How Working From Home Affects Productivity

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Abstract

This paper develops a modified neoclassical labour supply model that explicitly incorporates commuting time as a constraint on workers' available hours. By treating commuting as a time cost, the model reveals how shifts to working from home (WFH) can increase labour supply at a given wage rate. These changes influence the attainable utility, labour-leisure trade-offs and wage dynamics between a WFH worker and a commuter. Empirical analysis is employed, using UK data, which finds a positive relationship between WFH and productivity per hour, while accounting for pandemic-related shocks. The results suggest that WFH can improve individual utility and deliver aggregate economic gains and provide meaningful implications for labour economics, understanding wage setting and the future organisation of work.

AI Statement

I confirm that generative AI was not used in during the research or drafting of this paper.

Acknowledgments

I would like to thank my supervisor Anthony Savagar and my parents for their helpful support.

Introduction

This paper presents a novel adaptation of the neoclassical labour supply model to explicitly incorporate commuting time as a constraint on workers' available hours. Traditional models assume workers allocate time between labour and leisure, but omit the often substantial time cost associated with commuting. Including this time cost is significant with the widespread adoption of working from home (WFH) arrangements following the COVID-19 pandemic. By formally modelling commuting time as a distinct variable, this paper investigates how the presence or absence of commuting influences labour supply decisions, utility maximisation, and ultimately productivity. By treating commuting as a time cost, the theoretical model reveals that commuting introduces inefficiencies that reduce a worker's attainable utility and constrain labour supply at any given wage rate.

An empirical model is also employed to assess the relationship between the prevalence of WFH and productivity per hour worked within the UK, controlling for exogenous shocks during the pandemic. The WFH rate is found to have a positive impact on productivity, and the extent of the pandemic is found to have negatively impacted productivity, during the pandemic. Findings from this test and empirical evidence from related literature are then analysed to determine WFH's aggregated impact on output and productivity measures, providing evidence that WFH both enhances individual utility and can yield aggregate economic benefits. Analysing joint effects provides a comprehensive understanding of both the microeconomic and macroeconomic impacts of commuting and remote work, offering important insights into the evolving structure of modern labour markets. The findings have meaningful implications for labour economics, understanding wage setting and the future organisation of work.

Reviewing Background Literature

Barrero, Bloom and Davis (2021) provide an extensive cross-sectional survey on working arrangements and attitudes, which was launched in May 2020 to track evolving attitudes, behaviours, and expectations regarding remote work in response to the COVID-19 pandemic. The survey aimed to capture how workers and employers were adapting to large scale WFH transitions, and to inform projections about the persistence of WFH for when the pandemic had subsided, collecting ten waves of surveys on U.S. adults aged 20-64 who earned at least $20,000 in the prior year. Over the pandemic it was found that 60% of workers self-reported an improvement to their productivity while working from home, compared to 14% of workers who self-reported a worsening of their productiveness (Barrero, Bloom and Davis, 2021, p.17). It was also found that the perceived productivity benefits from WFH were 0.1% higher than anticipated and that this resulted in an increase in employers' future plans to continue WFH arrangements after the pandemic had ended (Barrero, Bloom and Davis, 2021, p.17). These future plans to continue WFH arrangements after the pandemic have since been followed through on. Data from the Office of National Statistics (2025) on the WFH rate shows that between the period of the pandemic and March 2025 the rate of workers exclusively WFH hit a lowest point of 9%, which is still relatively higher than the pre-pandemic WFH rate.

Further evidence which supports a persistent and continued shift towards WFH includes the sizable investments which were made to facilitate WFH during the pandemic (Barrero, Bloom and Davis, 2021, p.18). Large-scale lockdown measures resulted in the inability of much of the workforce to continue commuting to their location of work. This triggered a mass and sudden reallocation of workers towards WFH and therefore many workers were underequipped to be able to feasibly carry out WFH. As a result, workers had to forego large expenditures to enable a feasibility to WFH, where survey respondents reported an average of $561 of WFH related investments and 15 hours in lost time associated with WFH enablement between July 2020 and January 2021 (Barrero, Bloom and Davis, 2021, p.18). This amounted to an estimate of 0.7% of annual GDP when including the hours lost in terms of workers' wages (Barrero, Bloom and Davis, 2021, p.18). It is clear that the pandemic induced a costly expense of WFH associated investments which were necessary at the time, however if WFH was discontinued from the higher rates seen after pre-pandemic levels, then investments that have been made may become inefficient and potentially even render useless for some workers. Therefore, the cost to enable WFH is best spent while continuing to WFH, even if this is for instance only one day a week; otherwise, these investments become unutilised.

At the economy-wide level, WFH was estimated to have increased productivity by 4.6% after the period of the pandemic, relative to the WFH rate pre-pandemic, and this is predominantly brought on by reduced commuting time (Barrero, Bloom and Davis, 2021, p.29). However, estimates from Barrero, Bloom and Davis (2021, p.29) are based off of self-assessed worker productivities and so may be subject to some inaccuracy. Reduced commuting time frees up hours in the day for workers to optimize a higher number of hours worked, but any reduction in commuting time that improves productivity is not generally captured within 'conventional productivity measures' because of the occurrence of 'measurement errors' in conventional labour statistics (Barrero, Bloom and Davis, 2021, p.30), such as productivity measured per hour of work. Therefore, this survey is useful in grasping the scale of the effect that reduced commuting time has on productivity, at least in terms of workers perspectives. Productivity measures which fail to capture the effects from reduced commuting time are instead estimated to increase productivity, due to WFH, by 1% after the period of the pandemic (Barrero, Bloom and Davis, 2021, p.30). This sizable increase in productivity which is associated with time savings from reduced commuting is what motivates Chapter 1 in this paper, which addresses a way in which saved commuting time can be formally presented and how a worker may reallocate this saved time towards hours of work.

On the contrary, evidence from Gibbs, Mengel and Siemroth (2021, p.3) who conducted an analysis of the effects of WFH on a large Asian IT services company with over 10,000 employees, estimated that the productivity of the company's workers fell 8-19% over the incidence of the pandemic, despite the notion that an IT services company should have a strong feasibility to implement WFH practices. This resulted from an increase in the time worked per day, estimated between 2.1 and 1.6 hours, combined with an estimated output change of between -0.5% and -0.1% (Gibbs, Mengel and Siemroth, 2021, pp.14-15). Therefore, a slightly lower measure of worker output is being produced over a substantially longer period of working time, resulting in a lower output per hour worked.

Gibbs, Mengel and Siemroth (2021, p.21) illustrates that an increase in work related meetings and calls restricted workers abilities to complete individual tasks which contribute more directly towards output, categorised as 'coordination costs'. These coordination costs effectively occur because verbal communication between workers within the organisation, that can happen more seamlessly while working within the office, have to be scheduled in as meetings and subsequently restrict workers' abilities to simultaneously complete output generating tasks. This problem is less likely to occur during the office space as more free flowing coordination is more feasible. It was estimated that 'the increase in overall working hours takes place almost entirely outside of normal working hours' (Gibbs, Mengel and Siemroth, 2021, p.22), which supports the notion that workers struggled to meet output targets while experiencing these increased coordination costs within normal working hours.

It was also found that there was significant heterogeneity in how WFH affected productivity between employees; during the course of the pandemic, school closures resulted in longer hours worked but with a relatively smaller gain in output for parents, relative to workers with no children, with these effects being more severe for female parents (Gibbs, Mengel and Siemroth, 2021, pp.17-18). This meant that parents had a larger reduction in productivity per hour. It was also found that generally women were more negatively affected by WFH relative to men, even when controlling for childcare effects, but importantly these findings were found to have been contributed from the domestic cultural differences of women employees who are based in Asia (Gibbs, Mengel and Siemroth, 2021, p.18). These cultural differences include greater domestic expectations for women (Gibbs, Mengel and Siemroth, 2021, p.18); much like when childcare effects result in a constrain on the time parents have to use towards productive working activities, household expectations for women employees also constrain the ability to allocate time towards productive working activities. This finding is a useful predictor of the potential heterogeneity of WFH which may be present over the long term; while a high degree of childcare effects is only a short-term result of school closures during the pandemic, the adverse effects of WFH for women employees who experience greater domestic expectations will persist as a long-term problem.

Chapter 1 - Commuting

This chapter presents an adaptation of the neoclassical labour supply model to explicitly account for commuting time. Traditionally, the model allocates a worker's total time between hours worked and leisure, without acknowledging the time cost of commuting. This omission can distort the understanding of labour-leisure trade-offs, especially considering the growing relevance of WFH arrangements. The motivation behind this model is to analyse how transitioning from commuting based employment to remote working arrangements can increase the total number of hours worked, and also how this increases the labour supply at a given wage rate which leads to a positive impact on output. By introducing commuting time as a separate variable within the time constraint, the adapted model illustrates how commuting affects a worker's available time for both work and leisure, alters utility maximisation, and reshapes budget constraints. The chapter explores the implications of this structural change, particularly on the resulting inefficiencies in labour supply decisions for commuting workers. Through theoretical modelling and economic intuition, this framework provides a more accurate lens for evaluating modern labour choices.

