The Origin and Cost of Daily Labor Supply Biases

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March 12, 2025

Abstract

This paper argues that workers' daily labor supply is neoclassical when they know wages precisely. In these instances, workers deliberately trade off income and leisure, and behavior reflects normative preferences. However, when wages are uncertain, workers rely on heuristics, and their behavior is biased. Consequently, workers may appear rational or behavioral depending on the level of uncertainty. Empirically, London taxi drivers generally exhibit a large Frisch elasticity, but labor supply is non-monotonic and reminiscent of reference-dependence when wages are risky. I derive the welfare losses from this behavior, which are small—around one percent of income—because wages are rarely uncertain enough to trigger biases.

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1 Introduction

Labor supply responses to wage changes are the focus of a vast literature in economics and serve as parameters in models that inform normative topics, such as the efficiency of income taxes (Blundell and MaCurdy, 1999; Keane, 2011). However, in settings where workers have complete control over their daily labor supply, it is unclear whether decision-making is consistent with the neoclassical model. For example, New York cab drivers have been estimated to exhibit behavior in line with (Buchholz et al., 2023; Farber, 2005, 2008, 2015), and contrary to (Camerer et al., 1997; Crawford and Meng, 2011; Thakral and Tô, 2017), this canonical model.

Reference-dependence, which induces behavior like income targeting, provides a popular account of non-neoclassical labor supply (O'Donoghue and Sprenger, 2018). This poses problems for researchers. In particular, there is an ambiguity over whether the unequal treatment of gains and losses reflects genuine preferences (Bernheim and Taubinsky, 2018; Reck and Seibold, 2020). Further, the origin of reference dependence lies in decision-making under risk (Kahneman and Tversky, 1974, 1979; Kőszegi and Rabin, 2006), but there has been little consideration of the impact of uncertainty on daily labor supply choices.[1]

This paper seeks to make two contributions. First, it aims to understand when heuristics may be important for determining labor supply, if at all, by exploring the effect of wage risk on behavior. Second, it studies welfare losses due to heuristics by distinguishing between optimal and biased labor supply, where the former is revealed on occasions where wages are predictable.[2] The rise of gig work has given renewed importance to understanding how workers respond to fluctuating wages. The results in this paper suggest that excessive wage volatility inhibits workers' ability to exploit flexibility, which may concern policymakers.

Motivated by prospect theory, which is cast in the context of decision-making under risk (Kahneman and Tversky, 1979), I hypothesize and evince that when workers know their wages precisely, they exhibit large and positive labor supply responses. This behavior likely reflects normative preferences over income and leisure since individuals can deliberately trade off these factors. However, when the wage is uncertain, workers rely on heuristics and exhibit behavior like income or hours targeting.

[1] For example, Farber (2015) provides a variance decomposition of daily wages for New York cabdrivers but does not estimate separate labor supply responses for different levels of variance in the wage. Similarly, Buchholz et al. (2023) estimates a matrix describing the stochastic evolution of wages but does not consider how variance affects behavior.

[2] Broadly, I follow Kahneman and Tversky (1974) and use "heuristics" to describe a process of rule-of-thumb decision-making and "biases" to describe behavior that does not maximize normative utility.

Consequently, workers lose out when they cannot readily infer the wage because they do not ensure that their intratemporal optimality condition holds.[3]

The empirical context for this paper is the private hire taxi industry in London, UK. Several features of this setting are attractive for studying daily labor supply. Drivers pick when and where to operate and are paid by the job. Unlike the New York context, these drivers do not suffer from schedule rigidities stemming from shared medallions, and a third-party firm allocates them jobs. Drivers lease their vehicles from this firm, which can be used for leisure but not in the service of other ridesharing platforms, so there is no risk of conflating labor supply responses and multi-apping.

London Underground strikes offer a natural experiment that saliently stimulates demand and raises wages while plausibly leaving driver labor supply otherwise unaffected. Using information from the UK equivalent of a FOIA request, I date these strikes and study their impact on wages and daily labor supply. The most prominent strike increased wages by seven percent. In turn, drivers increase their labor supply in almost exact proportion, which implies a Frisch elasticity of one. From a normative perspective, the response is consistent with a quadratic cost to hours worked in a utility function that is linear over income and isoelastic in leisure.

To study labor supply further, I construct a new instrument for hourly earnings: the continuation mean wage (CMW). For a given driver-shift, the CMW is the average wage of drivers who start a shift at the same time and place as the driver under consideration ends their shift. It is an empirical counterpart to the wage drivers would expect to receive if they continued driving and has two advantages over the oft-used leave-out mean wage (LOMW). First, the CMW isolates wage variation that persists after a worker's shift ends, which is the relevant quantity to compare with drivers' marginal rate of substitution. Second, common labor shocks mean the LOMW is endogenous. The CMW uses variation from drivers who have made different extensive margin decisions and are, therefore, less likely to share shocks.

Using the CMW as an instrument for drivers' wages yields the same result as the Underground strikes natural experiment. That is, drivers exhibit large and positive behavioral responses to an increase in their hourly wage rate across the panel of data I observe and not just during strikes. The LOMW does not replicate this finding for the reasons discussed above. Therefore, this result validates the CMW as an instrument

[3] Kahneman and Tversky (1991) argues that reference-dependence can emerge in riskless settings and describes phenomena consistent with this (*e.g.*, the endowment effect (Kahneman et al., 1990)). However, given the significant wage risk that cab drivers face, uncertainty constitutes a plausible cause of reference-dependence, which I evince in this paper.

and provides additional support to the neoclassical view of daily labor supply, which puts a positive sign restriction on the Frisch elasticity.

However, reference dependence is not a blanket description of all behavior; rather, it provides a model that is relevant for certain settings. Prospect theory, which underpins reference dependence and is cast in the context of uncertainty, suggests that it is necessary to consider the impact of wage risk on behavior. Moreover, reference-dependent labor supply implies that hours are non-linear with respect to the wage (DellaVigna, 2009), so a more flexible conditional expectation function is needed to take non-neoclassical behavior seriously.

To measure risk in drivers' wages, I construct the variance of wages across drivers who start their shifts at the same time and place (*i.e.*, the second-order analog of the LOMW). Intuitively, it is possible to infer the variance in wages a driver faced by looking at their peers who made the same initial labor supply decision. Partitioning driver shifts into quintiles of this variance distribution reveals that the effect of wages on hours remains positive but decreases considerably as the uncertainty of the wage rises. In the top risk quintile, labor supply responses are all but mute.

To study the shape of drivers' labor supply functions under different levels of wage uncertainty, I use new semi-parametric methods in conjunction with a control function model (Cattaneo et al., 2024; Wooldridge, 2015). For shifts that fall into the 20 percent of wage risk, labor supply functions are non-monotonic and reminiscent of reference-dependent labor supply. Hours initially increase when wages are low but then begin to fall as the wage rises further until, eventually, they begin to rise again. The elasticity of hours for the intermediate range of wages is negative but greater than minus one, which suggests a role for income targeting alongside other biases.

I derive a behavioral welfare expression (BWE) for losses due to biased labor supply, imposing minimal structure. The approach assumes limited concerns over consumption and hours worked, which enter utility additively, and is applicable in other continuous decision-making settings. The BWE reveals the average marginal bias of suboptimal labor supply in terms of the wedge in the intratemporal optimality condition between a driver's wage and their marginal rate of substitution between consumption and leisure (MRS) (Allcott and Taubinsky, 2015). All else equal, hours targeting dominates income targeting because the latter induces a costly covariance between the average marginal bias and workers' hours (*i.e.*, when the value of leisure most exceeds the value of an additional dollar).

To estimate the BWE, I treat the labor supply curve from the control function model under the lowest quintile of wage risk as optimal because workers can deliberately trade off income and leisure. For biased labor supply, I take two approaches. First, I use the control function model estimate under the highest wage risk quintile. Second, I consider that two groups of workers comprise this aggregate function. The distinct slopes and kinks in the estimated labor supply function provide sufficient variation to identify a structural model where some fraction of drivers target hours and the remainder target income.

Estimates of the model's parameters imply that 85 percent of drivers target a shift length of 7 hours. This high proportion aligns with the BWE's intuition that hours targeting is generally less costly; most drivers optimally pick a less costly bias. However, these drivers face more severe reference dependence, so they are completely unresponsive to wage fluctuations. Drivers who target income aim to earn £130 per shift. Their hours fall between wage rates of £15 and £20 and rise elsewhere.

To address unobserved consumption, I assume consumption equals average daily income, which implies that workers have no additional income sources and that they perfectly smooth consumption.[4] Since labor supply is meaningfully biased only one-fifth of the time while consumption depends on the totality of behavior, this approach reasonably but mechanically attenuates the welfare impacts of biases. To assess the severity of the workers' biases when they are evident, I also present results under an alternative scenario in which behavior is consistently suboptimal, keeping consumption constant at the expected level of income given this pattern of labor supply.

The welfare effects of labor supply biases are small at around one percent of daily income because wages are seldom sufficiently risky to engage drivers' heuristics. This is robust to considering worker heterogeneity. Interestingly, the stronger reference dependence of drivers who target hours means they are not discernibly better off than those who target income. These results suggest that labor supply biases do not materially affect welfare in this setting. Interestingly, this finding masks the severity of behavioral biases. If drivers consistently deviated from their optimal labor supply in this way, welfare losses would be an order of magnitude larger. Consequently, attention should be paid to labor markets where wages are very unpredictable.

Related literature. This paper connects most closely to the literature studying daily labor supply choices in settings where workers have fine control over their hours.

[4] Ruling out whether drivers have other sources of income is not possible with this data, but seems a reasonable assumption given their full-time employment in this profession. Further, it is uncommon for individuals in this part of the income distribution to receive significant capital income.

