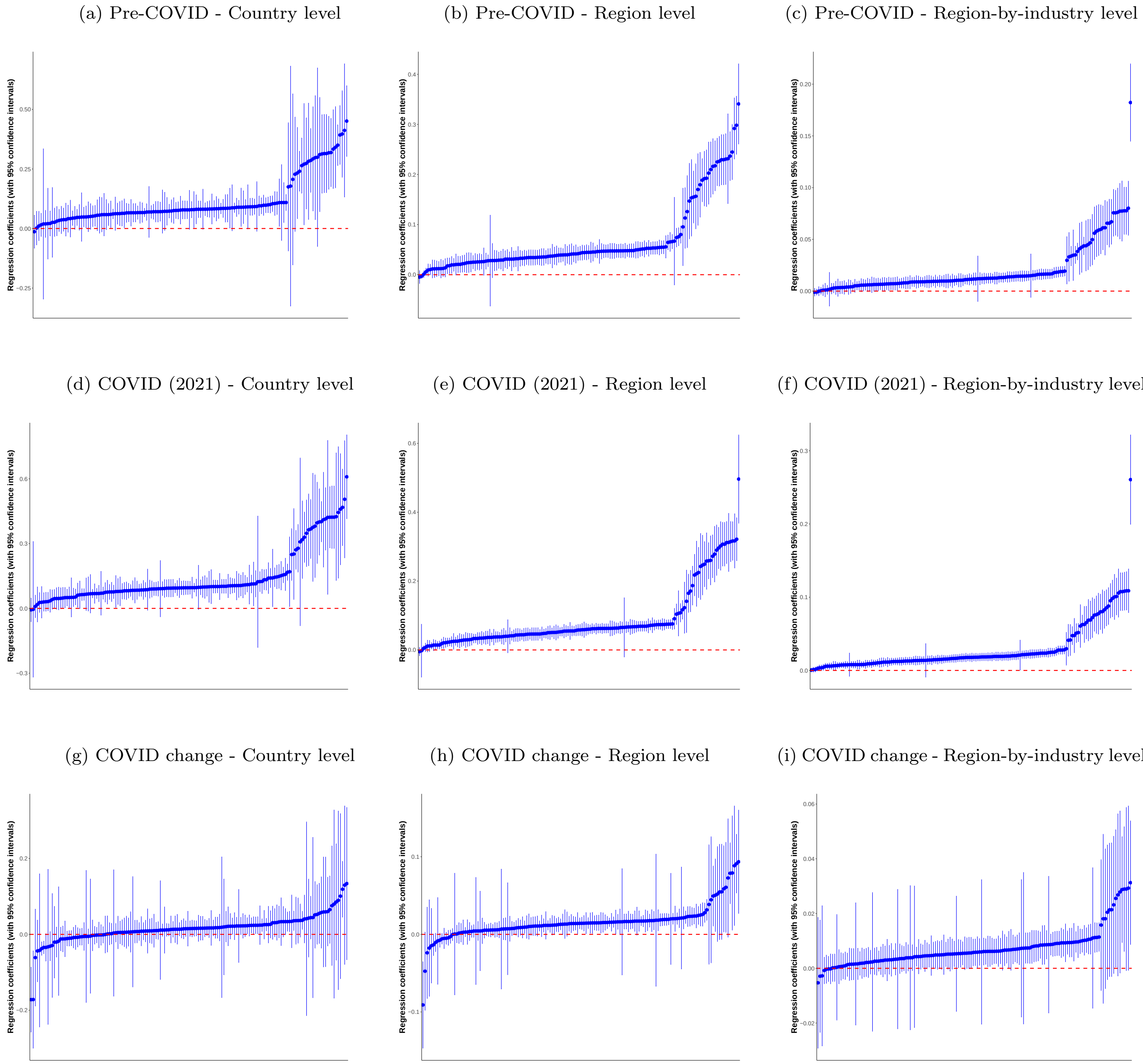



(d) Change in sometimes WFH from 2019 to 2021




*Notes:* In this figure, we recreate Panels (a) and (b) from Figure 1 for "mainly" WFH and "sometimes" WFH. Panels (a) and (c) are based on Panel (a) of Figure 1 and plot country-level means of WFH in 2019 and 2021 while Panels (b) and (d) are based on Panel (b) of Figure 1 and plot the country-level change in WFH from 2019 to 2021. Panels (a) and (b) present data for "mainly" WFH and panels (c) and (d) plot "sometimes" WFH. For all panels, the colors of the bars reflect the average manager trust within the country and countries are sorted by manager trust levels. For all panels, manager trust uses the "people are fair" definition of trust (average of managers across the 2014, 2016, and 2018 ESS surveys) and uses a broad definition of manager.

