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How does working from home affect the time spent on actual work?

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Abstract

To obtain a deeper insight into the effectiveness of remote working, I have looked at the research question “How does working from home affect the time spent on actual work?”. Previous research primarily finds positive effects from remote working, mainly through extra effort exerted and less time spent on side issues like commuting and breaks. But there are also some pitfalls raised, older people have a harder time adapting to the technology, and parents, most notably mothers, seem to be less productive. Finding new insights regarding the topic is extra important now, as we have just had a global pandemic that impacted the adoption of remote working rapidly. I have used survey data of the Dutch population provided by LISS panel to run OLS regressions of remote working on the time spent on actual work. Rather than doing a direct regression, I have taken the ratios of these variables divided by the number of hours they were contracted for. By controlling for prominent effects found in previous research, such as income, age, and more, I hope to have isolated the effect as much as possible. In the end, I did not find significant evidence for a relation between remote working and actual hours worked. I suspect this to be related to the survey data obtained. The data was based on a self-reported survey, and the respondents appeared to have a bias towards reporting their contracted hours as their actual time spent on work. For future research, I suggest focusing on accurately measuring the actual hours worked or finding a different proxy for productivity.

Introduction

With the increasing digitalization of the world and a major shift to the service industry in most Western countries, remote working has become more feasible and popular than ever before. In 2019, approx. 39% of the Dutch population worked remotely sometimes (Central Bureau for Statistics, 2020). The recent Covid pandemic sped this up even more, as people all over the world were forced to work from home during the lockdowns.

Now that the situation is going back to normal and remote working is no longer necessary, employers and employees around the world must decide how much of the recent changes they want to keep. Generally, employees greatly value the extra freedom and are willing to work extra hard to keep it (Felstead & Henseke, 2017).

The benefits for employers also seem evident through increased productivity (Bloom et al., 2013) and increased effort (Kelliher & Anderson, 2010). However, management, in many cases, is not convinced and afraid that the employees are shirking during work time due to a lack of supervision and monitoring (Laker et al., 2020).

It is important to find evidence whether shirking is indeed a major risk to remote working and if employers should go fully back to physical attendance or whether it is safe to keep (partial) remote working in the business to benefit from the many improvements research finds. To research this, I will be looking into the research question "How does working from home affect the time spent on actual work?".

First, I will look at the existing literature surrounding the topic of remote working. The literature primarily shows positive effects, through increased effort exerted by remote workers and through the cut of various side issues such as commuting. There are concerns raised for older employees and parents, however. After this, I will be discussing the data collected from LISS Panel. From the data I will only be looking at the Business, Financial and Educational sectors, as these were among the best-suited sectors for remote working (Dingel & Neiman, 2020). The data showed that in 2021, on average, people spent 1.017 times as many hours on work as they were contracted for. It also showed that approx. 38.2% of work was done remotely. Next, in the Methodology section, I will be discussing the OLS regression that will be used. Finally, I will discuss the results and form a discussion and conclusion.

In the end, I did not find a significant effect for remote working on the actual time spent on work. I found a potential issue with the data, where the respondents often self-reported the exact number of hours they were contracted for as the time spent on work. Even though I tried accounting for this by looking only at more extreme observations, I did not find a significant effect. I would recommend future studies to more accurately measure the time spent on work, perhaps through measuring software or by using another proxy for productivity.

Despite the lack of significance in the results, I am confident that this research will provide the existing literature with additional insights. Whether that is thanks to the findings as is, or as a starting point for follow-up studies surrounding the topic of remote working.

Literature and Hypotheses

In this section, I will be looking at the existing research to summarize what has been found on remote working already. First, I will look at the 'who' to find out what types of people and jobs remote working is best for. This will help refine the research question and potentially formulate a sub-question. Then, I will look at the 'what' to estimate the effect and formulate the hypothesis.

First, Hardill and Green (2003) research the remote working environment in their time. They first note that the traditional '9 to 5' jobs have become more flexible in general, giving employees more ownership over their schedule by working on the weekends for example. They find that part-time WFH has generally been well adopted and has great benefits for work-life balance, mainly due to cutting out time spent on commuting. They also find that WFH, for now, seems mostly adopted by professional and managerial employees.