Much of this literature has made use of observational data from cab drivers in New York City (Camerer et al., 1997; Crawford and Meng, 2011; Farber, 2005, 2008, 2015), but studies have also leveraged field experiments in other settings (Andersen et al., 2014; Fehr and Goette, 2007; Dupas et al., 2015), and the growth of ridesharing has provided another window into workers' behavior (Angrist et al., 2017; Chen et al., 2017). Yet, disagreement persists about the nature of workers' daily labor supply (see most recently Buchholz et al. (2023) and Thakral and Tô (2017)).

This paper's primary contribution is to reconcile these disparate findings. I evince that workers' labor supply is neoclassical when they know their wages precisely, but uncertainty gives rise to heuristics and labor supply biases. This is an application of an influential literature studying decision-making under uncertainty (Kahneman and Tversky, 1974, 1979). I use a forward-looking instrument for the wage rate, a point emphasized by Buchholz et al. (2023), which gives the general impression of neoclassical behavior. However, when uncertainty is severe, labor supply is consistent with targeting behavior. To my knowledge, this is the first paper to trace out an empirical labor supply curve reminiscent of reference dependence.

Further, this paper's description of daily labor supply fits the largely negative results on reference dependence found using field experiments (Andersen et al., 2014; Fehr and Goette, 2007). While these studies induce random variation in workers' wages, they simultaneously tend to introduce certainty; a point is made of explaining the experiment's treatment to subjects. Analogously, surge pricing on Uber triggers neoclassical behavior because the subsequent wage variation is explicitly known by drivers (Chen et al., 2020).

The paper's hypothesis also offers a way to study the normative implications of daily labor supply under the assumption that workers reveal their true preferences when they are fully informed of their choices (*i.e.*, when wages are predictable) (Allcott et al., 2019; Bernheim and Taubinsky, 2018; Mullainathan et al., 2011). In doing so, I derive a novel approximation for the average marginal bias of suboptimal labor supply that assumes limited concerns over income and leisure, which enter utility additively. The expression is broadly applicable to other continuous choice settings.

This paper proceeds as follows: section 2 describes the data and institutional setting, section 3 presents estimates of the Frisch elasticity of daily labor supply, section 4 uses a control function to trace out the shape of workers' labor supply, section 5 theoretically derives welfare losses when labor supply deviates from the optimum, section 6 quantifies welfare losses due labor supply biases, and section 7 concludes.

2 Empirical Setting and Data

This section discusses the institutional details of the empirical setting and the data available, as well as presenting some summary statistics for the analysis sample.

2.1 Institutional Details

This paper uses data from a private hire taxi firm in London. The firm leases cars to its self-employed drivers, who are allocated jobs to complete via an application on their mobile phone, which they can log in to work on at any time.[5] Jobs are requested by customers either on another application or over the phone. The car can be used for leisure but not for other commercial purposes, such as serving competing ridesharing platforms. As a result, there is no conflation between intensive margin labor supply responses and switching between other work (Caldwell and Oehlsen, 2018).

Jobs are allocated by a central computer system, which ranks a number of the closest cars according to how suitable they are for the job. The suitability of a car is determined by a number of factors, including distance to pick up, the size of the car, and whether the car is currently occupied. The top-ranked car is then allocated to the job.[6] *De jure*, drivers can decline a job, but it is rare because they are disadvantaged in future job allocations, and the destination of a job is not visible to drivers, meaning there is little basis for doing so.

Drivers are paid by the job and generally receive around 60 percent of the fare the customer pays. The fare is primarily determined by the distance of the journey, though it varies slightly with the type of job, the number of passengers, the number of stops, the time of day, and the location of the job.[7] There is neither separate compensation for the duration of a job nor any dynamic pricing. For some jobs, a value-added tax of 20 percent of the total transaction value is payable, and drivers must pay their share of this from the fare they receive, which I account for in the analysis below. Drivers' earnings are paid out on a weekly basis by the firm.

[5] A typical lease lasts for 12 weeks. Over the span of this data, the average cost of a lease is around £200 per week. The cost of a lease includes various maintenance costs and commercial insurance for the driver.

[6] Drivers can also sign up for pre-booked rides, but this is only done for the first job in a shift because drivers cannot ensure they will be sufficiently close to complete other pre-booked jobs on time.

[7] A linear regression of the passengers' fares on distance interacted with a dummy for the fare schedule yields an R-squared of over 0.8. The type of job is affected by the type of car requested and supplied (*e.g.*, Ford Galaxy or Toyota Prius) and the customer (*e.g.*, corporate client or individual customer).

2.2 Data

I observe job-level data from January 2014 to December 2019, which is electronically recorded from drivers' phone applications. Each job observation contains information on the driver's identity, the customer's fare, the start and finish time of the job, and the start and finish location, among other variables. I construct driver payments using a series of documents that describe the commission the firm deducted from customer fares over time. Using information from the UK equivalent of a FOIA request, I code whether a job occurred during a London Underground strike.

The raw data is cleaned analogously to Haggag and Paci (2014).[8] Broadly, this process removes shifts if they contain anomalous variables, are missing key variables, or are canceled. I follow the literature and aggregate job-level data into shifts by allocating jobs to the same shift if the same driver completes them and there is no break longer than six hours (Farber, 2015; Thakral and Tô, 2017). Then, I remove shifts that contain anomalous variables. Shift length is the difference in time between the start of the first job and the end of the last job, where I also deduct the excess duration of the breaks that exceed an hour.[9] Wages equal income divided by shift length.

To construct the study sample, I impose two restrictions on the data, which allow all the analysis to be conducted on one sample. First, drivers must have completed a shift during at least one Underground strike. Second, a shift must occur alongside at least one other shift.[10] This ensures the CMW, LOMW, and a measure of wage risk can always be calculated. This leaves over three million shifts driven by 5,500 drivers. Comparing variable means between this sample and the complete data in table A1 indicates there is no meaningful selection.[11]

2.3 Summary statistics.

Table 1a presents summary statistics at the job level. The typical job lasts half an hour with a standard deviation of 19 minutes. During this time, an average job covers 13 kilometers, and the driver receives £17. Table 1b displays shift-level summary statistics. On average, a shift lasts seven hours, which rises by 1.5 hours when excess break time is not deducted. The mean shift wage is £16 per hour. With shift length, this translates to a typical daily income of £104. Lastly, figures 1a and 1b illustrate the dis-

[8]Further details are provided in appendix A.

[9]This provides a more accurate picture of labor supply, and results below are robust to this adjustment.

[10]I define "alongside" using a measure of time and space in subsection 3.2.

[11]The age differences between samples arise mechanically because the Underground strikes occurred relatively late on in the data.

Table 1: Summary Statistics

(a) Job Summary Statistics

Statistic	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
Job time (minutes)	34.31	18.88	20	32	44
Job distance (kilometers)	12.72	13.43	4.45	7.96	15.94
Driver fare (£)	17.28	13.58	8.41	12.54	21.20

(b) Shift Summary Statistics

Statistic	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
Number of jobs	6.25	2.50	4	6	8
Shift length (hours)	6.81	2.50	4.86	6.62	8.51
... with breaks (hours)	8.34	3.15	5.94	8.22	10.55
Shift income (£)	104.04	44.96	70.90	98.60	130.80
Shift wage (£/hour)	15.54	4.61	12.23	14.88	18.11

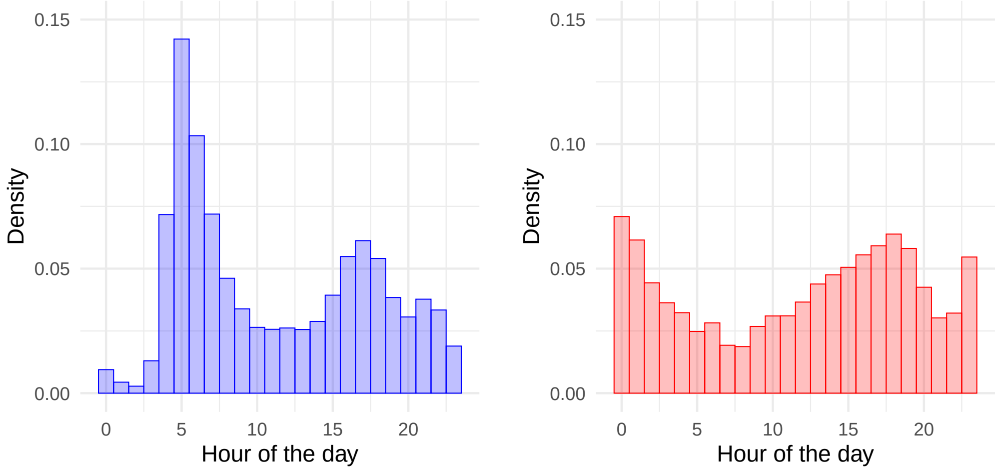
Notes: Table (a) presents summary statistics for the job-level data after data cleaning. Table (b) presents summary statistics for the shift-level analysis sample after data cleaning.

tribution of shift start and end times, respectively. Shifts most commonly start either early in the morning (*e.g.*, around 6 am) or late in the afternoon, while shifts typically end at 5 pm or midnight. Shift end times are more diffuse than shift start times.

3 The Frisch Elasticity of Daily Labor Supply

This section takes a variety of approaches to estimate a Frisch elasticity of daily labor supply. It uses a natural experiment, London Underground strikes, and a new instrumental variable, the continuation mean wage, to isolate exogenous variation in drivers' wages. Both strategies yield a positive Frisch elasticity close to one. However, heterogeneity analysis suggests this depends on the extent of wage risk: the more

Figure 1: Shift Start and End Times



(a) Shift start times

(b) Shift end times

Notes: These figures present the empirical distribution for shift start and end times in the analysis sample.

risky drivers' wages, the lower the Frisch elasticity estimate.