Figure B.6: Coefficient plot for workers that have "ever" WFH



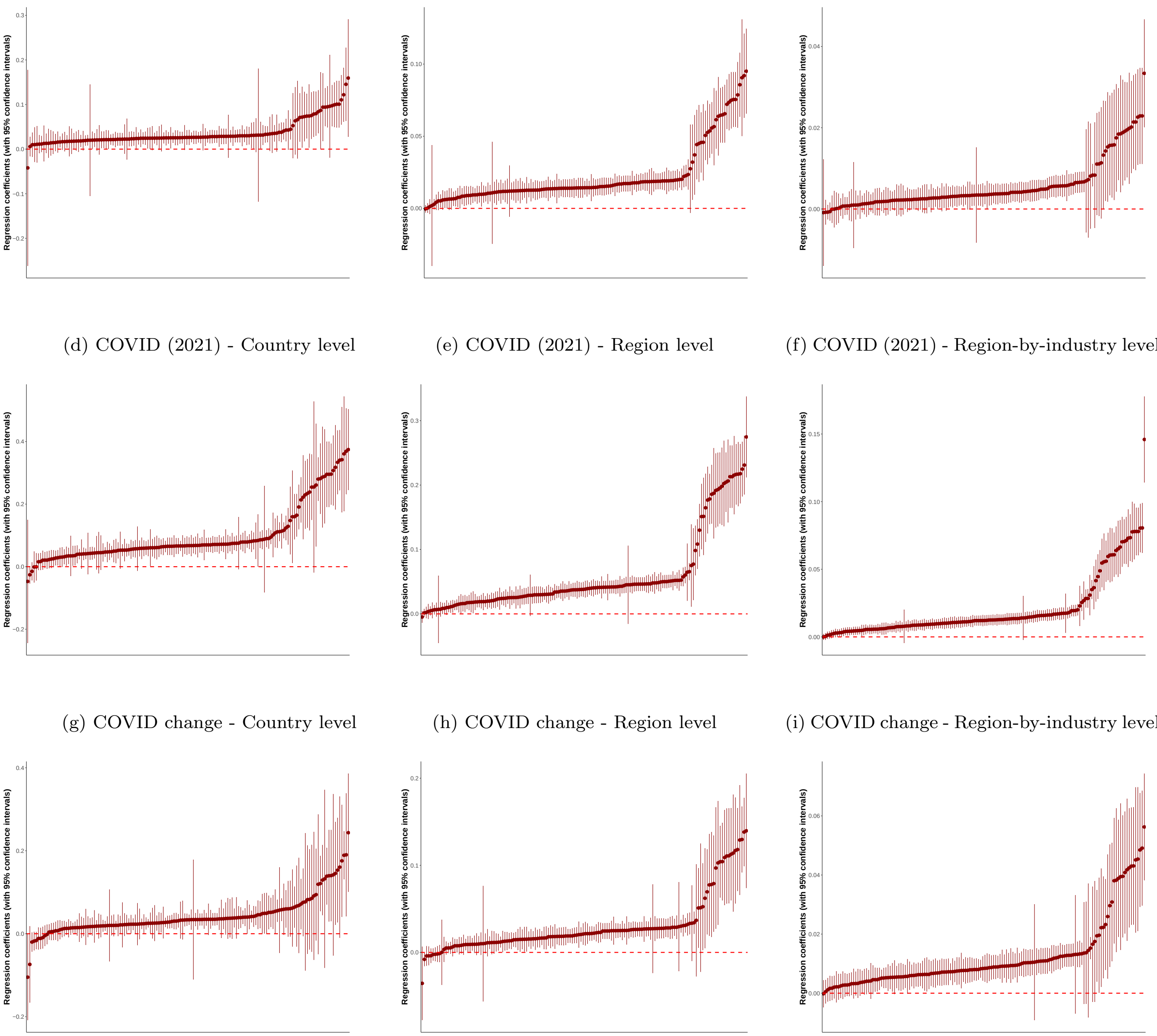

(a) Pre-COVID - Country level (b) Pre-COVID - Region level (c) Pre-COVID - Region-by-industry level