Dingel and Neiman (2020) also look at what type of work is best suited for remote working, with a focus on sectors. They find that in the U.S. about 37% of all jobs could be done fully remote, with most of these jobs being higher-paying jobs in the service industry. This is reflected by the fact that these jobs make up 46% of the total wages. The best-suited sectors are education, scientific and technical services, management, finance, and information. Because less developed countries have a lower share of these jobs, WFH could be less suited for them.

Gottlieb et al. (2021) support the findings of Dingel and Neiman (2020). They found that only about 10% of the total jobs can be done remotely in these countries. They also support the findings about the sectors and income, as it is primarily the higher-paying jobs that require more education that can be done remotely in developing countries. In the lower quintiles of household income, about 3.3% of total jobs can be done remotely, while in the top quintile of the wealthiest people 17.3% of the jobs could be done remotely.

To further investigate the wage effect, Emanuel and Harrington (2021) study the effects on productivity after wage increases. They find that when employees earn more money, their productivity increases. In general productivity increases even more than the amount the salary was raised with. This is because of two effects. On the one hand, the extra salary will motivate the current employees more. On the other hand, the higher salary will attract more productive people to the firm.

In summary, Hardill and Green (2003), Dingel and Neiman (2020), and Gottlieb et al. (2021) all find that remote working is more suited for certain types of work. Mainly higher-paying jobs, found predominantly in professional sectors, seem to be a good fit. That is why it is better to restrict my research to these sectors alone with the research question:

How does working from home affect the time spent on actual work?

Because each of these papers also mentions the fact that many higher-paying jobs are better suited, it is interesting to look further into this. The height of the wage could impact the time spent on actual work in many ways, for example through reciprocity to the employers for people with a high wage, the increased motivation for lower earners to get a promotion, the seniority of a position requiring more or less work, et cetera. I have formulated the sub-question:

Does the height of the wage affect the time spent on actual work?

When it comes to best practices, Staples (2001) looks at remote and non-remote workers to find the differences between them. Staples finds that for remote workers a feeling of trust in the manager has a significantly larger impact. It increases self-perceived performance and job satisfaction while reducing work-related stress. Frequent communication with the manager also had a larger effect on the remote workers.

Wang et al. (2021) looked at the experiences and data during the Covid pandemic. Supporting the earlier findings of Staples (2001), Wang et al. (2021) find that managers that build trust with and actively try to motivate their team are seeing better results. There should also be opportunities for team members to have informal conversations, to improve morale and decrease the chance of loneliness. Lastly, they find that it should be seen on a per-case basis whether remote working suits someone. Someone that struggles with discipline is better off going to the office for example.

Based on these papers I would expect the team situation a person is in to affect the time spent on work as well. (Remote) Workers in tight teams are more likely to spend more time on work, hence it is good to control for the satisfaction someone has for their team and colleagues.

To get a better idea of what kind of effect to expect for the research question, I will be looking at papers that have tried to measure the effect of remote working.

Felstead and Henseke (2017) find that remote working is beneficial for both employers and employees. Employees are willing to work more and do more unpaid work to make sure they get to continue working from home and enjoying their new freedom. This also leads to remote workers being more committed and satisfied with their jobs than their non-remote colleagues.

Kelliher and Anderson (2010) look at both flexible and remote workers, where flexible workers are workers who either work partly from home or work reduced hours. They find that flexible and remote workers are more satisfied with their work and work more intensively through extra effort. Kelliher and Anderson (2010) see this as a trade-off by these employees, where they are trading increased flexibility for more intense work, also to reciprocate to their employers. This is in line with the findings of Felstead and Henseke (2017). Because both of these papers explicitly mention that more effort is exerted, I would expect a positive effect of remote working on actual hours worked.

Looking at productivity more generally, Barrero et al. (2021) look at the future of WFH post-covid. They find that the average productivity of someone that starts working remotely rises by approximately 4.6%, with about half of this increase in productivity coming from the cut in commuting. They expect that about 20% of total work will be done remotely post-covid, which is 4 times more than the 5% it was before.

Like Barrero et al. (2021), Bloom et al. (2013) also look at productivity by using experimental data from CTrip, a Chinese travel agency. CTrip randomly assigned part of their call center staff to start working from home and found a 13% increase in their productivity. About 9% of this was attributed to more actual working hours done through fewer breaks and sick days, and the other 4% was attributed to higher output. When they later switched from random assignment to assignment by selection, productivity increased even further by 22%. This is in line with the findings of Wang et al. (2021) who found that WFH is better suited for certain people.