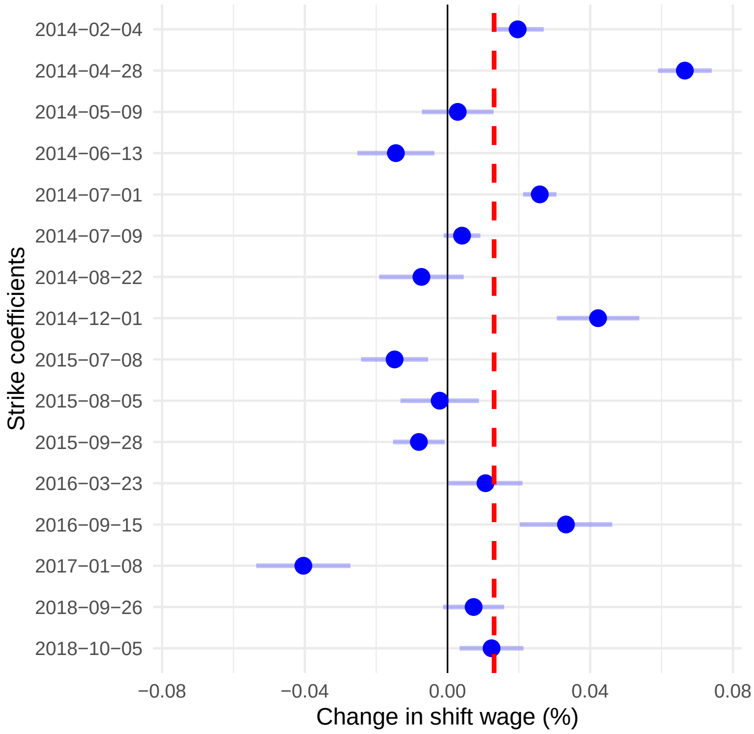
3.1 London Underground Strikes

London Underground strikes serve as a natural experiment to estimate a Frisch elasticity. They generally stimulate the demand for private hire taxis, which increases wages while leaving labor supply otherwise unchanged. That is, wages tend to rise because drivers spend a larger share of time carrying passengers. Given that strikes are short-lived, the marginal utility of income is likely constant, so this variation identifies a Frisch elasticity of daily labor supply.

Information on Underground strikes has been provided online by Transport for London (TfL) thanks to a Freedom of Information request, and I verified reported dates by checking historical media coverage.[12] Table 2 documents the first-stage effect of these strikes on the log wage. The table reports the average and individual effect of Underground strikes. This and all subsequent specifications include driver fixed effects and dummy variables for day of the week-month-year interactions, a coarsened measure of the start time of the shift (*e.g.*, early morning, afternoon rush

[12] Some of the strikes were canceled (*e.g.*, a strike by the National Union of Rail, Maritime and Transport Workers (RMT) on 05/24/20144), and some were too short to plausibly impact driver wages (*e.g.*, a strike from 21:30 on 03/07/2015 to 04:00 on 03/08/2015, again, by the RMT).

Figure 2: Strike First Stage Coefficients



Notes: This table presents coefficients from two regressions with the natural logarithm of the shift wage as the dependent variable. The red dashed line indicates the estimated coefficient on a binary dummy variable for whether a shift occurred during a strike. The blue dot and whiskers denote coefficient estimates on individual strike dummy variables.

hour, *etc.*), bank holidays, and Ramadan because a large share of drivers are Muslim.

Strikes have a modest, statistically significant effect on wages. The average strike raises wages by just over one percent, but this masks large heterogeneity. For example, the strike in April 2014 caused a seven percent increase in wages, while three strikes discernibly reduced the wage, likely due to their impact on traffic. Underground strikes increase traffic, as well as demand, because TfL provides more buses and people commute in their own vehicles. Drivers are not compensated for the increase in travel time, which can outweigh the increase in demand.

Given the relevance of Underground strikes for wages, the validity of the approach requires that strikes must not affect labor supply other than through their effect on the wage rate. Commonly cited reasons for Tube strikes are poor pay and working conditions. It is not obvious why these concerns should relate to drivers' labor supply. However, the determinants of strike timings may be different from their fundamental cause. Strikes may be set in order to cause maximum disruption, corresponding to when drivers cannot easily respond to an increase in demand.[13] This would attenuate positive labor supply responses. *Ex post*, this concern seems limited because of the large behavioral elasticities I estimate.

I consider two specifications for using Underground strikes as an instrument for the wage. First, a single dummy variable denoting a strike, and second, a series of strike-specific dummies. The single dummy estimate can be seen either as reflecting a constant treatment effect or as a LATE under the conditions from De Chaisemartin (2017), which are weaker than the standard monotonicity requirements that are likely violated given the heterogeneous impacts of strikes (Angrist et al., 1996). A single dummy also benefits from the results in Angrist and Kolesár (2024), which suggest attractive properties of just identified IV. The strike-specific instrument recovers a LATE under the conditions in Mogstad et al. (2021).

Table 2 presents the results from an OLS estimator in the first column. This estimate is negative, reflecting several sources of bias: division bias, correlated shocks to supply and demand, and aggregate shocks to labor supply that reduce wages for all drivers. Column two instruments for the wage with a uniform strike dummy variable, and column three instruments for the wage with strike-specific dummy variables. The F statistic for both instruments is large.

Unlike the OLS estimator, the estimates using 2SLS are positive and large because they circumvent the aforementioned sources of bias. As shown in table 2, instrumenting for the wage with a single strike dummy leads to a Frisch elasticity estimate of one, while using strike-specific dummies produces a larger estimate equal to 1.3. The difference between these numbers is statistically and quantitatively small. Moreover, these magnitudes align very closely with experimental results from Uber drivers in Angrist et al. (2017).

3.2 The Continuation Mean Wage

Underground strikes provide a useful window to study driver behavior, but their rare and binary nature makes it hard to investigate labor supply further. To resolve this, I develop a new instrument for drivers' wages: the continuation mean wage. For a driver-shift observation, the CMW is the average wage of drivers who start their shift at the same time and place as the respective driver ends theirs. In other words, it is

[13] See, for example, https://www.telegraph.co.uk/news/2017/01/08/government-accuses-union-bosses-co-ordinating-transport-strikes/.

Table 2: log(Shift Length) Regressions

	OLS	Strike	StrikeS	LOMW	CMW
log(Shift wage)	-0.15	1.01	1.26	0.17	0.93
	(0.00)	(0.16)	(0.08)	(0.01)	(0.03)
1st Stage F-Statistic	-	146.54	40.68	118,265.1	59,479.23
N	3,125,972	3,125,972	3,125,972	3,125,972	3,125,972
RMSE	0.335	0.428	0.465	0.343	0.417

Notes: This table presents estimates of the coefficient from linear regressions of shift length on the shift wage in natural logarithms. Column one uses an OLS estimator, and columns two to five use a 2SLS estimator. Column two uses the single strike dummy as an instrument, column three uses strike-specific dummies as an instrument, column four uses the LOMW as an instrument, and column five uses the CMW as an instrument. The first-stage F statistics for the instruments are reported, as are the sample sizes and RMSE of the estimators' predictions. Standard errors are in parentheses and are clustered at the driver level.

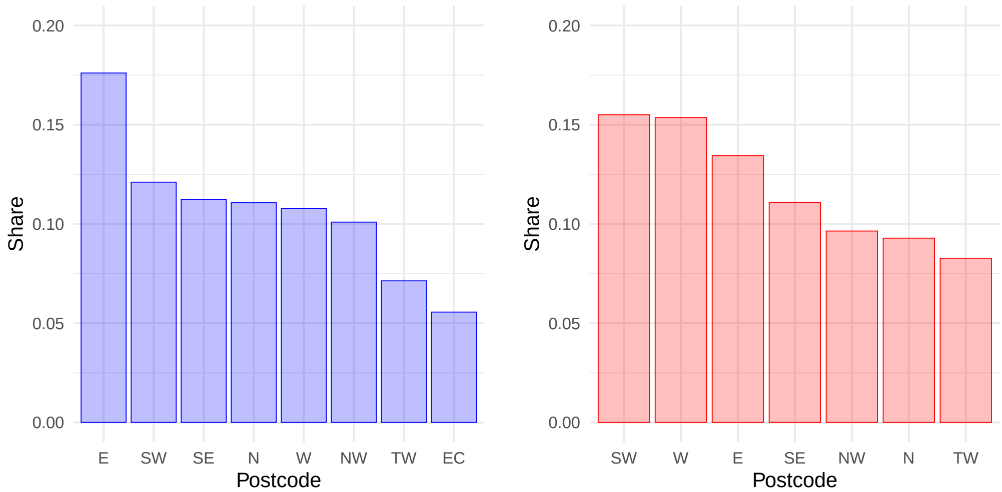
the wage the driver would expect to receive if they decided to continue their shift.

This variable requires defining "time" and "place". To discipline the approach, I use pre-existing measures of each. The firm creates a coarsened measure of time called the shift type, which breaks the day into eight blocks,[14] and UK postcode areas provide a convenient geographical unit. The top eight most common postcode areas to start and end a shift in are presented in figures 3a and 3b, respectively. Finer measures of time and place run into problems with sample size, but the results below are robust to alternative time blocks.