Adapting the Neoclassical Labour Supply Model for a Commuter

Firstly, an assumption which is made as a basis for this analysis is that commuting time is not a utility giving good; commuting time in itself does not provide a benefit to workers and it is only a means to mobilise labour to a particular place of work, therefore commuting will represent a time cost rather than a consumption or leisure good. Also, throughout this analysis both the WFH and commuting workers are assumed to be rational, utility maximising workers.

The neoclassical labour supply model traditionally defines total available time (T) as the sum of hours worked (h) and hours allocated to leisure (L), however, this formulation does not explicitly account for commuting time. This paper introduces an adaptation to the standard model by incorporating commuting time, 'co', as a separate variable, refining the time constraint to:

$$T = h + L + co$$

Commuting time is represented as its own distinct variable because it does not fit within the standard categories of leisure or working hours. Leisure time provides direct utility by allowing individuals to engage in personally valuable activities, and to engage in a preferred specific utility granting activity an individual must be able to freely choose how they prefer to use their time. Commuting time cannot be categorised under leisure as an individual does not have the same freedom of choice to engage in such preferred valuable activities while commuting. While leisure can be flexibly chosen and traded off against work hours, commuting is a function of employment and cannot be freely substituted for leisure without affecting labour supply. Commuting time is a function of employment, but hours spent commuting are not compensated with a wage and so cannot contribute towards a higher consumption. Commuting in theory can provide a value of utility to a worker but this would depend on the individual preference a worker has towards commuting and the capacity a worker has to engage in utility giving activities while travelling. Such interpersonal differences would be hard to measure and equate, so any possible utility granted from commuting can be ignored; hours worked, and leisure hours will be the only utility granting variables represented graphically via each axis.

The Standard Neoclassical Budget Constraint

In the standard model, consumption (C) is determined by the wage rate (w) multiplied by hours worked, plus any non-labour income (V)

$$C = w(h) + V$$

With the introduction of commuting time, the budget constraint is rewritten as:

$$C = w(T - L - co) + V$$

where commuting time directly reduces the available hours for both leisure and work, thereby restricting the worker's opportunity set.

Defining Commuting Time as a Function of Work

Commuting time is not freely chosen but rather a function of working hours, typically occurring on a per-day basis. To derive this relationship the following variables are also defined:

- α: The total commuting time per workday (assumed constant for a given job and location).
- β: The number of hours worked per workday
- $\boldsymbol{D}$: The number of days worked within T.

Since each workday requires commuting, $\boldsymbol{D}$ is defined as:

$$\boldsymbol{D} = \left\lceil \frac{h}{\beta} \right\rceil$$

Where $\left\lceil \frac{h}{\beta} \right\rceil$ is a ceiling function which ensures the following rules are consistent when deriving $\boldsymbol{D}$: Any work, even one hour, counts as a full workday ($\boldsymbol{D}$) where commuting must take place. Once working hours (h) exceed the number of hours worked per day (β), another full workday ($\boldsymbol{D}$) is counted since commuting is now taking place on two occasions. Hence, the use of a ceiling function ensures any fraction of a day always rounds up to a full day.

Thus, total commuting time is defined as:

$$co = \alpha(\boldsymbol{D})$$

which shows that commuting will increase as more workdays are worked. This relationship will create discrete shifts in the available time left which can be allocated towards $h + L$.

Further Extensions for Commuting Time

Within this adapted neoclassical labour supply model, the derivation of commuting time per workday assumes a constant length for each shift of hours worked each workday. In reality, the number of hours worked per workday can vary depending on the characteristics of a job, for example a zero-hour contract can have a varying number of work hours from day to day. How commuting time is derived can hence be changed to reflect different job characteristics, so long as commuting time is still defined as some function of work. Commuting time being a function of work is an essential relationship in explaining the trade-off of leisure hours and working hours for the commuter. No matter how total commuting time is derived, some increase in hours worked which leads to an increase in the number of days spent commuting will always constrain the available time left to be allocated towards either working hours or leisure hours. However, this paper only derives commuting time through a constant number of hours worked per day, and therefore commuting time will be modelled with respect to this.

The Impact on Utility Maximisation

In the traditional neoclassical labour supply model, a worker optimally chooses h and L to maximize utility:

$$U = f(C, L)$$

where the consumption of goods and leisure is transformed into an index of utility, U. However, with commuting time, as stated, the utility derived from leisure and work is indirectly affected by the disutility of commuting. As commuting increases, attainable consumption and leisure decline, which will also decline the maximum utility available between the two. The impact on utility maximisation is what differentiates the indifference curves and opportunity sets attainable between a WFH and commuting worker.

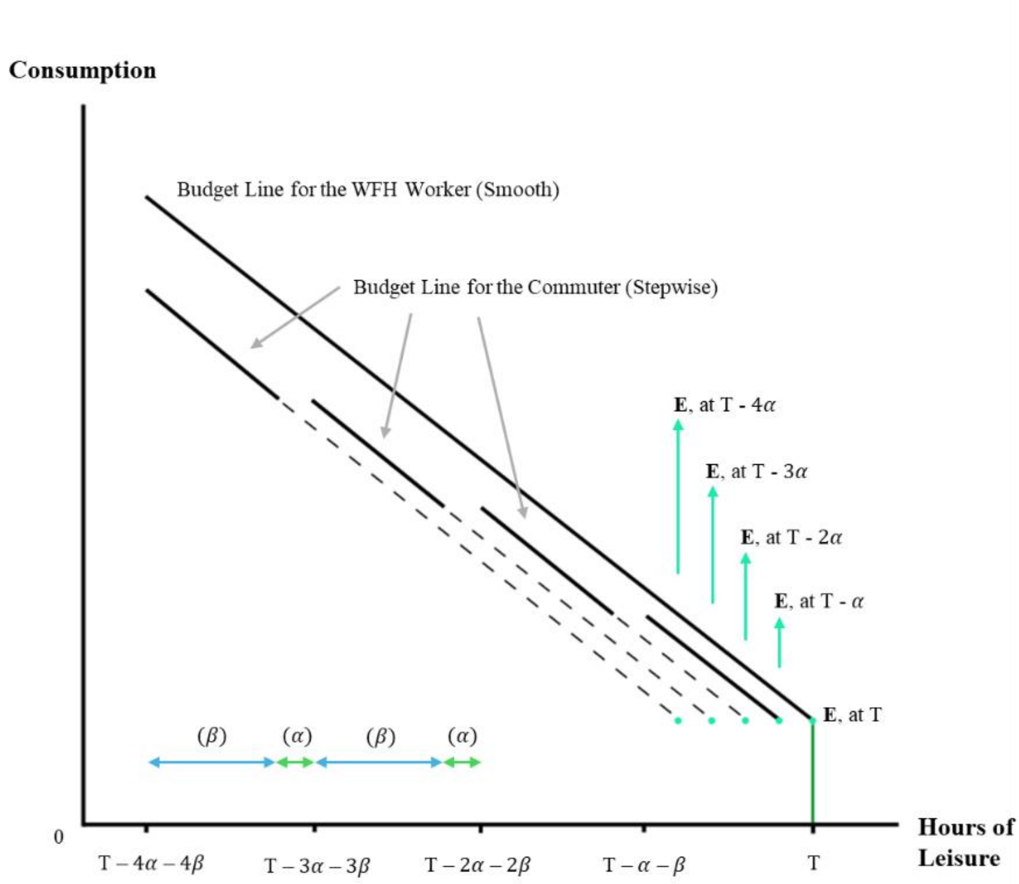
The Budget Constraint with Commuting Time

For a worker who commutes, this difference in attainable utility between leisure and consumption results in a smaller opportunity set than that of a WFH worker, which is smaller proportionally to the total number of commuting hours. Commuting hours take away from the possible sets of consumption baskets left within the opportunity set for a worker. Each increase in commuting hours subtracts from the frontier of the opportunity set and so only a lower indifference curve can be reached then that of a WFH worker; observable from the WFH worker and the commuting workers indifference curves in FIGURE 1-2.

Graphically, incorporating commuting time alters the opportunity set in the following ways:

- The endowment point shifts leftward along the x-axis as co increases, reducing the total available time for leisure and work.
- The budget line becomes stepwise rather than smooth, with discrete jumps occurring whenever an additional commuting day is required.
- WFH workers, where $co = 0$, face a standard neoclassical budget constraint, while commuting workers have the restricted opportunity set.

FIGURE 1-1 How the Budget Line Changes for the Commuter



Each incremental change in the endowment point (E) occurs as a leftward shift of α units. For each working day, where commuting time takes place for α hours, the potential for an allocation of leisure or work is lost by α hours. The total shift of the endowment point within a given T is equal to co units of hours. The budget line, derived from the budget constraint, $C = w(T - L - co) + V$, incrementally shifts to the left in line with the corresponding endowment point shifting α units leftward. The budget line is no longer smooth like the original neoclassical budget line because commuting time introduces these jumps at certain work hour thresholds; each increase in $\boldsymbol{D}$ is what prompts each incremental shift leftward of the budget line and the endowment point. The horizontal x-axis value of each incremental section is equal to the number of hours worked per workday (β), for the commuter.