While Barrero et al. (2021) and Bloom et al. (2013) do not look at effort or hours worked explicitly, they do find significant evidence for increased productivity in general. This could be shown by employees through more time spent on work. That's why based on these papers, I would also expect a positive effect of remote working on time spent on work.

There are also drawbacks to working from home. Bloom et al. (2013) also found that, despite their higher productivity, remote employees have a lower chance to get promoted.

Furthermore, Feng and Savani (2020) find that WFH during the pandemic had a particularly bad effect on mothers. While men generally had no changes or positive changes in their work productivity and satisfaction, both were measured to have a negative impact on women on average. This effect seems to be primarily driven by mothers working from home who spent more time taking care of their children. Of course, the pandemic was a unique situation as children were forced to be at home too. It is unsure if this effect would remain for WFH when the schools and daycares are open.

Nakrošienė et al. (2019) find a similar negative relationship between the number of children a person has and the benefits obtained from remote working. However, they find this negative effect on both parents, not just the mother as in the research by Feng and Savani (2020). These findings are contradicting older research such as that by Hartig et al. (2007), who found that remote working was extra well suited for employees with children.

Based on the papers by Feng and Savani (2020) and Nakrošienė et al. (2019) I would expect having children to negatively impact the time spent on actual work.

Another drawback is the technological nature of remote working. Employees need to set up their own working devices and need to install and use various software, from remote work trackers with key loggers to digital meetings. This is especially challenging for older employees, who have more trouble with adopting new technologies as shown by Ollon et al. (2011).

In summary, there seems to be evidence that working from home has a positive impact on the employees. Felstead and Henseke (2017), Kelliher and Anderson (2010), Barrero et al. (2021), and Bloom et al. (2013) each conclude that remote employees seem to be putting in more work and effort, in part to reciprocate to their employers for the freedom that they are given. Because of this, I would expect the research question "How does working from home affect the time spent on actual work?" to come to a positive effect. Therefore, the hypothesis is:

Employees who spend more time working from home, on average, spend more time on actual work compared to their colleagues that spend less time working remotely.

Because high-paying jobs seem more suited for remote work (Dingel & Neiman, 2020; Gottlieb et al., 2021) and higher earners appear to be more productive (Emanuel & Harrington, 2021), I expect a positive effect for the sub-question "Does the height of the wage affect the time spent on actual work?". The hypothesis is:

Employees with a higher salary, on average, spend more time doing actual work.

Now to summarize the other factors found in the literature. Older employees seem to have a tougher time working from home (Ollon et al., 2011) and may be less able to work long hours in general. Commuting has a significant impact on the time spent on actual work and is a big part of the boost in the efficiency of remote working (Barrero et al., 2021). Wang et al. (2012) see a positive effect of good team morale.

Feng and Savani (2020) and Nakrošienė et al. (2019) find a negative impact of having children on the success of remote working. Feng and Savani (2020) also highlight that this issue is predominantly found among women.

Data

For the next part, I will be discussing the data that will be used for the research. First, I will discuss the data source, the sectors that I will be looking at, and the variables that will be used. Then I will explain what I did to polish the data and create ratios for the actual working and remote working hours. Finally, I will summarize the data.

The data used for this research is obtained from LISS panel, a major Dutch data collector associated with Tilburg University. The data set I will be using from LISS panel is that of Work and Schooling by Streefkerk (2021). This was a survey held in Spring 2021 and asked participants various questions regarding their jobs, education, pensions, and more. The respondents of LISS panel consist of 5000 Dutch households totaling 7500 individuals. One household member provides the data in the questionnaires and ensures to keep them updated. As mentioned in the literature section, some sectors are more suitable for remote working than others (Dingel & Neiman, 2020; Gotlieb et al. (2021). These sectors were highlighted by Dingel and Neiman (2020). Of those most-suitable sectors, the dataset from LISS panel contains the Business, Finance, and Education sectors. I will only include the respondents that are working in these sectors. Other sectors that are known to be unsuitable for remote working could give a bias in the results. For example, the healthcare and transport industries have a much stronger requirement for physical attendance and are likely to have a lower remote working rate. If the actual hours spent on work in these industries are also different, for example, because night shifts are common in these industries, then that could create a bias for less remote working leading to more time spent on work. For the handling of the data, I will be using the statistical software "STATA".