The CMW has two key advantages over a popular alternative instrument for drivers' wages, the leave-out mean wage. First, the CMW isolates variation in wages that persists after a driver's shift. This is the relevant quantity for drivers to compare with their marginal rate of substitution between income and leisure when making their labor supply choices. Conversely, the LOMW contains variation in wages that has passed and is no longer relevant for workers' decisions at the margin. Second, labor supply shocks may be correlated across workers, and to the extent they are, the LOMW remains contaminated with shifts in labor supply as well as demand. This issue is less likely to affect the CMW because it leverages variation from drivers who have not

[14] The bins are: [12:00 AM, 5:00 AM), [5:00 AM, 9:00 AM), [9:00 AM, 5:00 PM), [5:00 PM, 7:00 PM), [7:00 PM, 9:00 PM), [9:00 PM, 12:00 AM).

Figure 3: Top Postcode Areas



(a) Starting postcodes (b) Finishing postcodes

Notes: These figures show the fraction of shifts starting and ending in postcodes with a greater than five percent share.

made the same extensive margin decision.

These advantages are evident from the estimates in table 2. While the LOMW instrument yields a positive coefficient in column four, it implies a materially smaller behavioral response than the Underground strikes. Conversely, the CMW estimate in column five is statistically indistinguishable from the single dummy instrument for strikes in column three.[15] This supports the exogeneity of the CMW as an instrument for drivers' daily wages, and the F-statistic confirms it is highly informative. Therefore, there exists a valid source of exogenous wage variation that can be readily constructed from observational data, which contains ample variation.

3.3 Heterogeneity by Wage Risk

Given the additional variation contained in the CMW, it is possible to examine heterogeneous behavioral responses to wage shocks. In particular, I study how the Frisch elasticity of daily labor supply changes depending on the uncertainty in the wage that drivers face. This focus follows from the literature's reliance on reference-dependence

[15] As a robustness check, I control for the distance between the end location of a driver's final job and their home. This is not always observable and hence not included in the primary specification. When it is included, the CMW estimate increases and falls between the two strike estimates, which are almost unchanged from the inclusion of the new control.

to explain estimates of negative Frisch elasticities and the fact that this theory's origins lie in decision-making under risk (Kahneman and Tversky, 1979).

To quantify wage risk, I measure the standard deviation of wages among drivers who begin their shifts at the same time and place, which are defined analogously to the formulation of the CMW. Figure 4 presents the distribution of wage risk across shifts. The modal standard deviation is around £4 per hour. Intuitively, by looking at peers, it is possible to infer the wage risk a driver faced when they began their shift. A driver would have received the wage of another driver who began working at the same time and place, were they not allocated different jobs.[16]

Figure 5 shows an estimate of the Frisch elasticity for each quintile of the wage risk distribution using the CMW as an instrument. These coefficients come from fully interacted models to avoid omitted variable bias (Feigenberg et al., 2023). A clear pattern emerges where drivers are less responsive to higher wages when they are exposed to greater wage risk. Consistent with the CMW estimates in table 2, the middle quintile implies a Frisch elasticity of around 1.2, while the lowest wage risk quintile gives an estimate slightly about 1.5. Conversely, labor supply responses are all but mute in the riskiest wage quintile.

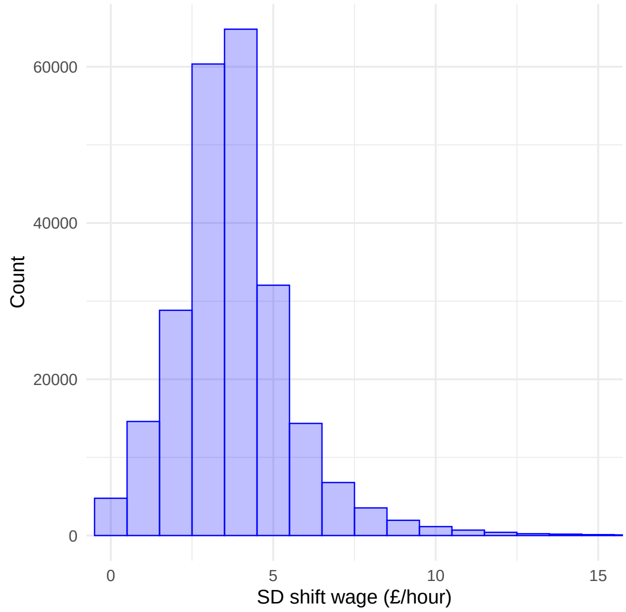
3.4 Discussion

A neoclassical model of labor supply cannot readily explain these patterns; reasonable degrees of risk aversion would predict only a negligible impact on the responsiveness of hours to wages as uncertainty increases. Conversely, prospect theory predicts that when wages are uncertain, drivers will use heuristics and exhibit behavioral biases, like income targeting (Kahneman and Tversky, 1974, 1979). This theory builds on two observations. First, people's decisions consider changes relative to a reference point. Second, individuals dislike lotteries that are neutral in expectation, but when forced into lotteries, they prefer smaller stakes.

Together, these phenomena imply a kinked utility function that generates a non-monotonic labor supply function. This poses an econometric challenge for the analysis above, which postulates a linear conditional expectation connecting hours and wages in natural logarithms. In other words, the decline in the Frisch elasticity when the wage is uncertain may reflect a differently shaped, as well as sloped, labor supply function. Section 4 deals with this issue by semi-parametrically estimating drivers'

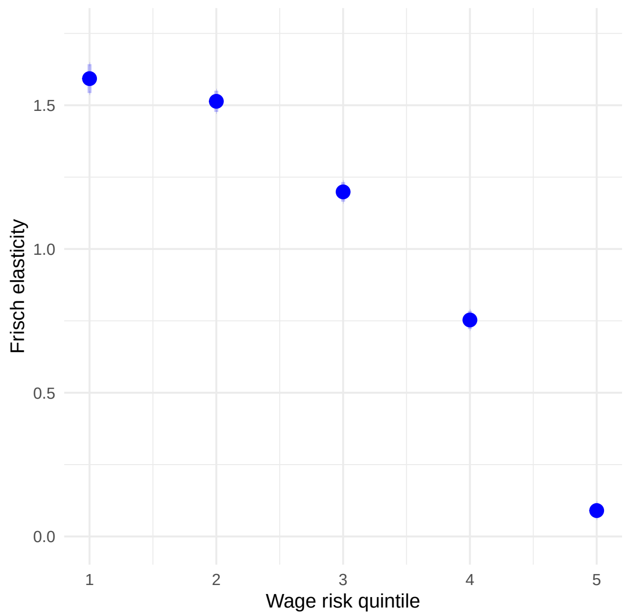
[16] In the empirical implementation, this logic is bolstered by the fact that it is conditional on driver fixed effects and other controls.

Figure 4: Standard Deviation of Shift Wages



Notes: This figure is a histogram of standard deviations in wages calculated at the postcode-shift type level. In the calculation, the denominator is $n-1$.

Figure 5: Frisch Elasticity by Wage Risk



Notes: This figure presents estimates of the Frisch elasticity by quintiles of the wage risk distribution analogously to the coefficient in column five of table 2.

behavior.

This argumentation also has normative implications; if transitory uncertainty induces the impression of different weightings for gains and losses, then it is unlikely to reflect normative preferences. Why would a driver's trade-off between a dollar and an hour of leisure vary with the variance in the distribution of wages they may have received? It is not impossible to formulate an answer to this question, but it is also plausible that drivers would rather behave as they do without heuristics, where they make an informed and deliberate choice. In sections 5 and 6, I pursue this logic to infer welfare losses by comparing labor supply when the wage is risky to when it is stable.

4 The Daily Labor Supply Function

This section estimates drivers' labor supply function without placing restrictions on the shape of the relationship between hours and wages. To do so, I use a control function in combination with new non-parametric tools. The results imply that during low-risk shifts, drivers' labor supply function is neoclassical and all but isoelastic. However, when wage risk is high, hours are non-monotonic and resemble reference-dependent labor supply.

4.1 Estimation

To deal with the endogeneity of drivers' wages, I use the CMW to construct a control function (Wooldridge, 2015). This necessitates stronger assumptions than those in section 3 because consistency requires that unobserved variables confounding labor supply are mean independent of the CMW. To test the plausibility of this more stringent assumption, I compare the Frisch elasticity of the labor supply function implied by the control function approach with results from the 2SLS estimator. They are very close, suggesting that this stricter requirement is satisfied.

Estimating drivers' daily labor supply function with a control function is done in several steps. First, I create residualized versions of the shift length, wage, and CMW variables by regressing them on all of the controls fully interacted with dummies for the quintile of wage risk. Then, I add their respective means so the variables are at the appropriate level. This ensures the subsequent analysis is conditional on the complete battery of controls used in the previous sections. Below, I assume the variables are residualized but do not refer to them as such for brevity.