The Adapted Model

FIGURE 1-2 Adapted Neoclassical Labour Supply Model with a Constant Wage Rate for Both Workers

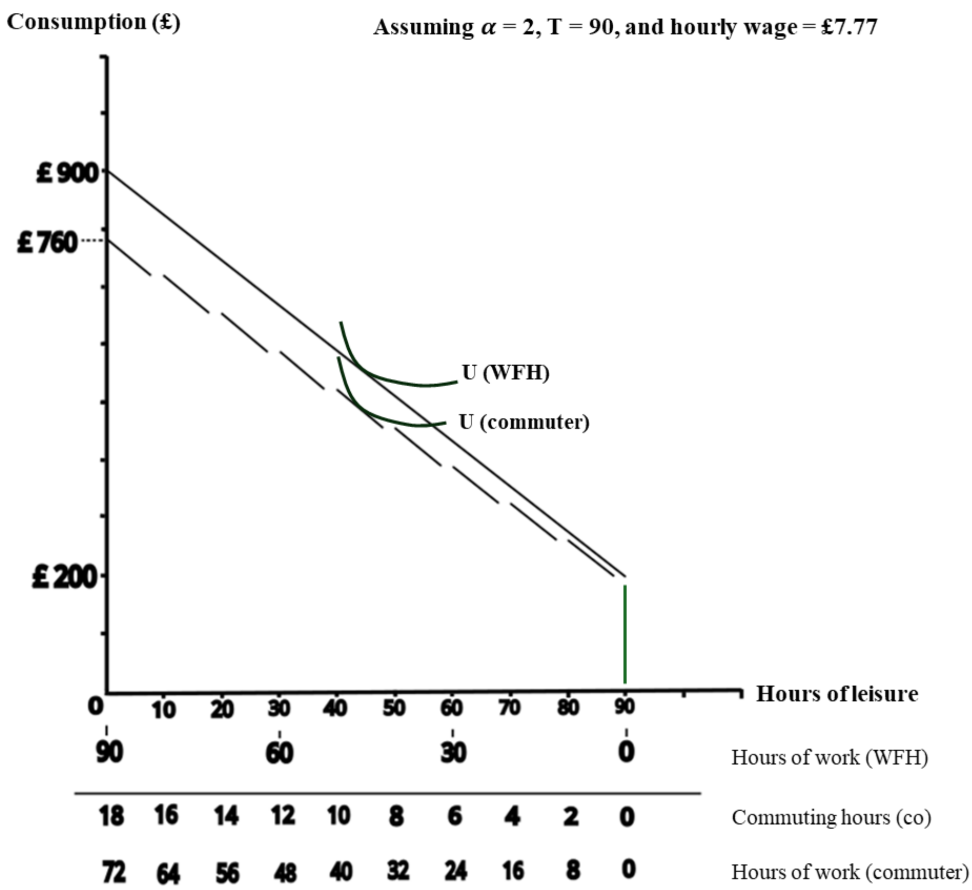


FIGURE 1-2 demonstrates such differences in attainable combinations of work hours and leisure hours using the following example figures: a total commuting time of two hours per workday, one hour to travel to work and one hour to travel back home, where $\alpha = 2$ hours, $T = 90$ hours, $\beta = 8$ hours, and therefore $\boldsymbol{D} = 9$ days. Both workers have an hourly wage rate of £7.77. Leisure hours and work hours are swapped out with each other at a 1:1 ratio for the WFH worker, just the same as the original Neoclassical Labour Supply model. For the commuter, the hours of work which correspond to a particular level of leisure hours, where leisure is labelled on the x-axis, are shown separately below the working hours of the WFH worker. The commuters working hours are coupled with the corresponding commuting hours taking place, where the commuting hours account for the differences in the hours of work between the two workers. £200 of non-labour income is also assumed to be endowed to both classifications of worker.

The indifference curves tangent to the budget line for both classifications of worker show the different levels of consumption attainable; an example is given that each worker has a preference to keep 45 hours of leisure, which is equal to half of the time constraint. While holding leisure constant at this level, the WFH worker is able to attain 45 hours of work earning a total wage of £350, while the commuter is only able to attain 35 hours of work earning a total of £272 – all rounded up to the nearest pound. If the WFH and commuting worker choose to maximise the highest level of possible hours worked within this time constraint it can be observed that the WFH worker is able to reach a consumption level of £900, while the commuter is only able to reach a consumption level of £760 because of losing 18 hours to commuting time, accounting for a difference of £140 – all rounded up to the nearest pound.

Therefore, at a constant wage rate between each worker, it becomes clear that the commuter must give up more leisure time to attain the same level of consumption as the WFH worker. The marginal rate of substitution (MRS) between leisure and consumption reflects the rate at which a worker is willing to give up leisure for more consumption. So, holding the wage rate fixed and the hours of leisure forgone fixed, for both workers, each unit of leisure given up is less effective in generating consumption for the commuter. This results in the commuter having a greater MRS, as a higher compensation is demanded to give up additional leisure; this also indicates that the commuter will have a steeper indifference curve. FIGURE 1-2 graphs the WFH and commuting workers budget lines when both workers have the same wage rate as to demonstrate the disparity between each worker's attainable utility between leisure and consumption - this represents what drives the commuters demand for a higher compensation to forego leisure hours (addressed later in FIGURE 1-5).

The full mechanism behind the shape of the budget line for the commuter is as follows; as hours worked (h) increase, you move along the budget line until h exceeds β. At this point the count of days worked ($\boldsymbol{D}$) increases by one, which causes the value of commuting hours (co) to increase by one unit of α. This decreases the available working hours (h) and leisure hours (L) by α hours under the time constraint of T, where $T = h + L + co$, and so you become endowed with less available $h + L$. For each incremental shift leftward the budget line makes, a lower combination of utility giving goods can be reached through an optimal tangency point between the budget line and an indifference curve.

FIGURE 1-3 The trade-off of an extra days commuting time

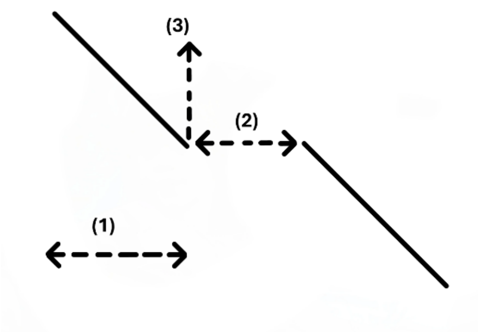


FIGURE 1-3 illustrates a magnified section of one of the incremental jumps the budget line of a commuter makes. Working tomorrow (1) a worker commutes an extra two hours, so they lose two hours of leisure (2), or they lose the potential to work two more hours (3) out of the remaining T in a period. The lost potential of working two more hours (3) is equal to a loss of $w(\alpha)$ units of consumption. These hours lost to commuting time would have otherwise been allocated into any combination of h or L.

It has so far been shown that the absence of commuting time will grant a WFH worker the ability to obtain a higher set of utility between some combination of leisure and consumption. At any level of foregone leisure hours which is held the same for both workers, the WFH worker can obtain a higher level of consumption. At any level of desirable consumption held the same for both workers, the WFH worker foregoes less hours of leisure to be able to reach this same level of consumption. As a result of these differences between each classification of worker, the wage rate which is required to incentivise additional hours of work to be taken up in replacement of leisure hours will need to be relatively higher for a commuter – for a given level of forgone leisure. This will lead to a relatively steeper relationship between the wage rate and hours of work for a commuter, and ultimately relatively less labour supply at any given wage rate.

Deriving the labour supply of a commuter and a WFH worker

The optimal consumption bundle summarises the optimal combinations of utility-granting goods, where at each optimal point, the last £1 spent on consumption goods grants a worker the same level of utility as the last £1 worth of wage, which is lost to time spent on leisure activities. To determine the wage rates that will motivate workers to willingly sacrifice a given number of leisure hours, in this example, the optimal consumption bundles of leisure hours and consumption for both the WFH and commuting workers are equated. The optimal consumption bundles for this example are as follows:

FIGURE 1-4 Optimal consumption bundles of the WFH and commuting worker

Leisure Hours	Consumption
70	£1200
60	£1600
50	£1640

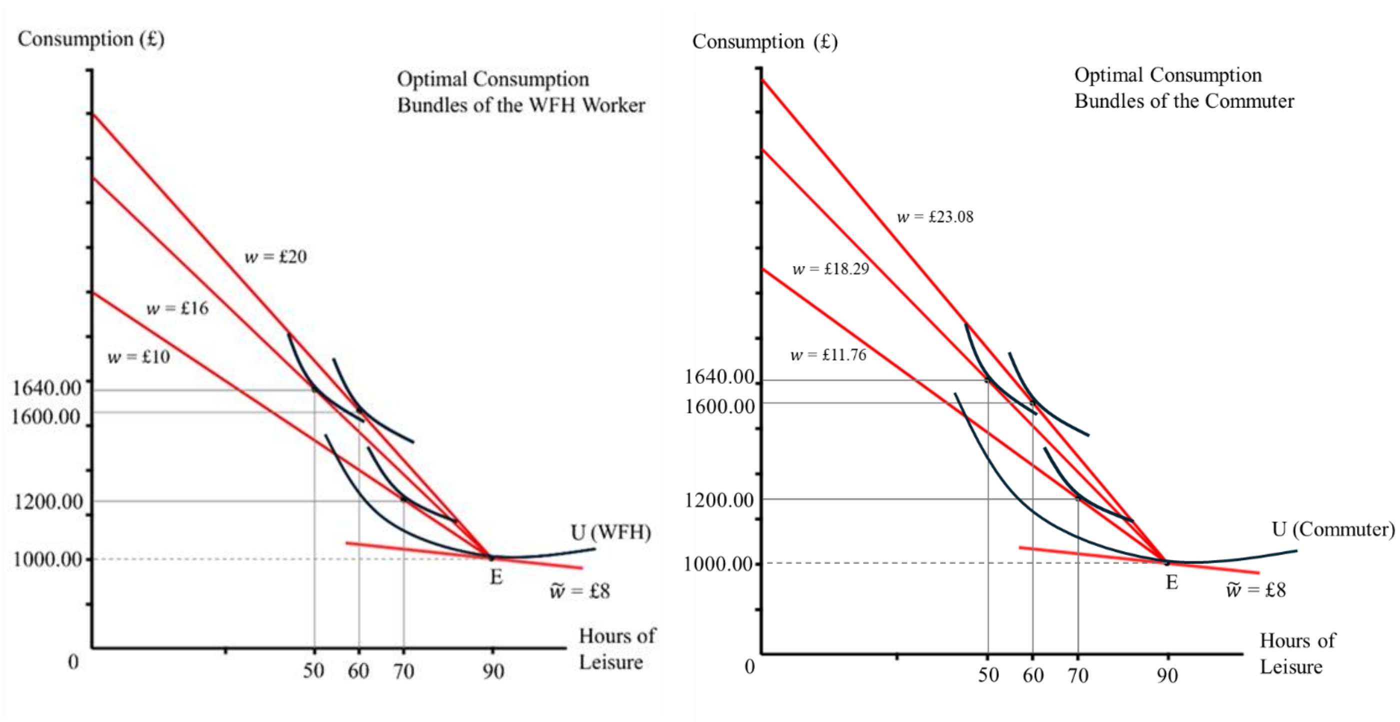
For these example values, £1000 of non-labour income is assumed to be endowed to both workers, and the total time constraint (T) = 90. This means that, for both the WFH and commuting workers, in order to forego 20 hours of leisure the workers must be rewarded with an extra £200 worth of consumption above their non-labour income levels, where $w(h)$ = £200.

According to an analysis by the Trades Union Congress (2019) the average commuting time in the UK during 2018 was 59 minutes per day, up from an average of 54 minutes a decade prior, where over the course of 2018 the average commuting hours totalled to 221 hours per worker in the UK. Therefore, further values for this example will include, for the commuter, a commuting time of one hour per working day which is counted at the commencement of every seven-hour shift. Due to this, in order for the commuter to attain their optimal consumption bundle when 20 hours of leisure are sacrificed, the commuter will require a wage rate of £11.76 per hour. In sacrificing 20 hours of leisure[1], the commuter can only work a maximum of 17 hours, as three hours have to be spent travelling to work. Contrarily, the WFH worker is willing to accept a wage rate of only £10 per hour as they are able to work 20 hours to attain the extra £200 worth of consumption.

The commuter will not be willing to accept a lower wage rate than £11.76 in return for sacrificing 20 leisure hours with commuting time. However, the commuter would be willing to accept less if they hypothetically had a lower commuting time; if the commuter had zero commuting time, they would be willing to accept a wage rate of £10 when forgoing 20 leisure hours, however, this is now just a WFH worker. Realistically a commuter has a fixed commuting time, and under a wage rate of £10, they would choose to sacrifice less than 20 leisure hours and also work less than 17 hours. Therefore, for a certain level of foregone leisure, the commuters demand for a relatively higher wage, because of only having the capacity to work relatively fewer hours, can also be modelled under the neoclassical labour supply framework. The wage rate demanded to attain each level of the optimal consumption bundle for both workers can be plotted graphically as thus:

[1] The commuter can still work up to 21 hours while only incurring three commuting hours, optimal leisure hours are just chosen as multiples of 10 for graphical simplicity and representation. In a scenario where a commuter chooses to only work 20 hours, this can be imagined as two seven-hour shifts followed by a six-hour shift; the wage rate will correspond to thus.

FIGURE 1-5 Optimal Consumption Bundles of the WFH and Commuting Workers



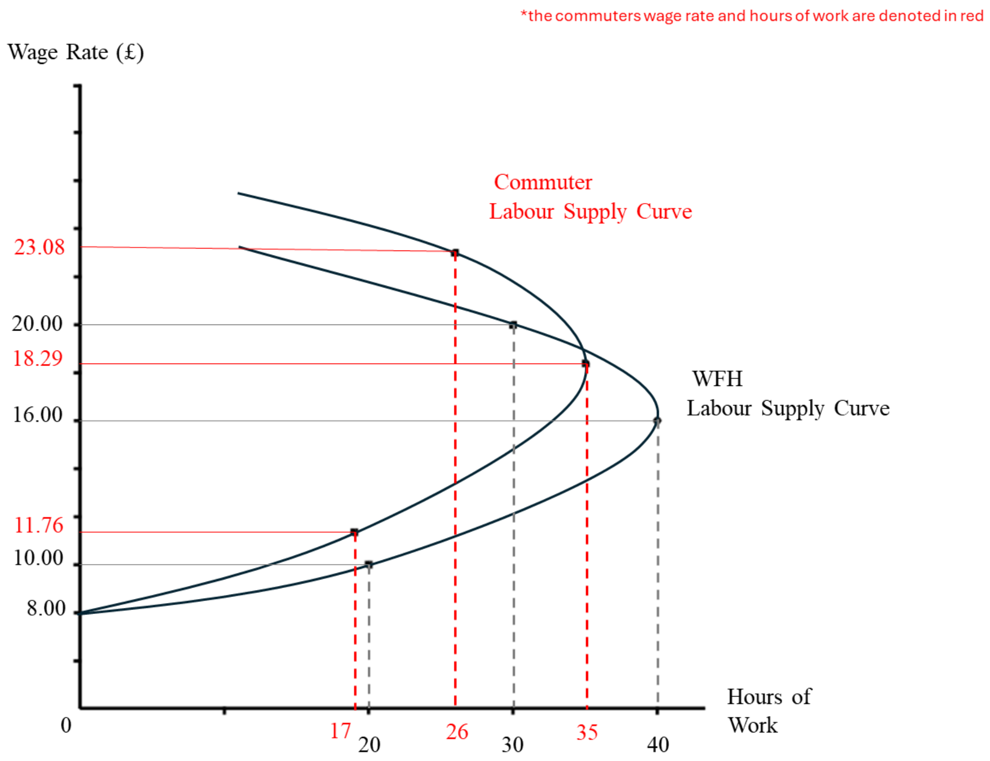
The reservation wage, which is the minimum wage required to incentivise a worker to work any hours more than zero, is simply assumed to be £8 for both workers. At any wage rate below the reservation wage the worker will choose not to work at all, and as the wage rate begins to increase above £8 the worker will begin to increase their hours worked. The indifference curves tangent to the budget lines show the combinations of optimal consumption bundles for each worker (from FIGURE 1-4). When an agent optimises their utility, the slope of each budget line shows the marginal rate of substitution (MRS); the marginal utility of leisure divided by the marginal utility of consumption, for each worker, which is the rate at which each worker is willing to give up leisure for more consumption. At the optimum, the MRS is equal to the wage rate (if we normalise the price of the consumption good is one), as the wage rate is the rate at which the market compensates each worker for giving up one unit of leisure in exchange for one additional unit of consumption. This relationship is formulated as follows:

$$\frac{\Delta C}{\Delta L} = -\frac{MU_L}{MU_C} = -w \qquad therefore, \qquad \frac{MU_L}{MU_C} = w$$

In order for each worker to attain their optimal combinations of utility granting goods, given from the optimal consumption bundle from FIGURE 1-4, each optimal level of leisure and consumption requires the wages depicted in FIGURE 1-5. At all points of the optimal consumption bundles of the commuter, the commuter will require a higher wage in order to reach the same consumption levels as the WFH worker holding constant the number of leisure hours sacrificed. Generally, the price of leisure hours is equal to the price of lost wages, or in other words the price of leisure is equal to the opportunity cost of leisure. It can be observed that leisure is relatively more expensive for the WFH worker because they are able to work a higher number of hours in replacement of a given number of leisure hours. The commuter demands a higher wage for leisure hours to become as expensive as they are for the WFH worker, otherwise the commuter will not be willing to sacrifice the same number of leisure hours.

The demanded wage by both workers to give up these specific levels of leisure can be plotted against the number of hours worked at each wage rate to derive the labour supply curves for both workers, based off of the wage required to attain the example figures from FIGURE 1-4, shown as thus:

FIGURE 1-6 Derived Labour Supply Curves for the WFH and Commuting Workers



From FIGURE 1-6 it is made more apparent the differences in the hours of work between the WFH worker and the commuter because of commuting time, where this gap grows as more leisure hours are foregone. Generally, the substitution effect describes when a worker devotes less time to expensive leisure activities due to the workers wage increasing, instead choosing to increase hours of work to attain a higher consumption. The upwards slope of the labour supply curves show the substitution effect initially dominating as increases in the wage rate incentivises higher hours of work. As the price of leisure is relatively less expensive for the commuter, the substitution effect of the commuter is relatively weaker. At the highest wage in which the substitution effect is still dominating for the WFH worker, when 40 hours are worked at a wage of £16, the commuter's substitution effect will still continue to dominate until a wage of £18.29 is earned when working 35 hours.