I will be using multiple variables of this dataset to work with. First, actual hours worked. This is a numerical value that showcases how many hours per week the respondent spends doing actual work. The number of hours worked from home is also a numerical value of how many hours the respondent spends working from home. Third, the contracted hours show how many hours per week the respondent has been employed for in their contract. For actual hours worked, hours worked from home, and hours contracted for, the question includes either the current employment or the previous employment in case of current unemployment. The variable monthly income shows the respondent's wage per month in euros. Age is a numerical variable with the respondent's age in years at the time of participating in the survey. The children variable is a dummy variable that is yes or 1 for respondents with children. The variable commuting time is a numerical value that shows the time in minutes that it takes for the respondent to get from home to work (one-way). Lastly, colleague satisfaction is a numerical rating between 0-10 that shows how satisfied the respondent is with the atmosphere among colleagues. The gender variable was also of interest, as Feng and Savani (2020) found evidence of a negative impact on remote working for women. This variable was not found in the dataset, so I must leave it as a recommendation for future research.

To polish the data, I have looked at outliers and missing variables. First, because I am limiting the research to the Financial, Business, and Education sectors, I have dropped all observations outside of these sectors. Second, for the variable 'colleague satisfaction', respondents had to give a rank between 0 and 10 or enter "I don't know". "I don't know" was assigned a numerical value of 999 in the dataset. This would cause trouble in the interpretation of the outcome, hence I have dropped all "I don't know" observations from the dataset. Furthermore, to filter out respondents who do not or have never worked, I dropped observations where the variable 'hours contracted for' was 0. Interestingly, even though I have now filtered for people with paid employment, the variable of monthly wage still shows over a quarter of its observations being 0. Because of the high unlikeliness that these people are in paid employment but still earn a salary of zero, I have replaced all zero observations as a missing variable. Because it causes issues to have missing variables in the dataset, especially considering that I do the regressions in three stages, I have dropped all observations in which one of the variables had a missing value. While this is my best solution at hand, I must note that it is by no means a perfect solution. It is uncertain whether these observations are missing because of random factors or whether there is a trend to be found in which respondents have some missing observations. I touch upon this in the discussion section.

To find evidence for the relationship between actual hours worked and hours worked from home, I am better off comparing both in relation to the number of hours someone is contracted for. If I do not take the ratio, I might have biases that lead to the results being less accurate. For example, perhaps people who work more hours, on average, get to spend more hours working remotely, but people who work more hours are also more likely to spend more hours on actual work. This would create a positive bias and that is why I take the ratio of both instead:

$$AW_{Ratio} = \frac{Actual\ Hours\ Worked}{Hours\ Contracted\ For}$$

And

$$RW_{ratio} = \frac{Hours\ Worked\ from\ Home}{Hours\ Contracted\ For}$$

Now that the data is prepared, I can summarize the variables that will be used.

Table 1

Variable	Mean	Std. Deviation	Observations
AW_{Ratio}	1.017	0.435	167
RW_{ratio}	0.382	0.401	167
Monthly wage	3251.281	1676.286	167
Age	40.749	12.968	167
Has Children	0.521	0.501	167
Commuting time	29.461	19.916	167
Satisfaction Colleagues	7.455	1.471	167

Notes: The table above shows the mean and standard deviations of all variables that will be used in the OLS regression. The data was polished and freed of outliers and missing observations, the total observations per variable are shown in the right column. The variables are further explained within the Data section.

Table 1 shows the mean and standard deviation of each variable. AW_{Ratio} has a mean value of 1.017, which means someone that is contracted for 40 hours per week, on average spent 40 hours and 41 minutes working per week. This is telling as people report to be working more than they are getting paid for, and if these self-reports are accurate then for the total group of workers, in person and remote, shirking does not seem to be an issue. The standard deviation is relatively small, which means a lot of observations lie close to the mean. RW_{ratio} has a value of .382, which means, on average, 38.2% of the respondents' work is done remotely. Respondents are approx. 41 years old on average, which makes sense as it is in the center of the working age which I have filtered for. They earn approx. 3251.28 euros per month and just over half (52.1%) of them have children. The average commute is 29.46 minutes, and the respondents are quite happy with their colleagues, ranking it a 7.5 out of 10.