Second, I regress the wage on a full interaction between the CMW and dummies for quintiles of the wage risk distribution. Using the parameter estimates, I construct the predicted error. Multiplying this variable with a constant parameter, which needs to be estimated, yields the control function in the next step. It is possible to construct a more flexible (*e.g.*, quadratic) control function by computing the square of the predicted error, and the results below are robust to this approach.[17]

The third and final step is to estimate drivers' labor supply function for different quintiles of the wage risk distribution. Denoting shift length, wages, and the predicted error as h, w, and ε, respectively, I consider estimating coefficients in the equation,

$$h_{i,s} = f\big(w_{i,s}; \boldsymbol{\theta}_{r(s)}\big) + \beta_{r(s)} \cdot \varepsilon_{i,s} + u_{i,s}, \tag{1}$$

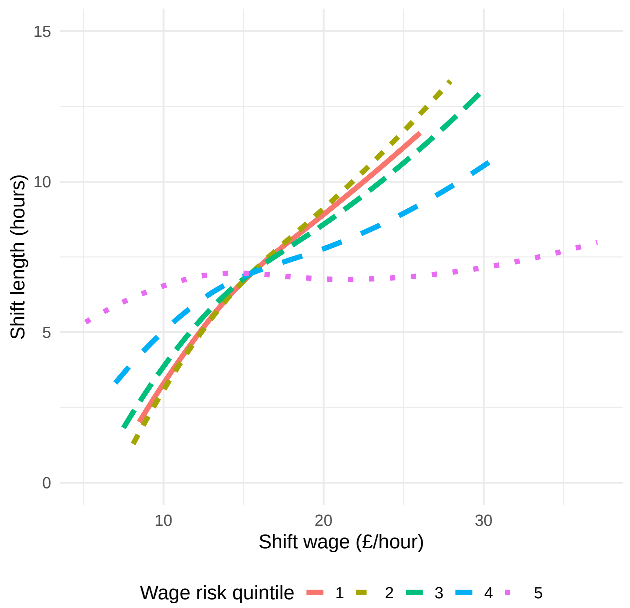
where i denotes an individual driver, s represents a particular shift, and the function $r(\bullet)$ determines the wage risk of a shift. The term $\beta_{r(s)} \cdot \varepsilon_{r(s)}$ is the control function. Note that setting $f(x; \boldsymbol{\theta}) = \theta \cdot x$ and estimating equation (1) with OLS is numerically equivalent to a 2SLS estimator with the CMW instrumenting for the wage.

Following Cattaneo et al. (2024), I set $f(x; \boldsymbol{\theta}) = \boldsymbol{\theta} \cdot \mathbf{b}(x)$, where $\mathbf{b}(\bullet)$ is a series of basis functions consisting of indicators that partition the wage into different bins. Therefore, $f(\bullet)$ is a function that is linear in constant coefficients but non-linear in the function's argument. Practically, I estimate equation (1) in `R` with the `binsreg` package, which minimizes the mean squared error, separately for each quintile of the wage risk distribution.

This strategy is essentially non-parametric in the relationship between hours and wages and can speak to the different functional forms predicted by non-neoclassical theories of labor supply. Importantly, it avoids the sensitivity of polynomial estimates to extreme values, which makes it possible to infer the slope of the labor supply function reliably at high or low wages. This is particularly important when trying to infer reference-dependence from the data, which implies a rising labor supply function when the wage is at either end of the distribution but a negative slope for an intermediate range of the wage.

[17] In doing so, it is necessary to square both sides of the original regression equation and estimate this new equation so as not to neglect Jensen's inequality. However, this approach is not without loss because it implies more structure on how the control variables from the first step affect wages and hours. Hence, it is not used in the main specification.

Figure 6: Labor Supply Function by Wage Risk



Notes: This figure presents predictions of labor supply as a function of wages for each wage risk quintile, using estimates from the control function method described in subsection 4.1.

4.2 Results

Figure 6 presents predictions of shift length as a function of the wage for different wage risk quintiles. The first three wage risk quintiles exhibit large and monotonic behavioral responses to increases in the wage rate. Running a log-log regression of hours on wages from the first quintile labor supply function implies a Frisch elasticity consistent with the strike estimates from table 2. Moreover, the R-squared exceeds 0.95, suggesting an isoelastic functional form. Therefore, this analysis paints a picture of behavior consistent with neoclassical labor supply when wages are predictable.

Conversely, labor supply in the top wage risk quintile is non-monotonic. It increases with the wage rate for low and high wages, but there is an intermediate range in which workers' hours decrease as their hourly earnings increase. This is most apparent when the fifth quintile labor supply function is presented alone, as in the blue line in figure 7. These changes in slope are highly statistically significant using the confidence bands constructed in the `binsreg` package (Cattaneo et al., 2024).

Behavior in the fourth quintile of uncertainty lies between this seemingly behavioral labor supply function and the neoclassical decision-making from less risky wage quintiles. Therefore, the non-parametric results from this section are in line with the heterogeneous Frisch elasticity estimates from linear regressions shown in figure 5. However, the most striking feature of figure 6 is how the *shape* of drivers' labor supply changes with uncertainty.

In particular, behavior in the riskiest quintile resembles reference-dependent labor supply. For example, a simplified version of gain-loss utility from prospect theory with a reference point over income would, theoretically, yield a qualitatively identical function (DellaVigna, 2009). In section 6, I show that estimated non-monotonic behavior is quantitatively consistent with two groups of drivers, one targeting income and the other targeting hours.

The following sections investigate the welfare consequences of this behavioral phenomena. I maintain the normative stance that behavior in low-wage risk quintiles reflects workers' genuine preferences over income and leisure, while labor supply when the wage is risky is biased and the consequence of heuristics that emerge because of uncertainty.

5 Behavioral Welfare Theory

Motivated by the empirical evidence in sections 3 and 4, I theoretically derive the welfare losses of workers who deviate from their optimal labor supply function. The expression, which I call the behavioral welfare expression (BWE), reveals the losses associated with biased labor supply as a wedge in the intratemporal optimality condition.[18] Further, a small number of readily estimable sufficient statistics comprise the BWE and map to familiar labor supply elasticities.

5.1 The Environment

Drivers derive utility from consumption c and disutility from hours worked h according to a utility function $U(c,h)$ subject to a budget constraint $c \leq w \cdot h + I$, where w is the wage rate and I is an exogenous, additional source of income. This implicitly assumes that workers have limited concerns over consumption and leisure. I impose standard conditions on the shape of the utility function and signs of the variables, and I omit exogenous income below since it is not important for what follows.

[18] The BWE relates closely to a continuous generalization of expressions for changes in consumer surplus stemming from a price change of a binary good (Allcott and Taubinsky, 2015), as shown in the appendix B.

Labor supply is suboptimal because drivers suffer from biases, which leads to two decision rules for consumption and hours, respectively,

$$\{\tilde{c}(w), \tilde{h}(w)\} \in \mathbb{B}(w), \tag{2}$$

where $\mathbb{B}(\cdot)$ is the choice set defined by the budget constraint inequality. If drivers were to behave optimally, then they would follow two optimal rules for consumption and hours, respectively,

$$\{c^*(w), h^*(w)\} \in \arg\max_{\{c,h\}\in\mathbb{B}(w)} U(c, h). \tag{3}$$

The object of interest is a money-metric measure of the change in utility due to a change from biased to optimal labor supply

$$\Delta U(w) = \frac{U\big(c^*(w), h^*(w)\big) - U\big(\tilde{c}(w), \tilde{h}(w)\big)}{U_c\big(\tilde{c}(w), \tilde{h}(w)\big)}. \tag{4}$$

This quantity varies with the wage rate. Therefore, I treat the wage as a random variable and consider the expected change in utility from a move to optimal behavior

$$\Delta U = \mathbb{E}_w\left[\Delta U(w)\right], \tag{5}$$

where $\mathbb{E}_w[\bullet]$ is the expectations operator that integrates over the distribution of wages.

5.2 Behavioral Welfare Expression

The theorem below presents an approximation of equation 4 that is estimable with a small number of sufficient statistics. Moreover, the sufficient statistics are familiar labor supply elasticities that can be taken "off the shelf".

Theorem 1 (BWE)**.** *If the utility function is additively separable in consumption and hours, $\Delta U(w)$ can be approximated to second order as*

$$\Delta U(w) \approx \Delta c(w) - \frac{1}{2}\cdot\eta(w)\cdot\frac{\Delta c(w)^2}{\tilde{c}(w)} - MRS(w)\cdot\Delta h(w) + \frac{1}{2}\cdot\Delta MRS(w)\cdot\Delta h(w), \tag{6}$$

where,

$$\mathit{MRS}(w) = \frac{v'(\tilde{h}(w))}{u'(\tilde{c}(w))}, \qquad \Delta h(w) = h^*(w) - \tilde{h}(w),$$

$$\Delta \mathit{MRS}(w) = -\frac{\mathit{MRS}}{\tilde{h}(w)/\gamma(w)} \cdot \Delta h, \qquad \gamma(w) = \frac{\tilde{h}(w) \cdot v''(\tilde{h}(w))}{v'\left(\tilde{h}(w)\right)},$$

$$\eta(w) = -\frac{\tilde{c}(w) \cdot u''\left(\tilde{c}(w)\right)}{u'(\tilde{c}(w))}, \qquad \Delta c(w) = c^*(w) - \tilde{c}(w).$$

Proof. See appendix B. □

Writing consumption solely as earned income, the approximation is made up of three intuitive components,

$$\Delta U(w) \approx \underbrace{(w - \mathrm{MRS}(w)) \cdot \Delta h(w)}_{\text{Wedge}} + \underbrace{\frac{1}{2} \cdot \Delta(w - \mathrm{MRS}(w)) \cdot \Delta h(w)}_{\text{Change in wedge}} \dots$$
$$\dots - \underbrace{\frac{1}{2} \cdot \eta(w) \cdot \tilde{c}(w) \cdot \left(\frac{\Delta \tilde{c}(w)}{\tilde{c}(w)}\right)^2}_{\text{Income effect}},$$

which highlight the source of welfare losses. In particular, a wedge in the workers' intratemporal optimality condition and an income effect. Consider a day when the wage is high, and a driver works less than the optimal amount. The *Wedge* term captures foregone income corrected for the cost of earning this income. The *Change in wedge* term modifies the Wedge term because the cost of earning income increases with hours already worked, and the *Income effect* corrects the Wedge term again for diminishing marginal utility of consumption.