(d) COVID (2021) - Country level (e) COVID (2021) - Region level (f) COVID (2021) - Region-by-industry level

(g) COVID change - Country level (h) COVID change - Region level (i) COVID change - Region-by-industry level

*Notes:* This figure plots the coefficients and the 95% confidence intervals for a series of regressions regressing if a workers ever WFH on manager trust at the country level (Panels (a), (d), and (g)), the region level (Panels (b), (e), and (h)), and the region-by-industry level (Panels (c), (f), and (i)). Panels (a), (b), and (c) are for the pre-COVID period (2016-2019) and Panels (d), (e), and (f) are for the during COVID period (2021). These regressions are based on the specification outlined in Section 4.1. Panels (g), (h), and (i) show the results for the change in WFH due to COVID and are based on the specification outlined in Section 4.2. Regression results are sorted by the coefficient estimates. Within these regressions, different control variables are used as well as different ways of defining the treatment variable, manager trust; a complete description of the regression specifications can be found in Appendix C.4.

Figure B.7: Coefficient plot for workers that "mainly" WFH




(a) Pre-COVID - Country level

(b) Pre-COVID - Region level

(c) Pre-COVID - Region-by-industry level

(d) COVID (2021) - Country level

(e) COVID (2021) - Region level

(f) COVID (2021) - Region-by-industry level

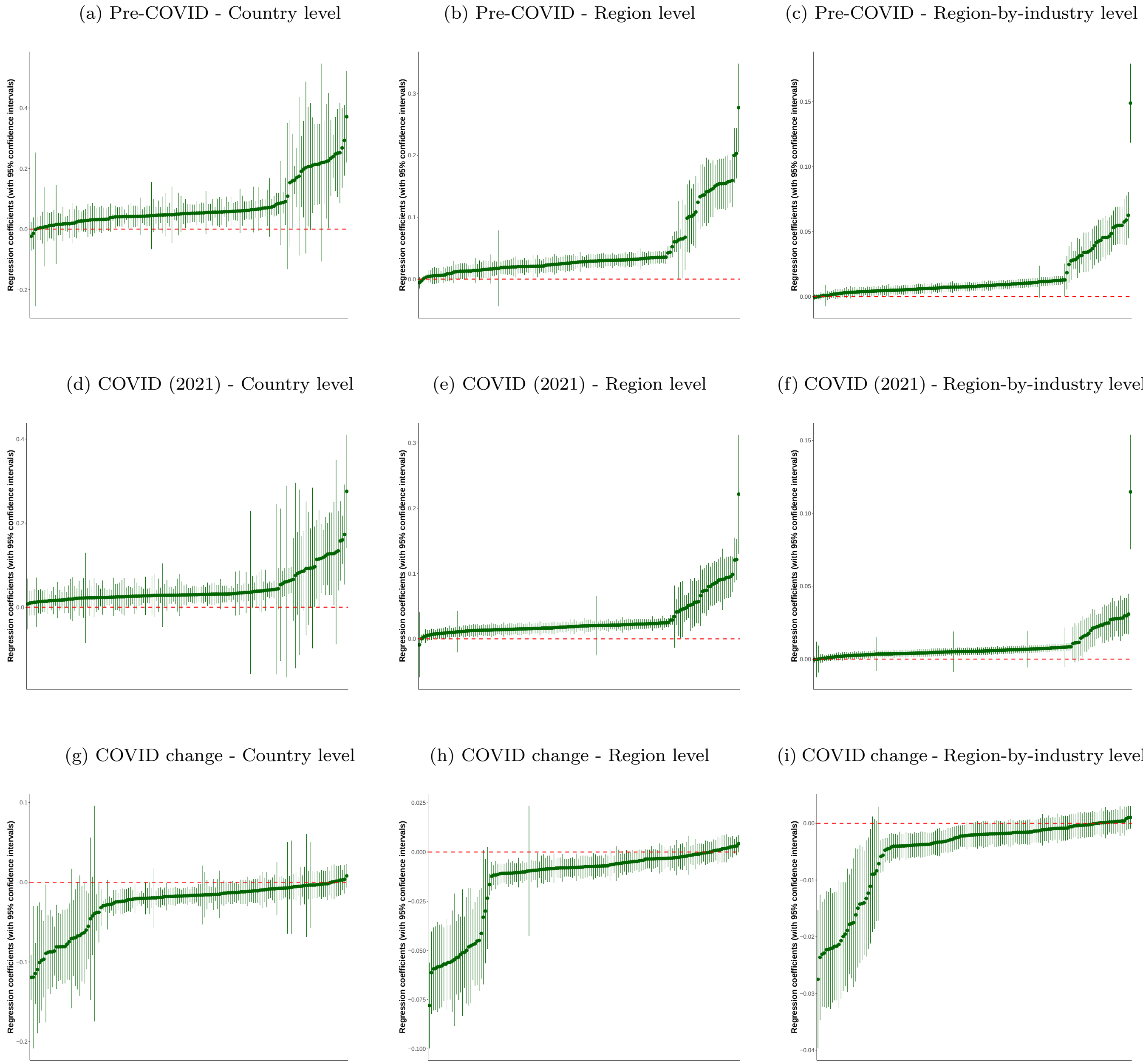
(g) COVID change - Country level

(h) COVID change - Region level

(i) COVID change - Region-by-industry level

*Notes:* This figure plots the coefficients and the 95% confidence intervals for a series of regressions regressing if a workers mainly WFH on manager trust at the country level (Panels (a), (d), and (g)), the region level (Panels (b), (e), and (h)), and the region-by-industry level (Panels (c), (f), and (i)). Panels (a), (b), and (c) are for the pre-COVID period (2016-2019) and Panels (d), (e), and (f) are for the during COVID period (2021). These regressions are based on the specification outlined in Section 4.1. Panels (g), (h), and (i) show the results for the change in WFH due to COVID and are based on the specification outlined in Section 4.2. Regression results are sorted by the coefficient estimates. Within these regressions, different control variables are used as well as different ways of defining the treatment variable, manager trust; a complete description of the regression specifications can be found in Appendix C.4.

Figure B.8: Coefficient plot for workers that “sometimes” WFH




(a) Pre-COVID - Country level

(b) Pre-COVID - Region level

(c) Pre-COVID - Region-by-industry level

(d) COVID (2021) - Country level

(e) COVID (2021) - Region level

(f) COVID (2021) - Region-by-industry level

(g) COVID change - Country level

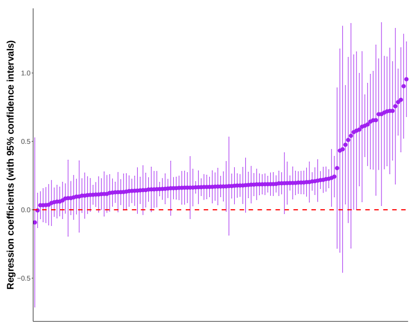
(h) COVID change - Region level

(i) COVID change - Region-by-industry level

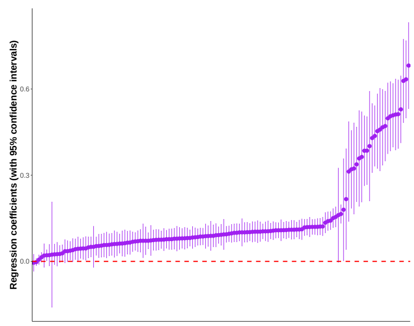
*Notes:* This figure plots the coefficients and the 95% confidence intervals for a series of regressions regressing if a workers sometimes WFH on manager trust at the country level (Panels (a), (d), and (g)), the region level (Panels (b), (e), and (h)), and the region-by-industry level (Panels (c), (f), and (i)). Panels (a), (b), and (c) are for the pre-COVID period (2016-2019) and Panels (d), (e), and (f) are for the during COVID period (2021). These regressions are based on the specification outlined in Section 4.1. Panels (g), (h), and (i) show the results for the change in WFH due to COVID and are based on the specification outlined in Section 4.2. Regression results are sorted by the coefficient estimates. Within these regressions, different control variables are used as well as different ways of defining the treatment variable, manager trust; a complete description of the regression specifications can be found in Appendix C.4.