Methodology

In the methodology section, I will go further into the OLS regression I will be using to find a relationship between the actual working hours and the remote working hours. First, I will be explaining the control variables used, and then I will present the OLS regression equation.

To find out whether working more from home increases the time spent on actual work, I will run an OLS regression. The dependent variable is AW_{Ratio} and the independent variable of interest is RW_{ratio}.

As seen in the literature research, there are quite some variables that could affect both the hours worked and the remote working situation. Monthly income could affect both, the actual hours worked through the number of hours in the contract (full-time often has a higher salary than part-time) and through more senior jobs potentially needing more or less work. Remote work is impacted as someone who earns more or has a more senior job may be given more freedom, I also found that many of the well-suited remote working sectors are also higher paying sectors. Having children as someone with children may find it attractive to work remotely but may also have less time to spend doing actual work. Other variables of interest are a person’s commuting time, Colleague satisfaction, and a person’s age, as these may each influence the time available to spend on actual work but may also influence the decision to work remotely. For more insight into these variables and their effects please see the last section of the literature research.

To mitigate the chances of Omitted Variable Bias (OVB) occurring, which happens when the independent variable (RW_{ratio}) picks up the effect of other correlated variables, I will include all these variables as control variables. That way the effect is included in the control variables and not hidden in the independent variable.

The OLS regression formula that is obtained is as follows:

$$AW_{ratio} = \beta 0 + \beta 1 * RW_{ratio} + \beta 2 * monthly\ income + \beta 3 * Age$$
$$+\beta 4 * has\ children + \beta 5 * commuting\ time + \beta 6 * satisfaction\ colleagues + \varepsilon$$

While the data and remote working is by no means perfectly randomized and adding these control variables is necessary, it should be noted that the time of gathering the data likely has a positive effect on the randomization of the remote working 'treatment'. Because the data was taken from a survey in the Spring of 2021, in the middle of the Covid pandemic, many people were forced to work from home. This makes it closer to random assignment, as it wasn't strictly self-selection of people who wanted to work remotely.

Results

The results of the OLS regression will be presented in this part. The results are presented in tables along with the coefficients and standard deviations of all variables. Due to a lack of variance in the AW_{ratio}, which could be due to issues with collecting the data, I will run a second regression with only extremer observations after.

I run three stages of the OLS regression. The first stage only uses the remote working ratio as the independent variable. For the second, I account for the monthly wage as a control variable as that seems to play a big role and is also used in the sub-question. Third, I do the full regression with all variables as laid out in the Methodology section. The results are in Table 2 below.

Table 2: OLS Regression results

Variable	Actual Working Ratio (1)	Actual Working Ratio (2)	Actual Working Ratio (3)
Remote Working Ratio	-.121	-.108	-.071
	(.080)	(.075)	(.079)
Monthly Wage		-.000	-.000

		(.000)	(.000)
Age			.004
			(.004)
Has Children			.036
			(.069)
Commuting Time			0.002
			(.001)
Satisfaction Colleagues			.010
			(.015)
Constant	1.063***	1.135***	.825***
	(.052)	(.112)	(.173)
Number of Observations	167	167	167

*Notes: Table 2 (above) shows the results of all three regressions. In each case, the Actual Working Ratio (AW_{Ratio}) is the dependent variable and the Remote Working Ratio (RW_{ratio}) is the dependent variable. In the second regression, the monthly wage is added as a control variable. In the third regression, Age, Children, commuting time, and colleague satisfaction are also added as control variables. In each regression, 167 observations were used. *, **, and *** represent the 10%, 5%, and 1%, significance levels, respectively. No asterisk symbol means that the coefficient was insignificant with respect to each of these levels.*

What is apparent is that none of the variables, except for the constant, appear to have a significant effect. Reflecting on the data section, I noted that there is not much variation in the Actual Working Ratio, with many observations being at or near the number 1. The exact distribution can be seen below.

Table 3: Actual Working Ratio Descriptive Statistics (elaborate)

Variable	Mean	Std. Deviation	Variance	10th Percentile	25th Percentile	50th Percentile	75th Percentile
AW_{ratio}	1.017	.435	.189	.75	1	1	1.125
Number of Observations	167						

Notes: The descriptive statistics of the independent variable Actual Working Ratio (AW_{Ratio}). The columns show the mean, standard deviation, variance, and the 10^{th}, 25^{th}, 50^{th}, and 75^{th} percentile values.