It is important to note that the furthest point as to where the substitution effect is still dominating, which shows the maximum number of hours that each worker is willing to work for at any given wage rate, occurs for the commuter at a higher wage rate and also a lower number of hours worked. It is also the case, that for any quantities of the identical optimal consumption bundles (from FIGURE 1-4) between the WFH worker and the commuter, the commuter will work less hours but at a higher wage rate relative to the WFH worker. This is observable from FIGURE 1-6 between each curve plot that achieves a specific preference of utilities from the optimal consumption bundles, as each plot of the commuter's labour supply curve is northwest to the WFH workers labour supply plot. This results in a steeper labour supply curve for the commuter, and it is shown later on that the steeper the labour supply curve is, the greater a negative effect is felt on output.

The backward bending segment of the labour supply curves indicate that the income effect is now dominating the workers' choices of hours worked. As the wage rate increases, leading to higher attainable consumption levels, the income effect causes a worker to begin to reduce the number of hours they work. This can happen for instance when a worker is satisfied with their consumption levels and their preference changes to optimally prefer a higher number of leisure hours. Since a commuter has a more constrained choice of either hours worked or leisure hours, so a lower $h + L$, the limited choice of leisure hours disincentivises the commuter to work as many maximum hours when compared to the amount a WFH worker is willing to work as a maximum.

Using the derived labour supply curves from the example set of optimal consumption bundles, a more general labour supply diagram can be graphed to depict a shift in working patterns from commuting to WFH and the effect this has on the wage rate and the output generated from each worker. It is assumed that the income effect is small and therefore negligible, therefore:

FIGURE 1-7 Shift in Working Patterns from Commuting to WFH

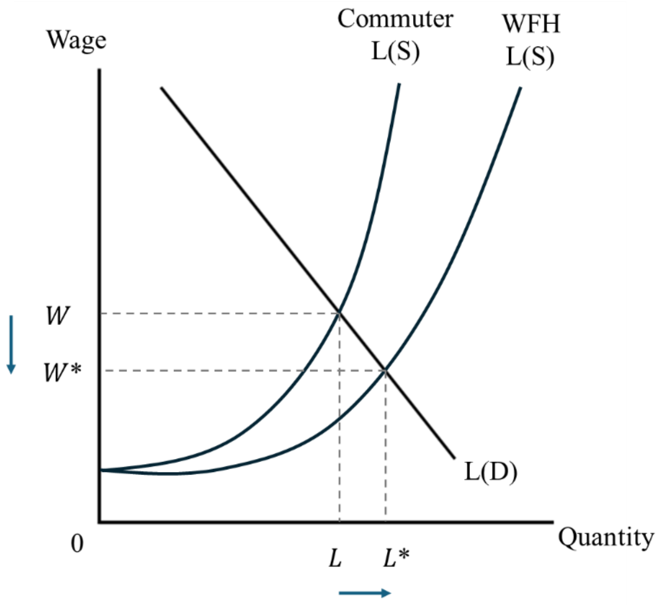


FIGURE 1-7 shows that for a given amount of labour, the commuter will require a higher wage rate relative to a WFH worker. When a worker shifts from commuting to WFH, the labour supply curve shifts to the right along the labour demand curve. The proposed theory behind this mechanism is now that the worker has made this shift, they will be willing to work at a lower wage rate as they have the capacity to work a higher number of hours, while holding hours of leisure foregone fixed. At a macro-level, this results in more labour hours able to be hired at a lower wage rate. This, in turn, increases overall output because of an increase in hours worked, and subsequently labour productivity as less input in terms of wages is being used to produce an increased level of output.

Ultimately, more labour is available at each wage level and so firms will be able to employ a higher quantity of labour at an average lower price. As mentioned before, when the commuting and WFH worker both have an identical optimal consumption bundle, the commuter will require a higher wage to achieve their desired consumption levels at every level of foregone leisure, where the higher this required wage, the steeper the commuter's labour supply curve.

The level this wage is required at will directly depend on how many hours the commuter must travel, as if commuting time was two hours instead of one this would further constrain $h + L$ resulting in a higher wage demanded to forego the same amount of leisure – as fewer working hours are replacing the same amount of leisure. Therefore, the higher the amount of commuting time, the greater the change in the wage rate that a worker will be willing to work at when a worker shifts from commuting to WFH. This also results in a greater change to output. The final value of the wage rate and output is the same regardless of commuting time. It is only the initial starting point of the wage rate and output which is *worse off* due to the commuter's steeper labour supply curve, because of a higher commuting time.

The survey conducted by Barrero, Bloom and Davis (2021) also collected responses from participants on the value of WFH in terms of a pay rise or cut. The results found that 63.1% of respondents would be willing to receive a pay cut in order to be able to WFH two to three days a week, with 8.6% of respondents not willing to receive a pay cut as they viewed WFH as a cost in itself, 28.2% of respondents had a neutral view (Barrero, Bloom and Davis, 2021, p.39). This evidence supports the validity that workers would be willing to accept pay reductions to WFH. The survey's questions do not accommodate a specific reason as to why respondents choose to value WFH in terms of a pay rise or cut, and therefore why, specifically, the majority of respondents, on average, were 'willing to accept pay cuts of 7 percent' (Barrero, Bloom and Davis, 2021, p.2). One explanation may be that, with an exposure to WFH brought on by the pandemic, workers have become more aware of the time savings effects when switching from commuting to WFH; such effects have been formally demonstrated through Chapter 1, and if workers are aware of their own benefit from time savings effects, this may explain a motivation as to why workers would be willing to receive a pay cut in order to WFH.

The Monetary cost of Commuting Time

It has been shown that commuting time imposes a time cost for workers, but commuting time also poses a monetary cost which is not considered within this model. However, monetary costs could also be represented, as commuting expenditures also result as a direct function of work. These costs are very specific to individual workers and are likely to not stay constant over time. For example, commuting by car will depend on varying fuel prices, while transportation by tube or train will vary depending on the rates of tickets. This being said, the average values of a worker’s monetary costs could be modelled very easily by decreasing the commuters wage rate respectively, effectively representing a more accurate *take-home wage* for the commuter. By representing a *take-home wage* of a commuter which factors in such monetary costs, for any given hours of work a lower level of consumption will be reached. This will have the implication of amplifying the following effects throughout this mechanism, including, increasing the relative wage rate a commuter will demand, from FIGURE 1-5, and steepening the commuter’s labour supply curve from FIGURE 1-7.

Chapter 2 – Testing WFH's Effect on Productivity

This chapter presents an analysis on the effect WFH has on productivity per hour within the UK. To quantify these effects, empirical analysis is presented to test the relationship between WFH and productivity per hour at the macro-level. WFH has become a prominent feature of modern employment due to its accelerated rate because of the Covid-19 pandemic, so understanding its impact on productivity per hour is critical. Combining WFH's hourly productivity impact along with its influence on total hours worked will allow for a complete picture to be built on WFH's aggregated effect on output and productivity levels. This analysis investigates whether higher rates of WFH are associated with higher or lower changes in productivity per hour, controlling for exogenous distortions to productivity per hour which were present during the period of the pandemic.

Deriving the Data Used to Test for a Relationship Between WFH and Productivity Per Hour

Data collected on the WFH rate is sourced from the Office for National Statistics (ONS) (2025), which provides survey data on UK working arrangements over the pandemic-period and after. Each data point recorded is the percentage of working adults that have worked from home only in the past seven days. The survey data records between one to four observations per month. Therefore, if a month has more than one data point recorded then each month's data points are averaged into a single monthly WFH rate percentage. The ending date that each data point spans corresponds to the month the data is averaged into. ONS data on working from home spans from the 14th of May, so an estimate is given for the month of April that WFH rates are 32%, equal to the average WFH rates seen in May. In January and February of 2020, '5.7% of the employed population were exclusively working from home according to the Understanding