To see how this plays out in expectation, consider a simple labor supply heuristic: perfect income targeting. Under this heuristic, drivers work until they earn their income target. Consequently, the elasticity of hours with respect to wages is minus one. Abstracting from second-order terms in equation (6) and taking expectations yields

$$\mathbb{E}_w\left[(w - \mathrm{MRS}(w)) \cdot \Delta h(w)\right] = \mathbb{E}_w\left[(w - \mathrm{MRS}(w))\right] \cdot \mathbb{E}_w\left[\Delta h(w)\right] \dots$$
$$\dots + \mathbb{C}_w\left[(w - \mathrm{MRS}(w)), \Delta h(w)\right],$$

where $\mathbb{C}_w[\cdot]$ is the covariance operator integrating over the distribution of wages. For further intuition, assume that the income target rule ensures $\mathbb{E}_w\left[(w - \mathrm{MRS}(w))\right] \approx 0$ (*i.e.*, drivers' intratemporal optimality condition holds on average).

Then, the welfare losses of this labor supply bias depend only on the covariance term. Under perfect income targeting, this is positive because when the wage is high, drivers reach their income target quickly and work too little relative to the optimum—$\Delta h(w)$ is positive, and the wedge between the wage and MRS is large. Conversely, when the wage is low, drivers work more than is optimal to reach their income target, so $\Delta h(w)$ is negative, and the MRS exceeds the wage so that the wedge is negative, too.

This highlights the generic inefficiency of perfect income targeting; it causes a costly covariance between hours worked and the wedge in the intratemporal optimality condition. Consequently, if a worker were to pick between perfect income targeting or perfect hours targeting, it is advisable for the worker to pick the latter because it does not induce this costly covariance. In reality, targeting behavior is not necessarily perfect; it depends on the extent of reference dependence. However, keeping the severity of targeting fixed, this result suggests that training workers to target hours rather than income may be beneficial.

Lastly, it is worth discussing the implications of using either a first- or second-order approximation for welfare losses. A first-order approximation provides an upper bound on welfare losses from suboptimal behavior because it does not correct for the increasing (or decreasing) disutility of working more (or less) to correct biases. On the other hand, a second-order approximation corrects for changing disutility from hours worked, but the correction can be too big or too small such that the first-order approximation may be more accurate. Consequently, both approaches provide useful information on the state of welfare losses.

6 Welfare Analysis

The empirical and theoretical evidence in this paper can be brought together to conduct a welfare analysis of drivers' labor supply decisions. Intuitively, this entails comparing optimal and biased labor supply and mapping these deviations to a money metric for welfare losses. In this section, I discuss the estimation and the magnitude of losses due to biased labor supply under a variety of conditions.

6.1 Estimation

Table 3 summarizes the different ingredients necessary for welfare analysis using equation (6). In this subsection, I discuss these different components and their estimation.

Table 3: Ingredients for BWE in Expectation

Notation	Object	Reference
$h^*(w)$	Optimal labor supply	Figure 6
$\tilde{h}(w)$	Biased labor supply	Figure 7
$\gamma(w) \approx \gamma$	Frisch elasticity	Figure 2
$\eta(w) \approx \eta$	Marshallian elasticity	Ashenfelter et al. (2010)
$MRS(w) = \theta \cdot \tilde{h}(w)^\gamma$	Level parameter	Figure 6
ν	Share hours targeting	Table 4
$f(w)$	Wage distribution	Figure 8

Notes: This table presents the different elements that go into the computation of welfare losses using equation (6) and provides references for them within the paper.

Labor supply. I specify optimal labor supply $h^*(w)$ equal to the function from figure 6 under the lowest quintile of wage risk. For biased labor supply $\tilde{h}(w)$, I consider two scenarios. First, drivers all follow the same labor supply curve given by the function in figure 6 for hours in the fifth quintile of wage risk.

Second, I posit that drivers use either an hours- or income-targeting labor supply rule when the wage is most uncertain. Specifically, I assume workers determine their hours according to either

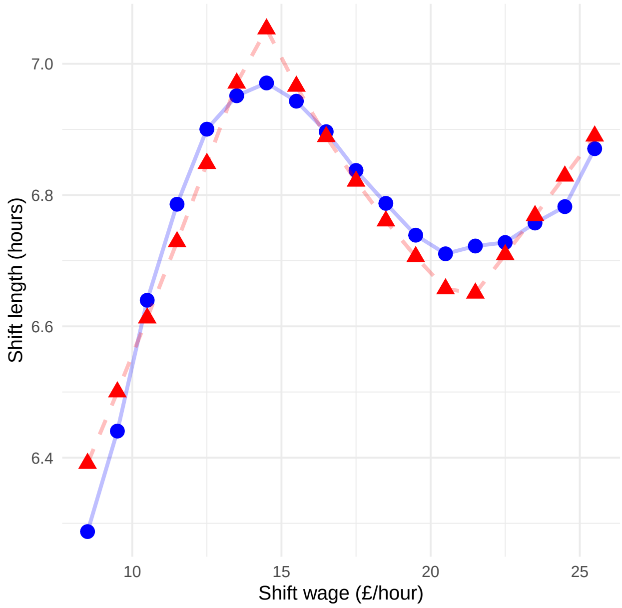
$$\tilde{h}_i(w) = \begin{cases} \left(\frac{(1+\alpha_i)\cdot w}{\theta}\right)^{\frac{1}{\gamma}} & w \leq \underline{w} \\ \frac{r_i}{w} & \underline{w} < w \leq \bar{w} \\ \left(\frac{(1-\alpha_i)\cdot w}{\theta}\right)^{\frac{1}{\gamma}} & w > \bar{w} \end{cases} \tag{7}$$

or

$$\tilde{h}_h(w) = \begin{cases} \left(\frac{w}{(1-\alpha_h)\cdot\theta}\right)^{\frac{1}{\gamma}} & w \leq \underline{\underline{w}} \\ r_h & \underline{\underline{w}} < w \leq \bar{\bar{w}} \\ \left(\frac{w}{(1+\alpha_h)\cdot\theta}\right)^{\frac{1}{\gamma}} & w > \bar{\bar{w}}, \end{cases} \tag{8}$$

where α_j and $r_j \; \forall \; j = h, i$ denote the strength of gain-loss utility and the reference

Figure 7: Model Fit



Notes: This figure plots the estimated prediction of labor supply under the fifth wage risk quintile in blue and the structural model's prediction in red.

point, respectively, for the hours- and income-targeting heuristics. These rules follow from the Farber (2008) adaptation of reference dependence in Kőszegi and Rabin (2006).[19] Importantly, both the hours- and income-targeting rule collapse to an isoelastic labor supply function absent reference dependence (*i.e.*, when $\alpha_h = \alpha_i = 0$). The share of drivers who follow income-targeting is given by ν.

To estimate α_j, $r_j \ \forall \ j = h, i$ and ν, I set $1/\gamma$ and θ as the slope and the level parameter, respectively, from a log-log regression of hours on wages from the optimal labor supply function. The regression has an R-squared in excess of 0.95. Therefore, this corresponds to the situation where biased behavior is essentially optimal if $\alpha_j \ \forall \ j = h, i$ is estimated to be zero. Then, the reference dependence parameters are selected to minimize the distance between the implied aggregate labor supply function $\tilde{h}(w) = \nu \cdot \tilde{h}_i(w) + (1 - \nu) \cdot \tilde{h}_h(w)$ and labor supply under the fifth wage risk quintile. Figure 7 shows that the model fits the data well and table 4 presents the parameter estimates.

Estimating the structural model reveals that the majority of drivers pursue an

[19] I present the decision utility functions that microfound these labor supply curves in appendix B, alongside the definitions of the thresholds $\underline{w}$, $\bar{w}$, $\underline{\underline{w}}$, and $\bar{\bar{w}}$.

Table 4: Structural Parameter Estimates

Labor supply target j	Gain-loss strength α_j	Reference Point r_j
Hours h	0.78	6.7
Income i	0.31	130
θ $= 3.64$	γ $= 0.76$	ν $= 0.16$

Notes: This table presents structural parameter estimates from minimizing the squared error between the red and blue points in figure 7. The parameters θ and γ are calibrated outside of this estimation.

hours-targeting labor supply function when the wage is risky. Precisely, 85 percent of drivers follow this rule of thumb. These drivers have a reference point of 6.7 hours, and their reference dependence is very strong, so that on average they hit this target at all wage rates. The minority of workers who implement an income-targeting heuristic have a reference point of £130 and a moderate degree of reference dependence, so their labor supply is only downward sloping for an intermediate range of wages between £15 and £20.

Normative parameters. In the structural labor supply model above, the Frisch elasticity $\frac{1}{\gamma}$ and level parameter θ are held constant, which is a normative statement because these objects are selected to reflect optimal labor supply. For example, it implies the convexity of workers' disutility from hours is constant. Two factors support this choice. First is the fact that the optimal labor supply function is all but isoelastic. Second, this is an approximation rather than a strong assumption since it amounts to holding some elements of equation (6) constant.

Treating $\eta(w)$ as constant, too, noting, again, that this is an approximation, has convenient implications. In particular, it implies that the MRS is given by $\tilde{\theta} \cdot c(w)^{\eta} \cdot h(w)^{\gamma}$. This is without loss.[20] Therefore, adding an additional assumption that consumption is fixed (*i.e.*, workers smooth their consumption), discussed below, supports setting the MRS equal to $\theta \cdot h(w)^{\gamma}$, as in the structural estimation.

Still, calculating the income effect component of equation (6) requires η. Fortunately, combining the Frisch elasticity with a Marshallian elasticity identifies this parameter.[21] There is no permanent wage variation to estimate an uncompensated

[20]In other words, $\{\eta(w), \gamma(w)\} = \{\eta, \gamma\} \iff MRS(w) = \tilde{\theta} \cdot c(w)^{\eta} \cdot h(w)^{\gamma}$

[21]This follows from the fact that labor supply responses to a permanent change in the wage rate are made up of both income and substitution effects.

elasticity in this setting, so I use the value of -0.2 from (Ashenfelter et al., 2010). This estimate leverages a taxi fare change for New York City, which lead to a permanent change in drivers' earnings. This implies a value of η equal to 1.44.