Figure B.9: Coefficient plot for manager that have "ever" WFH

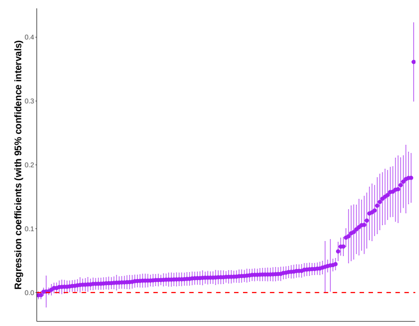
(a) Pre-COVID - Country level



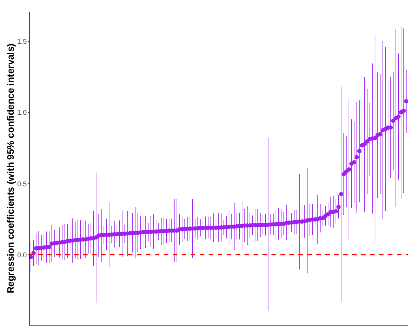

(b) Pre-COVID - Region level



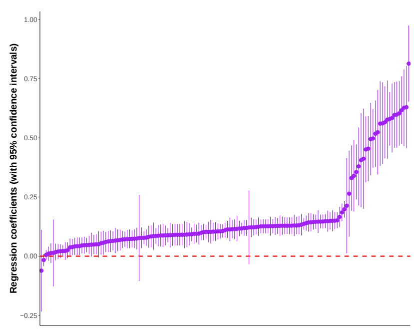

(c) Pre-COVID - Region-by-industry level



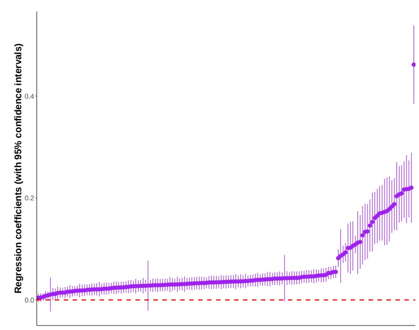

(d) COVID (2021) - Country level



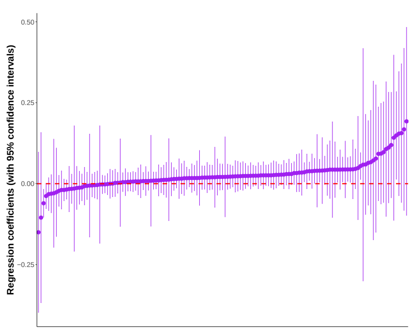

(e) COVID (2021) - Region level



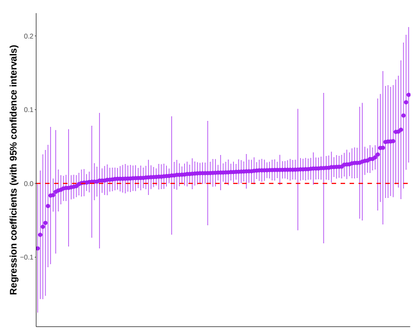

(f) COVID (2021) - Region-by-industry level



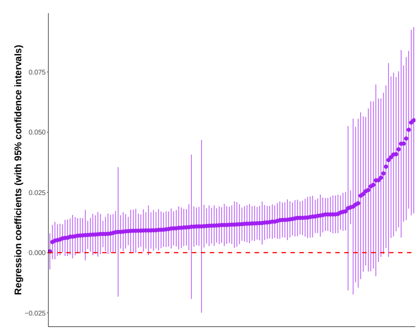

(g) COVID change - Country level




(h) COVID change - Region level




(i) COVID change - Region-by-industry level




*Notes:* This figure plots the coefficients and the 95% confidence intervals for a series of regressions regressing if a managers ever WFH on manager trust at the country level (Panels (a), (d), and (g)), the region level (Panels (b), (e), and (h)), and the region-by-industry level (Panels (c), (f), and (i)). Panels (a), (b), and (c) are for the pre-COVID period (2016-2019) and Panels (d), (e), and (f) are for the during COVID period (2021). These regressions are based on the specification outlined in Section 4.1. Panels (g), (h), and (i) show the results for the change in WFH due to COVID and are based on the specification outlined in Section 4.2. Regression results are sorted by the coefficient estimates. Within these regressions, different control variables are used as well as different ways of defining the treatment variable, manager trust; a complete description of the regression specifications can be found in Appendix C.4.