Table 3 shows that for a large part of the percentiles the value is simply 1. Because the data comes from a self-reported survey, it is likely that the respondents were in some way biased to answer the exact number of hours they were contracted for. After all, it is highly unlikely that more than half the people in the survey work the exact number of hours as in their contracts, and not an hour more or an hour less. Further reasoning is given in the discussion section.

If these observations are indeed skewed towards 1 for these reasons, and not because they are the true values, then these observations are unusable as they do not reflect the real situation. From the 75^{th} percentile and upwards the values start to get larger than 1 and from the 10^{th} percentile and below lower than 1. Because observations are significantly further away from 1, it is more likely that they have been truthfully answered and not been benchmarked against the hours in the contract. For this reason, it would be interesting to rerun the regression using only observations with an AW_{ratio} greater than or equal to 1.1, or smaller than or equal to .9 and see if I find a significant result. If the observations were indeed not accurate before, then I would now expect to find a significant positive effect of remote working on actual hours worked, just like initially hypothesized.

In table 4 below are the descriptive statistics for the more extreme values of AW_{ratio}.

Table 4: Actual Working Ratio Descriptive Statistics (elaborate)

Variable	Mean	Std. Deviation	Variance	10^{th} Percentile	25^{th} Percentile	50^{th} Percentile	75^{th} Percentile
$\boldsymbol{AW_{ratio}}$	1.021	.637	.406	0	.9	1.125	1.25
Number of Observations	78						

Notes: The descriptive statistics of the independent variable Actual Working Ratio (AW_{Ratio}) for values greater than or equal to 1.1 or smaller than or equal to .9. The columns show the mean, standard deviation, variance, and the 10^{th}, 25^{th}, 50^{th}, and 75^{th} percentile values.

As can be seen from Table 4, the mean of AW_{ratio} is almost identical, from 1.017 to 1.021. This shows that there are extremes both above and below 1, but that they seem to be balancing each other out such that the mean is kept. The variance is up significantly, from.189 to .406. This shows that the suggested effect has occurred, and I now have more variance in the data. The number of observations has decreased from 167 to 78, again telling for the large number of observations being at or close to 1. The full descriptive statistics can be found in Appendix A.

Next, I will rerun the OLS regression in the same way, with the same control variables, as before. The results are shown in Table 5 below.

Table 5: OLS Regression results for extremer Actual Working Ratios

Variable	Actual Working Ratio (1)	Actual Working Ratio (2)	Actual Working Ratio (3)
Remote Working Ratio	-.300	-.258	-.195
	(.199)	(.191)	(.210)
Monthly Wage		-.000	-.000
		(.000)	(.000)
Age			.008
			(.008)
Has Children			.109
			(.142)
Commuting Time			.005
			(.004)
Satisfaction Colleagues			.037
			(.047)
Constant	1.123***	1.226***	.446
	(.108)	(0.209)	(.490)
Number of Observations	78	78	78

Notes: Table 5 (above) shows the results of all three regressions, filtered to observations with an Actual Working Ratio (AW_{Ratio}) of less or equal to 0.9 or equal to or larger than 1.1. In each case, the AW_{Ratio} is the dependent variable and the Remote Working Ratio (RW_{ratio}) is the dependent *variable. In the second regression, the monthly wage is added as a control variable. In the third regression, Age, Children, commuting time, and colleague satisfaction are also added as control variables. In each regression 78 observations were used. *, **, and *** represent the 10%, 5%, and 1%, significance levels, respectively. No asterisk symbol means that the coefficient was insignificant with respect to each of these levels.*

As can be seen in Table 5, even after filtering for more extreme observations, none of the variables show a significant effect. RW_{ratio} did not come to a significant effect in any of the regressions, and hence I must reject the initial hypothesis "*Employees who spend more time working from home, on average, spend more time on actual work compared to their colleagues that spend less time working remotely.*"

The monthly wage variable also does not show a significant effect in any of the regressions. The hypothesis "*Employees with a higher salary, on average, spend more time doing actual work*" for the sub-question: "*Does the height of the wage affect the time spent on actual work?*" must also be rejected.