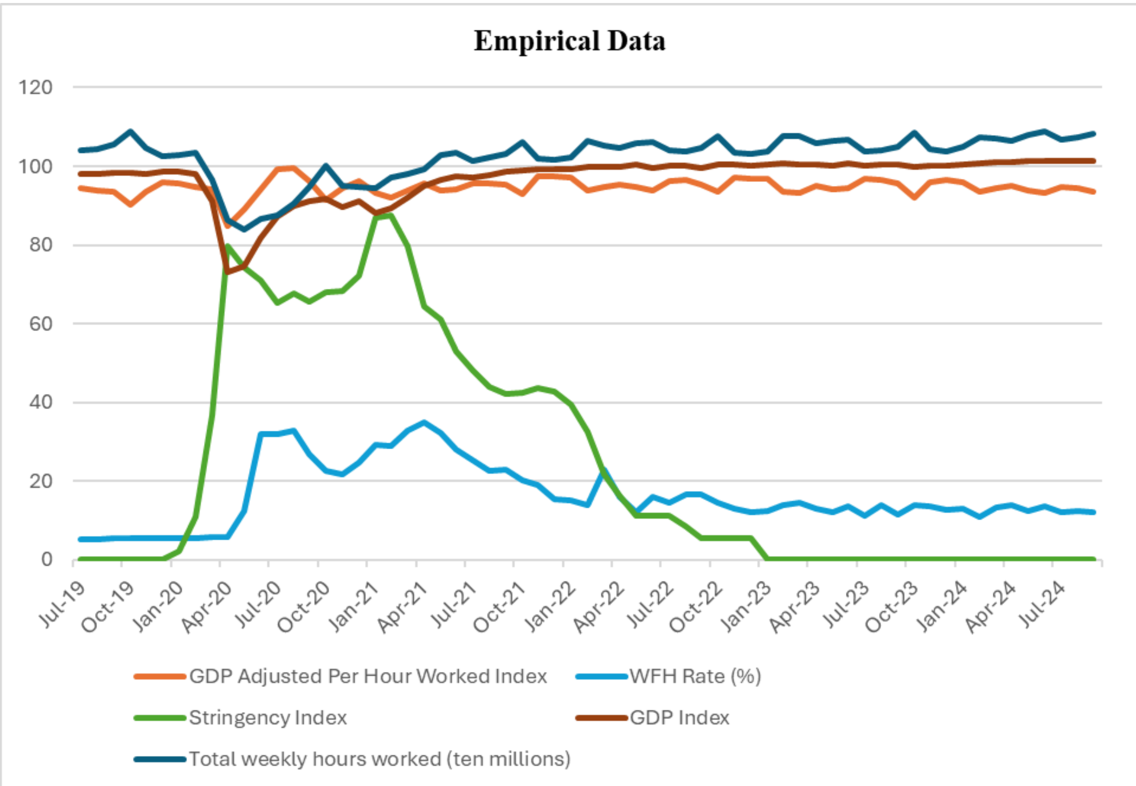
Society Covid-19 Study' (Felstead and Reuschke, 2020, p.5). During 2019, 4.7% of the employed population were exclusively working from home (Felstead and Reuschke, 2020, p.5), so for every two-month period preceding January 2020, the WFH rate has been estimated to drop 0.1%. The stay-at-home order was announced on the 23rd of March and was made legally effective on the 26th of March. Advice to avoid all non-essential contact was given on the 16th of March. Therefore, for the month of March, a WFH average is estimated. After the announcement on the 23rd of March to stay at home, days are weighted to equal a WFH rate of 32%, the same as April. On the day of the announcement and preceding the announcement, days are weighted to equal a WFH rate of 5.7%, the same as February. This results in March having an estimated average WFH rate of 12.487%.

A GDP Adjusted Per Hour Worked Index is used as a proxy for productivity within the UK, and is derived from ONS data of a monthly GDP Index (Office for National Statistics, 2025), with a reference year of 2022 = 100, and from separate ONS data on actual weekly hours of work (Office for National Statistics, 2025). The data on actual weekly hours of work offers an average calculation of total weekly hours worked over three-month intervals. Each three-month period overlaps so that there are 12 three-month periods in one year, for instance Jan-Mar is followed by Feb-May. Each monthly GDP Index is divided by the corresponding middle month in each three-month period of total weekly hours worked. To preserve the interpretability of the GDP Index, once the monthly GDP index is divided by the corresponding month's total hours worked, this value is multiplied by 10^9. For instance, for the month of April, which has a GDP Index of 73.20 and 862,142,615 total hours worked, the GDP Adjusted Per Hour Worked Index is 84.90. A stringency index which measures the severity of the pandemic over time is also used and is sourced from the Oxford COVID-19 Government Response Tracker (2021), which contains daily observations and so this data has also been averaged into monthly observations.

FIGURE 2-1 Descriptive Statistics

Variable	Observations	Min	Max	Mean	Standard Deviation
GDP Adjusted Per Hour Worked Index	63	84.90	99.53	94.66	2.24
WFH Rate (%)	63	5.30	35.00	16.28	8.15
Stringency Index	63	0.00	87.50	24.63	29.93
GDP Index	63	73.20	101.43	97.00	5.99
Total Weekly Hours Worked (millions)	63	839.57	1088.59	1024.51	58.17

FIGURE 2-2 Empirical Data Graphed



There are 63 monthly observations for each variable spanning from July 2019 to September 2024, apart from the WFH rate which spans from May 2019 to July 2024 because of a two-month lead. Total weekly hours worked fell relatively less on average than the GDP index, which explains why the GDP Adjusted Per Hour Worked Index is averagely lower than the GDP Index. The smaller range of the WFH rate relative to the stringency index explains why the WFH rate has a relatively lower standard deviation. The ranges of these variables are important to note when interpreting the effect of these independent variables on GDP per hour worked from the results.

The data is regressed using the following formulation:

$$Productivity\ (GDP\ adjusted\ Index)_t = \beta_0 + \beta_1\, WFH_{t+2} + \beta_2 Stringency_t + \epsilon_t$$

The Stringency Index of the pandemic's severity is used as a control variable. The stringency index aims to capture the broader macroeconomic shocks which affected productivity levels which were not related to the WFH rate, over the course of the pandemic.

WFH data is led by two periods. This is done due to the slow innovation of WFH accessibility during the beginning of the pandemic. Firms who implemented WFH for their employees would have needed time to implement the necessary digital infrastructure, communication tools and management practices to support remote operations effectively, such as the communication costs highlighted by Gibbs, Mengel and Siemroth (2021, p.21). Employees could have also faced their own adaption period, for instance if they needed time to create suitable home workspaces, adapt to new routines or ensure they have a stable and sufficient internet access. Burdett et al. (2024, p.19) describes that there was a need for workers and firms to sort themselves into locations which best suited ‘individual-specific productivity outcomes’. This meant that certain workers or employment roles were better suited to be carried out WFH, but other jobs were less suited to WFH, and there was a delay in establishing which location was better suited to specific workers and which location employment roles were more productive to operate at. These effects were also worse among parents who were ‘less able to sort into their most productive locations’ (Burdett et al., 2024, p.19), because of widespread school closures resulting in the need for parents to look after their children during working hours. A lower WFH accessibility during the commencement of the pandemic is also consistent with the evidence presented on childcare effects by Gibbs, Mengel and Siemroth (2021, p.18), and financially costly WFH enablement presented by (Barrero, Bloom and Davis, 2021, p.18). Leading the WFH variable aims to capture the WFH rates’ effect on the GDP Adjusted Per Hour Worked Index, for when the accessibility of WFH is better implemented, using current rates of WFH, instead, at two monthly periods into the future. This aims to examine the overall effects of WFH at the best levels of accessibility and implementation possible. The regressed formulation produces the following results:

Results

FIGURE 2-3 Results

Remote Working, Pandemic Stringency and Exploring a Relationship with GDP Adjusted Per Hour Worked. July 2019 - Sep 2024, at monthly intervals	
	GDP Adjusted Per Hour Worked Index
Predictors	*Estimates*
Baseline GDP Adjusted Per Hour Worked Index	92.498*** (0.593)
WFH Rate (%)	0.215*** (0.045)
Stringency Index	-0.054*** (0.012)
Observations	63
R^2 / R^2 adjusted	0.293 / 0.270
F Statistic	12.442*** (df = 2; 60)
Residual Std. Error	1.914 (df = 60)

Note: *** p<0.01, ** p<0.05, * p<0.1

The coefficient of the WFH rate returns a value of 0.215, which means for each 1% increase in the WFH rate, GDP per hour worked is estimated to increase by 0.215 index points. The positive coefficient estimates that a higher rate of WFH will increase productivity per hour worked. The P-value measures statistical significance and shows the probability of the null hypothesis of no relationship between the dependent and independent variable being true and the data being as we have, where a statistically non-significant result would indicate that there is a lack of evidence to reject the notion that the variation explained is down to chance. The P-value for the WFH rate returns a value of 0.0000105, far below a P-value of 0.05, where a P-value less than 0.05 is considered statistically significant, which suggests the WFH rate has a true causal effect on productivity and the correlation is highly unlikely to be resulting from random chance.

The R-squared value of 0.293 indicates that the independent variables; the WFH rate (%) and the Stringency Index, explain 29.32% of the variability in the dependant variable; the GDP Adjusted Per Hour Worked Index. This leaves 70.68% of variation unexplained as during the pandemic there were numerous explanatory factors influencing GDP per hour worked. The adjusted R-squared value of 0.270 is 2.3% lower than the R-squared value of 0.293, which can be explained by the fact that there are only two independent variables. The pandemic stringency index only acts as a proxy for broader macroeconomic distortions, so a lower level of explained variation is expected relative to a model which perfectly decomposes every variable which had an effect on GDP per hour worked over the pandemic period. While there are unobserved factors driving variation in GDP per hour worked, as long as this proxy is accurately representing broader distortions present during the pandemic period, a lower R-squared value is acceptable.