# C Additional Data Descriptions

## C.1 Region breakdown

Table C.1: Breakdown of Regions by Country

| Country Code | Country | Number of Regions | NUTS level |
|---|---|---|---|
| AT | Austria | 3 | Lvl 1 |
| BE | Belgium | 11 | Lvl 2 |
| BG | Bulgaria | 6 | Lvl 2 |
| CH[‡] | Switzerland | 7 | Lvl 2 |
| CY | Cyprus | 1 | Lvl 2 |
| CZ[‡] | Czechia | 8 | Lvl 2 |
| DE | Germany | 16 | Lvl 1 |
| DK | Denmark | 5 | Lvl 2 |
| EE | Estonia | 1 | Lvl 2 |
| ES | Spain | 19 | Lvl 2 |
| FI | Finland | 5 | Lvl 2 |
| FR[*] | France | 21 | Lvl 2 |
| HR[+] | Croatia | 2 | Lvl 2 |
| HU | Hungary | 8 | Lvl 2 |
| IE[‡] | Ireland | 3 | Lvl 2 |
| IS[†‡] | Iceland | 1 | Lvl 2 |
| IT | Italy | 5 | Lvl 1 |
| LT | Lithuania | 2 | Lvl 2 |
| LV | Latvia | 1 | Lvl 2 |
| NL[‡] | Netherlands | 1 | Lvl 0 |
| PL[*] | Poland | 16 | Lvl 2 |
| PT[*] | Portugal | 5 | Lvl 2 |
| SE | Sweden | 8 | Lvl 2 |
| SI | Slovenia | 2 | Lvl 2 |
| SK[‡] | Slovakia | 4 | Lvl 2 |
| | **Total** | **161** | |

[*] Not all the regions from the NUTS level 2 classification are present in the ESS data, so those that are dropped are not included here.

[+] The NUTS classifications changed in 2019, so the new, more granular classifications are combined to fit the old, less granular classifications.

[†] Data for the ELFS ends at 2020.

[‡] Demographic data for some variables is missing for these countries, so they are dropped for some analysis. Switzerland is missing data on partner and children and Czechia, Iceland, Ireland, Netherlands, and Slovakia are missing data on age.

## C.2 Industry categorization

In order to ensure we have enough observations per comparison cell in the regressions, we categorize our industries into 9 categories. These industry categories come from the industry categorization used in the UK LFS (variable INDE07M).

***Industries:***

[1] = A (Agriculture, forestry and fishing)

[2] = B (Mining and quarrying), D (Electricity, gas, steam and air conditioning supply) E (Water supply; sewerage; waste management and remediation activities)

[3] = C (Manufacturing)

[4] = F (Construction)

[5] = G (Wholesale and retail trade; repair of motor vehicles and motorcycles), I (Accommodation and food service activities)

[6] = H (Transporting and storage), J (Information and communication)

[7] = K (Financial and insurance activities), L (Real estate activities), M (Professional, scientific and technical activities), N (Administrative and support service activities)

[8] = O (Public administration and defense; compulsory social security), P (Education), Q (Human health and social work activities)

[9] = R (Arts, entertainment and recreation), S (Other services activities), T (Activities of households as employers; undifferentiated goods - and services - producing activities of households for own use), U (Activities of extraterritorial organizations and bodies)

## C.3 Occupations by Quartile

We divide our non-manager occupations into quartiles by pre-pandemic WFH levels. To get a better understanding of how our quartiles are constructed, we list the top 10 occupations by number of ELFS respondents with that occupation for each quartile.