While I cannot take any conclusions due to the insignificance, the signs, and with them the direction of the effects, are worth noting. I expected RW_{ratio} to have a positive effect, as previous literature found a lot of benefits. But each regression, both before and after the correction, shows a negative sign. Similarly, the monthly wage also has a negative sign in each of the regressions while previous research would expect higher-paying jobs to have a positive effect. Age, having children, and Commuting time, are positive in both regressions, whereas previous literature expected them to be negative. Colleague satisfaction has a positive sign which is in line with the literature.

Discussion

In the discussion section, I will touch upon the results of the research and discuss what may have caused some issues in the research. Finally, I will make a recommendation for future research into remote working.

I did not find significant evidence for the effect of remote working on actual work done by employees. I expect this is strongly affected by the data used, as there was very little variance found in the Actual Working Ratio. Most observations simply had the value of 1 or were very close to it. Once I removed most of those observations, I still did not see a significant effect. The number of observations left after this change was much less, however, so I cannot conclude too much from this.

The reason for the lack of variance is likely due to the way the data was collected by LISS Panel. They held a survey among Dutch households, where respondents self-reported their actual hours worked. It seems probable that the respondents had a bias towards the number of hours they were contracted for, which led to the ratio being 1 or close to 1. The bias could be due to a variety of reasons, either they did not think of it too much and entered their contracted hours out of simplicity, wanting to feel productive and telling themselves that they do indeed work all the hours they are employed for, a worry of the data being shared with their employers, or something else.

In a repeat study, I would recommend obtaining real data from the practice. For example, by using software to measure the actual time worked or by looking directly at the output per employee.

Furthermore, there was a significant drop in the useable observations due to the large number of zero or empty inputs in the monthly wage field. Given the fact that I had already accounted for people with (past) paying employment, it is unlikely that these people are in employment but still do not have a positive monthly wage. A possible explanation for the large number could be that there is a taboo around sharing your wage, and possibly the respondents did not feel comfortable sharing it in the survey. For future research, it would be better to get this data from an official source or to make the respondents feel more at ease with answering this question, for example by letting them select a range instead of entering their exact wage.

The solution that I now used for the missing variables was simply dropping them from the dataset. As briefly touched upon in the data section, this is not a perfect solution. I cannot say with certainty whether these missing or zero input observations for the wage variable were distributed randomly or whether there was a trend to be found. It could be, for example, that the height of the wage makes respondents more reluctant to answer this question. This could either be people who have a relatively low wage, a relatively high wage, or both persons. The result of this could be that the data used in the regression was less random, and in fact, excluded or underrepresented a certain group(s) of people. This, in turn, would make the results unrepresentative. A solution for future research could be using statistical imputation techniques to replace these missing values or using official data sources rather than relying on self-reported numbers.

In addition, it would be interesting to include a variable for women to see if there is indeed a different effect for women and mothers.

Conclusion

By using the survey data from LISS Panel, I ran OLS regressions that accounted for and controlled for multiple factors described in the literature. I did not find a significant effect for remote working on the time spent on actual work. My initial hypothesis "*Employees who spend more time working from home, on average, spend more hours on actual work compared to their colleagues that spend fewer hours working remotely.*" must be rejected. Even after limiting the data to more extreme observations of the Actual Working Ratio, I did not find a significant effect.

The monthly wage variable has also not shown a significant effect in any of the regressions. The hypothesis "*Employees with a higher salary, on average, spend more time doing actual work*" for my sub-question: "*Does the height of the wage affect the time spent on actual work?*" must also be rejected.

I believe this could be due to the way the data was collected by LISS Panel, and highly recommend additional research with better data for actual working hours or productivity.

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Appendix A: Descriptive Statistics for AW_{ratio} >= 1.1 or <= 0.9

Variable	Mean	Std. Deviation	Observations
AW_{Ratio}	1.021	0.637	78
RW_{ratio}	0.340	0.370	78
Monthly wage	3371.538	1864.742	78
Age	41.782	13.718	78
Has Children	0.526	0.503	78
Commuting time	27.897	17.294	78
Satisfaction Colleagues	7.679	1.254	78

Notes: The table above shows the mean and standard deviations of all variables that will be used in the OLS regression. The data was polished and freed of outliers and missing observations, as well as observations with an AW_{Ratio} below or equal to 0.9 or above or equal to 1.1. The number of observations is shown in the right column. The variables are further explained within the Data section.