Consumption. I also consider two alternative scenarios about consumption, which is unobserved in the data. First, drivers' consumption equals their average income across all shifts. Under this assumption, income from high-risk shifts makes up only one-fifth of consumption. Consequently, correcting suboptimal behavior during these shifts has a more muted effect on consumption. Second, I assume that consumption is solely comprised of income during high-wage risk shifts. This corresponds to a situation where drivers are consistently biased and, therefore, gives a sense of the severity of biases. In particular, the estimates from this case do not depend on the variance of wages observed in this precise setting.

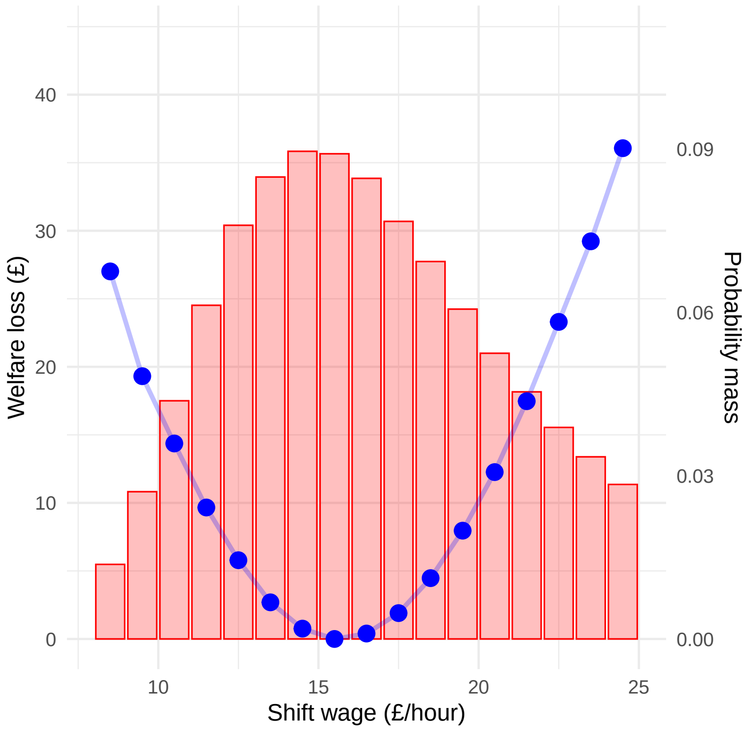
6.2 Results

To begin, for illustrative purposes, I present welfare losses for different wage rates according to equation (6), where biased labor supply equals the control function estimate from figure 6, and consumption depends entirely on daily income (i.e., there is no consumption smoothing). The losses for this naïve but instructive case are in figure 8. Welfare losses are near zero at the mean wage because biased and optimal labor supply almost coincide. However, when wages deviate significantly, behavior is suboptimal. For example, a one standard deviation increase the wage from causes welfare losses of around £10, which grow quickly thereafter.

Table 5 presents results for the more plausible situation where consumption is smoothed by workers. To read the table, each row corresponds to an assumption about biased labor supply. The first row assumes that workers determine their hours according to the semi-parametric control function model estimate when their labor supply is biased. The second and third rows present results for hours and income reference-dependent drivers, respectively, as estimated from the structural model.

The first two columns present expected changes in income and hours worked from correcting biases for shifts when labor supply is indeed biased. Reverting to optimal labor supply yields considerable returns for all variants of biased labor supply as measured by the ratio of average income changes to average hours changes. For example, an aggregate labor supply bias implies that workers could work 16 more minutes in expectation and expect to earn an additional £12 over the course of a shift.

Figure 8: Welfare Losses



Notes: This figure presents the empirical wage distribution in red bars and welfare losses at a given wage rate, assuming one-to-one pass through with consumption, in blue.

At an extreme, income targeters would reduce the number of hours they expect to work while increasing their expected income.

Next, columns three and four present welfare losses under the assumption that consumption equals the average of income across all shifts for both the first and second-order approximation of the BWE. Reiterating the discussion from section 5, the first-order approximation provides an upper bound on welfare losses, while the bias in the second-order approximation is unclear because it may over- or under-correct for curvature in the utility function. Regardless of the approximation, welfare losses are small and roughly equal to one percent of income.

The small welfare losses associated with this scenario arise for two interrelated reasons. First, behavior is not biased very often. It is only twenty percent of shifts when the wage is sufficiently risky to trigger workers' biases. Second, as a result, consumption is overwhelmingly determined by income earned from days when labor supply is optimal. Therefore, the assumptions about consumption realistically, but

Table 5: Welfare Losses

			$\Delta c = \frac{1}{5} \cdot \mathbb{E}[\Delta i]$		$\Delta c = \mathbb{E}[\Delta i]$	
$\tilde{h}(w)$	$\mathbb{E}[\Delta i]$	$\mathbb{E}[\Delta h]$	ΔU-1st	ΔU-2nd	ΔU-1st	ΔU-2nd
Aggregate	12	16	1.6	0.84	8.2	3.4
Hours targeting	14	20.4	1.7	0.83	12	7.4
Income targeting	7.1	-5.52	2.1	1.1	7.7	2.7

Notes: This table presents estimates of income and hours changes and welfare losses from correcting biased labor supply. Column one refers to the biased labor supply function under consideration in each row. Columns two and three present the expected income and shift length changes, respectively, on shifts where labor supply is biased. Columns four and five present first- and second-order approximations of welfare losses, respectively, assuming driver behavior is only biased one-fifth of the time and consumption is smooth. Columns six and seven present first- and second-order approximations of welfare losses, respectively, assuming driver behavior is always biased and consumption is smooth. The third column is measured in minutes, and columns two and four to seven are measured in GBP.

mechanically, attenuate estimates of welfare losses.

To quantify the severity of biases without this effect, columns five and six consider the case where consumption is smooth, but behavior is always biased. Here, it is apparent that drivers' heuristics cause a material distortion away from optimal behavior with major welfare consequences. Workers who target hours lose the most because their strength of gain-loss utility is so high that they never respond to changes in the wage. The estimates imply welfare losses of up to £12—over ten percent of average income—for these drivers. Losses are smaller but still significant for income targeters and workers who follow the aggregate biased labor supply function. For both of these groups, the first- and second-order approximations imply losses roughly equal to £8 and £3, respectively.

To benchmark the economic importance of these losses, it is useful to compare them with welfare costs from frictions and biases in other contexts. Drivers typically work 200 shifts a year, so the numbers in table 5 indicate annual losses somewhere in the range of £150 to £400. Handel and Kolstad (2015) find average losses due to suboptimal health insurance choices, which are made annually, of approximately £1,200.00.[22] These losses are notably larger than the most plausible results in this paper, indicating that daily labor supply biases are not a major concern in this particular context. However, losses from persistent labor supply biases could readily

[22] Handel and Kolstad (2015) model information frictions and hassle costs as the source of suboptimal choice.

exceed this benchmark, which suggests that reference-dependent labor supply may be meaningfully costly in more volatile settings.

7 Conclusion

This paper examines the role of wage uncertainty in shaping daily labor supply decisions and its normative implications. Empirically, London taxi drivers' behavior is consistent with a neoclassical model of labor supply when their wages are predictable. However, when wages are uncertain, labor supply is non-monotonic in the wage and reminiscent of reference-dependent preferences.

I take a normative stance that labor supply choices reveal preferences when the wage is known with near-certainty because workers can deliberately trade off income and leisure. Under mild assumptions, this makes it possible to approximate welfare losses from labor supply biases under a range of scenarios. Losses stem from workers' failure to equalize the wage rate with their marginal rate of substitution.

The results suggest that the welfare impact of labor supply biases is likely small relative to informative benchmarks. This is because the wage is rarely volatile enough to trigger workers' heuristics, which masks the severity of biases when they are in action. If behavior was persistently biased, the evidence suggests the losses could be as much as ten percent of average daily income.

These findings have implications for workers, contracting firms, and policymakers, especially given the rise of gig work. Firms can mitigate their workers' losses by improving the predictability of wage fluctuations. However, this may not be profit maximizing, in which case there is a role for policymakers to increase wage transparency. Moreover, regulators should be concerned *ex ante* by labor markets that exhibit a large variance in earnings. Lastly, the theoretical results have implications for workers; *ceteris paribus*, hours targeting is less costly than targeting income.

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A Data Cleaning

The raw data is at the job level. In anticipation of a final shift-level dataset, I construct shifts as thoroughly as possible by piecing together job-level observations. Then, I drop shifts that contain anomalous job-level data or are themselves anomalous because, for example, they are unusually long. This ensures that the shifts observed in the final dataset are reliable and does not introduce selection, provided anomalous job-level data is randomly distributed across shifts. Through discussions with the firm, it seems the anomalous data stems primarily from errors in measurement due to hardware and software failures rather than driver behavior, which suggests this assumption is reasonable.

To clean the data, I go through the following steps. First, I flag jobs where

- The job was canceled,
- The start time of the job is not observed (neither the arrival of the driver nor the allocated time),
- The completed time of the job and the duration of the job is not observed,
- The job duration is missing or negative,
- The fare or gross total transaction value is missing,
- The job distance is missing,
- The fare or gross total transaction value per kilometer falls below the 0.5 percentile or exceeds the 99.5 percentile of their distribution,
- The job distance exceeds 160 kilometers,
- The job duration is less than one minute or exceeds three hours,
- The job distance is less than 500 meters,
- The fare or gross total transaction value is below one GBP,
- The waiting time fee or other fees exceed the 99.5 percentile of their distribution,
- The service group is not a “standard car”,
- The job is outside of London.