Table C.2: Top 10 occupations in each quartile

| *Quartile 1 (Lowest WFH)* |
|---|
| 911 – Domestic, hotel and office cleaners and helpers |
| 833 – Heavy truck and bus drivers |
| 513 – Waiters and bartenders |
| 541 – Protective services workers |
| 722 – Blacksmiths, toolmakers and related trades workers |
| 933 – Transport and storage laborers |
| 821 – Assemblers |
| 721 – Sheet and structural metal workers, molders and welders, and related workers |
| 941 – Food preparation assistants |
| 932 – Manufacturing laborers |
| *Quartile 2* |
| 522 –Shop salespersons |
| 532 – Personal care workers in health services |
| 432 – Material-recording and transport clerks |
| 711 – Building frame and related trades workers |
| 723 – Machinery mechanics and repairers |
| 322 – Nursing and midwifery associate professionals |
| 741 – Electrical equipment installers and repairers |
| 712 – Building finishers and related trades workers |
| 412 – Secretaries (general) |
| 422 – Client information workers |
| *Quartile 3* |
| 311 – Physical and engineering science technicians |
| 334 – Administrative and specialized secretaries |
| 411 – General office clerks |
| 331 – Financial and mathematical associate professionals |
| 431 – Numerical clerks |
| 611 – Market gardeners and crop growers |
| 341 – Legal, social and religious associate professionals |
| 613 – Mixed crop and animal producers |
| 531 – Child care workers and teachers' aides |
| 312 – Mining, manufacturing and construction supervisors |
| *Quartile 4 (Highest WFH)* |
| 234 – Primary school and early childhood teachers |
| 332 – Sales and purchasing agents and brokers |
| 242 – Administration professionals |
| 233 – Secondary education teachers |
| 251 – Software and applications developers and analysts |
| 214 – Engineering professionals (excluding electrotechnology) |
| 241 – Finance professionals |
| 263 – Social and religious professionals |
| 243 – Sales, marketing and public relations professionals |
| 235 – Other teaching professionals |

## C.4 Coefficient plot descriptions

### C.4.1 Construction of specifications and figures

In order to check the robustness of our trust results, we run a series of many regressions using different specifications and control variables and plot them together. We perform this analysis for our main outcome variable – workers who ever WFH – which can be found as Figure B.6, as well as for the outcome variables of those that mainly WFH, those that sometimes WFH, and managers that ever WFH (Figures B.7, B.8, and B.9, respectively). In all of these figures, we run our analysis at the country level (Panels (a), (d), and (g)), the region level (Panels (b), (e), and (h)), and the region-by-industry level (Panels (c), (f), and (i)).

We run a series of regressions for the pre-COVID period (2016-2019), the during COVID period (2021), and the change in WFH due to the pandemic. The pre-COVID and during COVID regressions are based on the specification described in equation 7 and the change in WFH is based on the specification in equation 4.2. At the country level, we run 28 regressions for the pre-COVID analysis and 30 regressions for the during COVID and change due to COVID analyses. At the region and region-by-industry levels, we run 30 regressions for the pre-COVID and change in WFH analyses and 32 regressions for the during COVID analysis. When looking at "managers that ever WFH" outcome, we do not include the specification controlling for if an individual is a manager to avoid colinearity, so there is one less regression for each (only 27/29 at the country level and only 29/31 at the region and region-by-industry levels). The details of the specifications are listed below with the aggregate level of the additional control variable listed next to it. For each level of analysis, outcome variable, and timing, each of the relevant regressions are run five times, once for five different treatment variables. The five treatment variables are (i) trust defined continuously using the "people are fair" question for a broad definition of managers; (ii) trust defined continuously using the "people are fair" question for a narrower definition of managers (defined as only managers in occupations where the workers have a high potential to WFH); (iii) trust defined continuously using the "can you trust people" question for a broad definition of managers; (iv) trust defined continuously using the "can you trust people" question for a narrower definition of managers; and (v) trust defined as a binary variable (trust of $\geq 7$ is set to one) using the "people are fair" question for a broad definition of managers. The narrower definition for managers is associated with managers that work with employees that have some potential to WFH (ISCO codes 1120, 1200-1299, 1324, 1330, and 1340-1349). This combination of regressions gives us 140/150 coefficients at the country level and 150/160 at the region and region-by-industry levels. All the specifications use year fixed effects and demographic controls (as defined in Section 4.1) unless otherwise specified. Standard errors are always clustered at the associated geographic level (country level, region level, or region-by-industry level).