To quantify how well the stringency variable captures these broader distortions which explain variation in GDP per hour worked, the statistical significance of the stringency variable can be analysed. The P-value for the stringency index returns a value of 0.0000369, which is also far below a P-value of 0.05, so the stringency index is statistically significant meaning it has a true causal effect on productivity. Therefore, the high statistical significance of the stringency index can be attributed to the stringency index providing an accurate and representative proxy for these broader distortions to GDP per hour worked during this period. Although the decomposed effects on GDP per hour worked are not accounted for and tested individually, an overall cumulative effect on GDP per hour worked is being successfully captured by the severity of the pandemic. This proxy capturing wider economic distortions therefore helps to isolate the individual effect WFH is having on GDP per hour worked. Without this proxy capturing a causality as to why GDP per hour worked falls, this decrease could be attributed instead to the WFH rate and not due to pandemic related distortions; without the use of a control variable, a spurious correlation could arise between the WFH rate and GDP per hour worked.

During the first full month of lockdown measures in April of 2020, the GDP per hour worked index fell to 84.90, down from 94.85 two months prior. During this same month in April, the stringency index increased to 79.63, up from 11.01 two months prior, and the WFH rate increased to 32%, up from 5.7% two months prior. While the pandemic created large supply and demand side shocks which resulted in large distortions to GDP, total hours worked, and consequently GDP per hour worked, the pandemic was also responsible for the large and statistically impactful increase in the WFH rate, predominantly as a result of lockdown measures. Due to the relatively large changes in GDP per hour worked and the WFH rate, which were both caused by the pandemic in a short window of time, without a control variable to provide an explanation of any pandemic related distortions the statistical relationship between GDP per hour worked and the WFH rate would cause this spurious correlation. The coefficient of the stringency index returns a value of -0.054, which means that each 1 unit increase in the stringency index is estimated to decrease GDP per hour worked by 0.054 index points.

How did increases in the pandemic's severity result in lower productivity per hour worked?

Observations of GDP falling relatively more than total weekly hours worked as a percentage (from FIGURE 2-2), explain how GDP adjusted for hours worked is observed at relatively lower levels than pre pandemic figures. However, while this persisted during the initial months of the pandemic, spikes in GDP per hour worked above pre pandemic levels are also observed.

For instance, during the months of July and August 2020 the GDP Adjusted Per Hour Worked Index rose to 99.39 and 99.53 index points. To understand the source of these fluctuations, the accounting framework of Baily et al. (1992) can be used to explain these productivity changes at a decomposed level, which have already been applied to the period of the pandemic for the UK by Bloom et al. (2021) to understand what was driving pandemic induced fluctuations in productivity.

Bloom et al. (2021) uses the accounting framework of Baily et al. (1992) to decompose the drivers of productivity changes over the pandemic period into 'within-firm' and 'between-firm' effects. The within-firm effects detail how the intermediate costs of firms increased, and total sales decreased, leading to a drop in aggregate within-firm labour productivity per hour (Bloom et al., 2021, p.8). The increase of intermediate costs was a direct result of the measures taken during the pandemic to reduce the spread of covid-19. Firstly, personal protective equipment (PPE) was a regulation by government which created a new expense which firms had to pay to continue safe working practices during the pandemic; the pandemic both affected the costs associated per worker for firms because of PPE, and also incurred added inefficiencies in capacity utilisation (Bloom et al., 2021, p.8). This was because social distancing measures also effected the workplace, such as extra 'spacing between workstations' and 'fewer tables at restaurants' (Bloom et al., 2021, p.8), so unit costs also increased as pre pandemic capacity levels were being used to produce less units at lower pandemic output levels; firms were unable to fully utilise the full potential of their capacity levels.

Within the UK, sales were estimated to have dropped an average of 30% in the second quarter of 2020, with total hours worked estimated to have dropped relatively more than sales in 2020Q2 and 2020Q3, however it was found that on average, real sales per employee were positive as total hours worked converged to sales after 2020Q3 (Bloom et al., 2021, pp.7-8). Despite a positive effect on average real sales per employee, the negative effect on labour productivity caused by higher intermediate costs was relatively stronger, and so within-firm labour productivity per hour was estimated to have averagely fallen by -3% from 2020Q2 to 2021Q4 (Bloom et al., 2021, p.8). In essence, greater inputs were required in the production process, because of higher intermediate costs, which were used to produce a relatively weaker increase in output, resulting in a negative within-firm effect on output to all inputs and labour productivity.

The between-firm effect on labour productivity can be described as the change in total labour productivity across the whole economy that arises due to a disproportionate reallocation of worker input between either lower productivity firms or higher productivity firms. If higher productivity firms' worker inputs were negatively affected relatively more than lower productivity firms' worker inputs, then there would be a further negative impact on aggregate total labour productivity within the economy on top of the within-firm impact. However, if lower productivity firms' worker inputs were negatively affected relatively more than higher productivity firms' worker inputs, then there would be a positive impact on total labour productivity within the economy, offsetting, to some degree, the within-firm negative impact on labour productivity. Firstly, it was found that there was large heterogeneity in sales between different industries; the relatively low productivity sector of accommodation and food and recreational services experienced an estimated drop of 80% in 2020Q2 sales, a very large difference from the average across all industries of 30% in 2020Q2 (Bloom et al., 2021, p.7). This was due to large sectoral shutdowns during lockdown periods where industries such as 'non-food retail, restaurants and hotels, passenger transport, personal services and arts and leisure services' (Joyce and Xu, 2020, p.2) where most effected, being typically lower productivity industries.

Evidence from Bloom et al. (2025, p.29), shows that these sectoral shutdowns resulted in the between-firm effect on labour productivity to be most significant in lower productivity industries, where such industries involve a large number of ‘face-to-face interactions’ with workers and customers; this indicates that lower productivity industries were the most restricted in their ability to provide services while employees worked from home. Sectoral shutdowns disproportionately affected the levels of labour inputs in lower productivity sectors compared to the levels of labour inputs in higher productivity sectors, because of a larger reduction in total hours worked for lower productivity firms within these sectors. The findings show that this between-firm effect was greatest during 2020Q2, peaking at an estimated 10.6%, and then peaking a second time during the second lockdown wave in 2021Q1, at a lower estimated level of 5%, but otherwise trailing off after the first peak (Bloom et al., 2025, p.37). A positive between-firm effect on labour productivity meant that a relatively higher share of lower productivity workers was either absent or had some share of their hours decreased from the workforce, resulting in an inflation of total labour productivity within the economy. Bloom et al. (2025, p.29) also states how this between-firm reallocation is not a ‘process of creative destruction’, characterized by ‘Schumpeter’, which is when innovations in the production process replace outdated production, but rather mostly just ‘destruction’. Due to lockdown procedures resulting in the inability of lower productivity sectors to continue operating, these sectors were in essence frozen without the creation of new productions or firms as alternatives. Without this creation, the market for these sectors remained without supply and workers were put on furlough, funded through the government, to prevent mass redundancies.

Hence, this introduces a potential drawback to this paper’s empirical analysis as the positive between-firm effect on total labour productivity could result in an omitted variable bias. The lockdown stringency is associated with a negative effect on GDP per hour worked, but a higher period of the stringency index can also be associated with higher levels of lockdown measures and thus sectoral shutdowns concentrated in lower productivity industries. This means the model may be subject to overestimating the WFH rate’s positive effects on productivity, if the stringency index control variable is overestimating its own negative effects on GDP per hour worked. A clear limitation of this model is that it also does not incorporate the heterogeneity of labour productivity across sectors, which may help to account for these between-firm effects. To test for the severity of the positive between-firm effects on labour productivity, a quantitative analysis is made to measure the extent to which workers, out of work during a given period over the pandemic, were concentrated in either lower or higher productivity sectors, relative to normal employment distributions.

Assessing the Distribution of Furloughed Workers by Sectoral Productivity

Quantifying the extent of positive between firm effects is aimed in identifying that the possibility of an omitted variable bias could be present within the independent variables, which would provide evidence of a potential limitation to the empirical analysis. Data from the furlough scheme is sourced from HM Revenue & Customs (2021) for this analysis, which provides a comprehensive measure of the levels of absent workers due to the pandemic, including the number of workers on furlough per sector. Using sectoral productivity levels from 2017 as a baseline, sourced from a report by Castañeda-Navarrete and López-Gómez (2022, p.12), the following formulation identifies the concentration of workers from either high or low productivity sectors furloughed during the pandemic, compared to the normal economy-wide distribution from 2017:

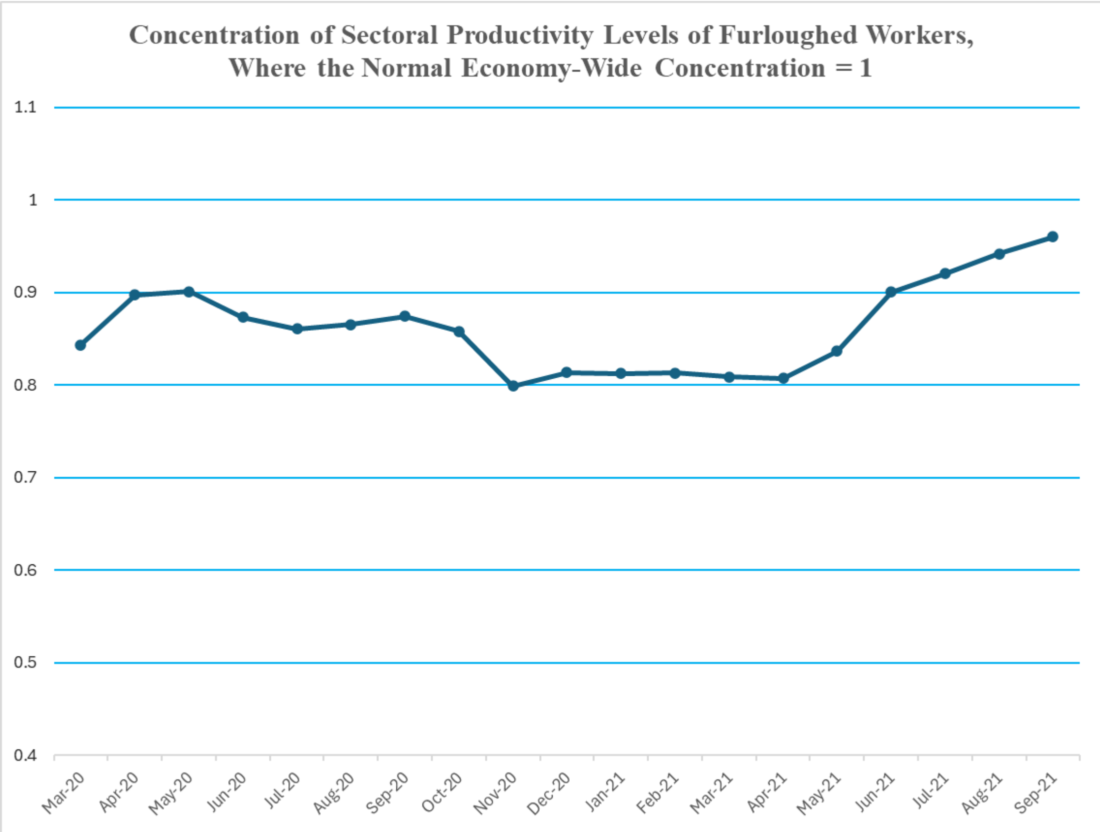
FORMULA 2-1

$$Furlough\ Concentration_{\ t} = \sum_{i=1}^{n} \left(\frac{Furloughed\ workers\ in\ sector\ i,_{t}}{Total\ furloughed\ workers_{\ t}} \times Sectoral\ productivity\ level\ i \right)$$

Each sector share of the work force furloughed, at period t, is multiplied by the corresponding sectoral productivity level, which is a ratio of sector productivity relative to the whole economy productivity level from 2017, used as a baseline.

Aggregate productivity is dependent on the productivity levels of contributing sectors and also the 'relative size' of each sector contribution (Castañeda-Navarrete and López-Gómez, 2022, p.14). The sectoral productivity levels taken from Castañeda-Navarrete and López-Gómez (2022, p.12) show the output per worker for a given sector as a ratio to the output per worker of the whole economy. The baseline levels of sectoral productivity taken from 2017 prices, with respect to the number of workers corresponding to each sector, provides an index value of output per worker for the whole economy in 2017 equal to 1. From FORMULA 2-1, instead of weighting sectoral productivity levels by sectoral employment shares, sectoral productivity levels are weighted by furloughed worker shares for each sector. By comparing the sector distribution of the furlough scheme to a pre-pandemic baseline year, this analysis accesses the extent to which furloughs were concentrated in lower or higher productivity sectors compared to normal economy wide distributions of sector productivity. If FORMULA 2-1 outputs a result less than 1, it can be interpreted that a relatively higher number of furloughed workers come from lower productivity sectors, relative to the normal economy-wide distribution of sector productivity. If FORMULA 2-1 outputs a result more than 1, a relatively higher number of furloughed workers come from higher productivity sectors, relative to the normal economy-wide distribution. FORMULA 2-1 outputs the following results:

FIGURE 2-4 Concentration of Sectoral Productivity Levels of Furloughed Workers



The HM Revenue & Customs (2021) dataset on the total number of workers furloughed per sector includes daily observations, which are then averaged into monthly values. Monthly averages are then converted into their monthly sectoral share of the workforce furloughed and weighted by normal economy-wide sectoral productivity levels from 2017. Each weighted sectoral share of the work force furloughed is then summed to give the monthly distribution of furloughed workers with respect to their sector specific productivities, relative to normal economy-wide productivity levels.

It is found that a disproportionately higher share of workers are furloughed from lower productivity sectors persistently throughout all months of the furlough scheme. This strongly suggests that the share of workers absent from the workforce and on the furlough scheme would have contributed to a rise in between-firm effects on labour productivity. Workers were disproportionately reallocated away from lower productivity sectors which would have resulted in an inflation to labour productivity, as a higher proportion of high productivity workers will have remained in the workforce relative to low productivity workers. The severity of the contribution that furloughed workers had towards an increase in between-firm effects is relative to how much the output result for each month deviates below 1, and the share of furloughed workers relative to the workforce for each month. Hence, this result supports the potential for an omitted variable bias of the WFH rate.

However, positive between-firm effects only explain a potential omitted variable bias during the pandemic period. As this empirical analysis stretches from 2019 to 2024, WFH's positive effect on productivity still persists even after the end of the pandemic. Also, considering the stringency index has a larger range and mean relative to the WFH rate, it makes sense as to why the WFH rates' positive effect on productivity per hour is relatively larger than the stringency index's negative effect on productivity per hour. Therefore, the supporting evidence of positive between firm effects from FIGURE 2-4 is not likely to overturn the positive estimation of WFH on productivity.

Combined Effects & Concluding Remarks

WFH is found to have a positive relationship with productivity per hour but is subject to the possibility of some omitted variable bias. Existing literature from Barrero, Bloom and Davis (2021, p.30) also considers that WFH has a positive effect on productivity per hour, by the amount of a 1% increase relative to pre-pandemic levels. When also considering reduced commuting time, Barrero, Bloom and Davis (2021, p.29) estimate an aggregate increase of 4.6% to overall productivity due to increased working hours increasing total output, where theory on switching to WFH from commuting is demonstrated in Chapter 1 of this paper. These cumulative effects result in a significantly enhanced positive impact on total productivity per worker.

Future research on WFH and its effects on productivity may find that using productivity per worker is a more economically meaningful measure of productivity when wanting to account for reduced commuting time effects; for instance, using a metric of output per hour when a reduction in commuting time results in an increase in total hours of work may fail to capture productivity meaningfully. For example, if productivity per hour decreases by 1%, but total hours worked have increased by 5%, then output per worker still increases by 3.95%, but crucially, the number of workers does not change with this increase in hours of work.

An argument could be made that an increase in hours of work across a constant number of workers could result in an increased strain on workers, for instance in the form of increased stress and fatigue, where if this strain is extreme enough this could even lead to a lower productivity per hour which offsets a positive effect on productivity per worker. However, labour supply theory from FIGURE 1-2 demonstrates how a worker could still feasibly increase their work hours while maintaining a constant ratio of work hours to leisure hours when switching to WFH arrangements. Holding the ratio of hours worked to hours spent indulging in leisure constant, increases in hours worked can still be compensated with more leisure time with a switch to WFH, which may benefit in reducing any extra strain on workers associated with working longer hours. Ultimately, workers' choices come down to their preferences, and optimal levels of work and leisure will vary from worker to worker. However, at a macroeconomic level, shifts towards WFH through the labour supply mechanisms discussed within this paper are guaranteed to generate, to some degree, increases in total hours worked. This will not only benefit workers by improving their labour-leisure trade-offs, allowing them to reach higher levels of utility under the theory presented in Chapter 1, but employers will also benefit from the ability to employ a greater number of work hours at a given wage rate.

In conclusion, if an increase in total hours worked at the economy-wide level is accompanied by an increase in productivity per hour, these effects will result in an even larger increase in productivity, for instance when measured using a per worker metric. When also considering that this increase in hours of work could be accompanied by a downward pressure on the wage rate, in this best-case scenario of how WFH can affect productivity, employees labour costs could also be relatively lower. If however an increase in total hours worked at the economy-wide level is accompanied by a decrease in productivity per hour, then the productivity per worker could instead decrease; evidence from Gibbs, Mengel and Siemroth (2021, p.3) is presented within this paper and demonstrates how an IT services company experienced a large fall in worker productivity during the pandemic, even though this type of firm should typically have a strong feasibility to implement WFH practices. Despite productivity per worker having decreased in this scenario, a shift to WFH creating downward pressure on the wage rate could in effect compensate for a lower productivity per worker. However, this scenario does raise an issue of wasted resource allocation with respect to hours of work and decreased worker efficiency.

Appendix

FIGURE 2-4 Concentration of Sectoral Productivity Levels for Furloughed Workers

Year/Quarter	Month	Concentration
2020 Q1	March	0.843
2020 Q2	April	0.897
2020 Q2	May	0.900
2020 Q2	June	0.873
2020 Q3	July	0.861
2020 Q3	August	0.865
2020 Q3	September	0.874
2020 Q4	October	0.858
2020 Q4	November	0.799
2020 Q4	December	0.813
2021 Q1	January	0.812
2021 Q1	February	0.813
2021 Q1	March	0.809
2021 Q2	April	0.807
2021 Q2	May	0.837
2021 Q2	June	0.900
2021 Q3	July	0.920
2021 Q3	August	0.942
2021 Q3	September	0.960

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