Second, I construct shifts by combining jobs completed by the same driver that has a break of no longer than six hours. Third, I flag shifts where

- The shift contains less than three jobs

- The number of jobs per hour in the shift (including breaks) exceeds the 99.5 percentile of their distribution,
- Shift length (including breaks) is less than two hours or exceeds 18 hours.

Fourth, I drop jobs with flags or jobs in a shift with a flag. Fifth, I reconstruct the shifts and their associated variables.

Table A1: Comparison of Sample Sizes and Means

	Full	Analysis	Robust
Number of jobs	6.2	6.22	6.24
Shift length w/o breaks (hours)	6.79	6.8	6.8
Shift length w/ breaks (hours)	8.33	8.33	8.31
Shift income (£)	106.94	105.83	104.69
Shift wage (£/hour)	16.01	15.83	15.66
Driver age	45.83	46.88	47.63

Notes: Comparison of variable means across samples.

B Theory

In this appendix, I prove theorem 1, derive an analogous expression for changes in consumer surplus caused by price changes, and present the reference-dependent utility functions used in the structural estimation in section 6.

B.1 Proof of Theorem 1

In order to derive (w) in terms of sufficient statistics, I make use of the fact that utility is assumed to be additively separable in consumption and hours worked. To start, I will work with consumption utility. I consider a change in consumption induced by switching from a biased consumption rule to an optimal consumption rule at a given wage rate. I use a second order Taylor series approximation to show,

$$\begin{aligned}
&u(c^*(w)) \approx u\big(\tilde{c}(w)\big) + u'\big(\tilde{c}(w)\big) \cdot \big(c^*(w) - \tilde{c}(w)\big) + \frac{1}{2} \cdot u''\big(\tilde{c}(w)\big) \cdot (c^*(w) - \tilde{c}(w))^2 \\
\iff &\frac{u(c^*(w)) - u(\tilde{c}(w))}{u'(\tilde{c}(w))} \approx c^*(w) - \tilde{c}(w) + \frac{u''(\tilde{c}(w))}{u'(\tilde{c}(w))} \cdot \frac{(c^*(w) - \tilde{c}(w))^2}{2}.
\end{aligned}$$

The same operations with hours disutility yield,

$$\frac{v(h^*(w)) - v(\tilde{h}(w))}{u'(\tilde{c}(w))} \approx \frac{v'(\tilde{h}(w)}{u'(\tilde{c}(w))} \cdot (h^*(w) - \tilde{h}(w)) + \frac{v''(\tilde{h}(w))}{u'(\tilde{c}(w))} \cdot \frac{(h^*(w) - \tilde{h}(w))^2}{2}.$$

Combining these terms gives,

$$\begin{aligned}
\frac{U\big(c^*(w), h^*(w)\big) - U\big(\tilde{c}(w), \tilde{h}(w)\big)}{u'(\tilde{c}(w))} \approx & c^*(w) - \tilde{c}(w) + \frac{u''(\tilde{c}(w))}{u'(\tilde{c}(w))} \cdot \frac{(c^*(w) - \tilde{c}(w))^2}{2} + \dots \\
& \dots \frac{v'(\tilde{h}(w)}{u'(\tilde{c}(w))} \cdot (h^*(w) - \tilde{h}(w)) + \frac{v''(\tilde{h}(w))}{u'(\tilde{c}(w))} \cdot \frac{(h^*(w) - \tilde{h}(w))^2}{2} \\
\approx & c^*(w) - \tilde{c}(w) + \frac{1}{2} \cdot \frac{\tilde{c}(w) \cdot u''(\tilde{c}(w))}{u'(\tilde{c}(w))} \cdot \frac{(c^*(w) - \tilde{c}(w))^2}{\tilde{c}(w)} + \dots \\
& \dots \frac{v'(\tilde{h}(w)}{u'(\tilde{c}(w))} \cdot (h^*(w) - \tilde{h}(w)) + \frac{1}{2} \cdot \frac{v''(\tilde{h}(w))}{u'(\tilde{c}(w))} \cdot (h^*(w) - \tilde{h}(w))^2 \\
\approx & c^*(w) - \tilde{c}(w) + \frac{1}{2} \cdot \frac{\tilde{c}(w) \cdot u''(\tilde{c}(w))}{u'(\tilde{c}(w))} \cdot \frac{(c^*(w) - \tilde{c}(w))^2}{\tilde{c}(w)} + \dots \\
& \dots \frac{v'(\tilde{h}(w)}{u'(\tilde{c}(w))} \cdot (h^*(w) - \tilde{h}(w)) \dots \\
& \dots + \frac{1}{2} \cdot \frac{\tilde{h}(w) \cdot v''(\tilde{h}(w))}{v'(\tilde{c}(w))} \cdot \frac{v'(\tilde{h}(w))}{u'(\tilde{c}(w))} \cdot \frac{(h^*(w) - \tilde{h}(w))^2}{\tilde{h}(w)},
\end{aligned}$$

which is in the same form as equation (6) without the simplified notation.

B.2 Change in Consumer Surplus Due to Price Change

In this subsection of the appendix, I consider the change in consumer surplus due to a wage change from w' to w but keep the biased policy rules that define behavior constant. Take a second order Taylor approximation of the value function at wage w around the wage w',

$$\begin{aligned}
V(w) =& U\big(\tilde{c}(w), \tilde{h}(w)\big) \\
\approx & V(w') + \frac{dV(w')}{dw}(w - w') + \frac{1}{2}\frac{d^2V(w')}{dw^2}(w - w')^2.
\end{aligned}$$

It is not possible to apply the Envelope theorem because the policy functions do not maximize utility, so,

$$
\begin{aligned}
\frac{dV(w')}{dw} =& U_c\left[\tilde{h}(w') + \left(w' + \frac{U_h}{U_c}\right)\frac{d\tilde{h}(w')}{dw}\right], \\
\frac{d^2V(w')}{dw^2} =& U_c\left[\frac{d\tilde{h}(w')}{dw} + \frac{d\tilde{h}(w')}{dw} + w'\frac{d^2\tilde{h}(w')}{dw^2}\right] + U_{cc}\left[\tilde{h}(w') + w'\frac{d\tilde{h}(w')}{dw}\right]^2 \dots \\
& \dots + U_h\frac{d^2\tilde{h}(w')}{dw^2} + U_{hh}\left[\frac{d\tilde{h}(w')}{dw}\right]^2.
\end{aligned}
$$

where I have assumed additively separable utility in consumption and hours. Rearranging the Taylor series approximation and substituting in the above yields:

$$
\begin{aligned}
\frac{V(w) - V(w')}{U_c} =& h \cdot \Delta w + \frac{1}{2} \cdot \Delta h \cdot \Delta w - \frac{1}{2} \cdot \frac{\eta}{c} \cdot (\Delta hw)^2 \dots \\
& \dots + (w - \text{MRS}) \cdot \Delta h + \frac{1}{2} \cdot \Delta(w - \text{MRS}) \cdot \Delta h,
\end{aligned}
\tag{9}
$$

where $\eta = \frac{-cU_{cc}}{U_c}$, $\gamma = \frac{hU_{hh}}{U_h}$, $\text{MRS} = -\frac{U_h}{U_c}$, $h = \tilde{h}(w')$, $\Delta h = \tilde{h}(w) - \tilde{h}(w')$, $\Delta w = w - w'$, $c = \tilde{c}(w')$, $\Delta hw = \tilde{h}(w)w - \tilde{h}(w')w'$, and $\Delta(w - \text{MRS}) = \Delta w - \gamma \cdot \frac{\text{MRS}}{h} \cdot \Delta h$. Relative to the BWE, this expression incorporates the mechanical change due to the price change as well as changes in the internalities. Further if the consumption and hours policy functions were optimal rules, the wedge between the wage and the MRS would always be zero such that equation (9) would collapse to the first line.

B.3 Reference-Dependent Utility

The reference-dependent labor supply functions are micro-founded by the following utility functions

$$
U_i(w \cdot h, h) = \begin{cases} (1+\alpha_i) \cdot (w \cdot h - r_i) + \theta \cdot \frac{h^{1+\gamma}}{1+\gamma} & \text{if } w \cdot h \leq r_i, \\ (1-\alpha_i) \cdot (w \cdot h - r_i) + \theta \cdot \frac{h^{1+\gamma}}{1+\gamma} & \text{if } w \cdot h > r_i, \end{cases}
$$

and

$$
U_h(w \cdot h, h) = \begin{cases} (1+\gamma) \cdot (\frac{w \cdot h}{\theta})^{\frac{1}{1+\gamma}} - (1-\alpha_h)^{\frac{1}{1+\gamma}} \cdot (h - r_h) & \text{if } h \leq r_h, \\ (1+\gamma) \cdot (\frac{w \cdot h}{\theta})^{\frac{1}{1+\gamma}} - (1+\alpha_h)^{\frac{1}{1+\gamma}} \cdot (h - r_h) & \text{if } h > r_h. \end{cases}
$$

The thresholds in the labor supply functions are defined as $\bar{w} = \left(\frac{\theta}{1-\alpha_i}\right)^{\frac{1}{1+\gamma}} \cdot r_i^{\frac{\gamma}{1+\gamma}}$, $\bar{\bar{w}} = \theta \cdot (1+\alpha_h) \cdot r_h^{\gamma}$, $\underline{w} = \left(\frac{\theta}{1+\alpha_i}\right)^{\frac{1}{1+\gamma}} \cdot r_i^{\frac{\gamma}{1+\gamma}}$, $\underline{\underline{w}} = \theta \cdot (1-\alpha_h) \cdot r_h^{\gamma}$.