*Specifications used in all coefficient plots*:

1. Only using year fixed effects (no demographic controls)

2. Only using year fixed effects and demographic controls
3. Control for if the worker is a manager – individual level (not used with the “manager ever WFH” outcome variable)
4. Control for trust in the legal system – region level
5. Control for trust in politicians – region level
6. Control for trust in the police – region level
7. Control for individualism – region level
8. Control for WFH potential – country level (from Dingel and Neiman 2020)
9. Control for human development index – country level
10. Control for digital use category (continuous) – region level
11. Control for digital use category (binary) – region level
12. Control for digital use in minutes used – region level
13. Control for percentage with basic digital skills – country
14. Control for percentage of households with broadband internet access – country
15. Control for population – region level
16. Control for occupational structure (percentage of workers in each WFH occupation quartile) – region level
17. Control for GDP per capita in PPS terms – country level
18. Control for days employers want WFH (from GSWA) – country level
19. Control for days employees want WFH (from GSWA) – country level
20. Control for WFH willingness to pay (from GSWA) – country level
21. Control for WFH productivity perceptions (from GSWA) – country level
22. Control for commuting time (from GSWA) – country level
23. Control for fraud per hundred thousand inhabitants – country level
24. Control for corruption per hundred thousand inhabitants – country level
25. Control for money laundering per hundred thousand inhabitants – country level

26. Control for bribery per hundred thousand inhabitants – country level
27. Control for computer system attacks per hundred thousand inhabitants – country level
28. Saturated regression (as is found in Table 2)

*Additional specifications at the region and region-by-industry levels for the during COVID analysis*:

29. Control for country fixed effects
30. Saturated regression with country fixed effects

*Additional specifications for the During COVID and COVID changes analyses*:

- Control for excess COVID deaths
- Control for COVID policy stringency index

### C.4.2 Additional data descriptions

When running the regressions for the coefficient plots, we tried to construct a set of reasonable specifications that explore all alternative channels beyond trust that might explain differences in WFH. While many of these variables are discussed in Section 3, some go beyond that discussion so we expand on them in this section.

First, we use additional country-level variables to control for alternate WFH related channels including WFH potential, preferences, and perceptions. For a measure of WFH potential, we use data derived by Dingel and Neiman (2020) where they use create a binary measure for whether an occupation can be performed at home, using task composition, and aggregate it up to the country level. For additional WFH-related variables, we use data from the "Global Survey of Working Arrangements" (GSWA) which is a cross-country survey that asks about worker and employer preferences towards WFH and similar questions (Aksoy et al. 2022). The survey was run over two waves (both during COVID) and we combine the individual responses from the two waves and aggregate them to the country level in order to construct our control variables. We have data for eight countries in both the GSWA data and our combined ESS-ELFS sample. From this survey data, we use data on preferences for both employers and employees on WFH (employers' expectation on offering WFH in number of days per week, employees' number of days per week they want to WFH, and employee's willingness to pay for WFH). Additionally, we use data on perceptions about how productive workers can be when working from home. While both perceptions and preferences are likely endogenous with trust to at least some extent, we still include them as controls to check the strength of relationship between manager trust and WFH take up. This survey also contains data on commuting time, which we include as a control as well.

To get an idea of a country's general well-being, we use country-level data from the Human Development Index (United Nations Development Programme (UNDP) Human Development Report; processed by Our World in Data). To get an idea of well-being during the pandemic, we use a country-level measure of COVID policy stringency, which aggregates different government restrictions and recommendations into a standardized index. We measure COVID policy stringency using the average stringency from the Oxford Coronavirus Government Response Tracker (OxCGRT) covering the period March 2020 through September 2021 (Hale et al. 2021; processed by Our World in Data).

For an alternative measure of digital use, we also include data on the percentage of the population with basic a basic level of digital knowledge and skills (from the EU Survey on the Use of ICT in Households and by Individuals, accessed through Eurostat). In one specification we also control for the region-level population of an area to remove any size effects we may be capturing using 2019 population data from Eurostat (aggregated to the NUTS level of the corresponding region). Finally, to proxy for more general trends about trust towards white collar workers and potential workplace relationships, we add controls for police-recorded white collar crimes per hundred thousand inhabitants (from Eurostat). We include controls for fraud, corruption, money laundering, bribery, and computer system attacks as individual controls.