Health-driven occupational changes

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Abstract

Poor health impacts labour supply in varied and complex ways. This paper examines an under-explored aspect of this relationship: how suffering a health shock affects occupational mobility. Occupational change commonly occurs after health shocks. Individuals are 10-15 per cent more likely to change occupation or employer in subsequent months relative to those who remain healthy. We document how these newly chosen occupations differ from the occupation mobility patterns of the healthy. Those who newly report a physical disability switch to less cognitive and less manual occupations, those who report worsening mental health switch to less cognitive occupations, and those who report a new chronic health condition switch to less manual occupations, relative to their healthy counterparts. Lower cognitive intensity jobs are jobs with lower overall task complexity, while less manual jobs can be more suitable for those with certain health conditions. Individuals who do not hold a degree and report worsening mental health appear to be particularly vulnerable; we observe the largest declines in overall task intensity for this group.

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1 Introduction

Poor health impacts an individual's labour market trajectory in many different ways. Some are 'demand side' changes imposed by an employer, others are 'supply side' changes where an individual modifies their labour supply to better manage their health condition. We focus on the latter. While there has been significant research on extensive margin labour supply adjustments to poor health, including early retirement (French, 2005) or stopping work to access disability benefits (Low and Pistaferri, 2015), there has been very little attention paid to some intensive margin adjustments, especially occupation mobility. Our paper seeks to fill this gap. We believe that we are the first to analyse the impact of different types of poor health shocks on the likelihood and nature of occupation change.

We report the following findings. First, we show that individuals who suffer a health shock are 10-15 per cent more likely to change occupation or employer in the subsequent twelve months compared to employees who do not suffer a health shock, and they are also more likely to modify hours worked. We define occupational change broadly, and include changes to tasks and responsibilities within an organisation, such as a promotion or a lateral move to a new team. A health shock is defined as a newly reported or newly worsened health condition in our survey data, which we categorise into physical disabilities, mental health conditions, and chronic health conditions.

The welfare implications of this increased propensity to change occupation are unclear, as the relationship between health and occupation choice is complex. To provide a framework to interpret our empirical analysis, we outline a two-stage labour supply model. In the first stage, an individual who is currently working and has suffered a recent health shock identifies which occupation offers them the highest wage. The individual then chooses between switching to this highest-wage occupation, or exiting the labour force and seeking sickness benefits. Occupations are modelled as bundles of cognitive, manual, and interpersonal tasks that vary in intensity, and an individual's task-specific productivity is reduced by health shocks. A crucial component of our framework is that different types of health shocks have different impacts on task-productivity, and therefore wages. For example, an individual who suffers a physical health shock such as becoming paralysed will no longer be able to perform highly manual tasks, but their injury should have no impact on their ability to perform cognitive tasks. This health shock will more likely lead to occupation change if the individual previously worked in a highly manual job. The existence of alternate occupations that individuals can switch to therefore functions as a form of partial insurance from the wage losses caused by poor health.

The next part of our chapter examines the types of occupations selected by those who recently suffered a health shock. We use GMM estimation to compare the cognitive, manual, and interpersonal intensity of occupations newly selected by those who suffered a physical disability, chronic health shock or mental health shock over the previous six months, compared to the occupation transitions of the healthy. We find that individuals who suffered a physical disability or mental health shock switched to occupations with lower cognitive intensity relative to the healthy. These are typically occupations with fewer responsibilities and lower overall task complexity. Since cognitive intensity is strongly associated with pay levels, this result maps onto these individuals selecting occupations that offer lower wages. We also find that, relative to the healthy, those who suffered a physical disability reduced the manual intensity of their occupation. In theory, the relationship between health shocks and manual task intensity is ambiguous. While jobs with more intense manual requirements may be unsuitable for people with certain disabilities and health conditions, many low-skilled occupations with easy entry conditions also have medium-to-high manual content, and therefore may be chosen by individuals whose health forces them to leave their prior occupation. We do not find any evidence for this latter case. We also obtain some interesting results from our heterogeneity analysis. The decline in occupational cognitive task intensity is concentrated among those who do not hold a university degree. Individuals who do not hold a degree and suffer a worsening of their mental health appear to be particularly vulnerable; we observe the largest declines in cognitive and manual task intensity for this group relative to the healthy.

Finally, we find no relationship between health shocks and subsequent changes to occupation interpersonal intensity. Productivity in performing interpersonal tasks could be unaffected by most health shocks. While we think this is unlikely to be true, especially for mental health shocks, there is very little research on this topic. More highly interpersonal jobs, such as medical practitioners, restaurant owners, teachers, and social workers, may also offer individuals more opportunities to advocate for themselves for support in the workplace, and individuals who work in highly interpersonal jobs may be more skilled in doing so. While we cannot test these hypotheses using our data, we do find some evidence that flexibility, a key job trait desired by those in poor health (Florisson et al., 2022), is positively correlated with interpersonal intensity, but negatively correlated with cognitive intensity. Better understanding this relationship would be a valuable avenue for further research, especially as there is increasing evidence of the value of high-interpersonal jobs (Deming, 2017), which are increasingly commanding higher wages and are less vulnerable to automation (Autor, 2015), especially for individuals who might otherwise struggle to access high-quality jobs (Aghion et al., 2023).

The public policy relevance of this work is clear. A current major UK public policy objective is to better support those with disabilities and chronic health conditions remain in or re-enter the workforce (HM Treasury, 2023). There is increasing concern over the sharp rise in the number of people in the UK out of work and receiving sickness benefits. As of mid-2024, over 10 per cent of the UK's working age population received at least one health-related benefit, and this share is projected to grow further, with significant government budgetary implications (Ray-Chaudhuri and Waters, 2024). Better supporting older workers, who are more likely to be in poorer health, remain in the workforce will also help reduce the fiscal burden of an ageing population. Despite this clear policy relevance, research on the labour market trajectories of those in poor health who remain in the workforce instead of stopping work is scarce. Indeed, a recent UK government report by the Department of Work and Pensions (Salis et al., 2021) highlighted this lack of literature and called for further research into better understanding labour market transitions of those in poor health. We hope this chapter can contribute to this research gap, although much more work is needed.

The rest of our chapter proceeds as follows. Section 2 summarises the relevant literature, section 3 provides a theoretical framework for understanding the impact of health shocks on occupational choices, section 4 describes our data, focussing on how we model health and occupations, section 5 reports our empirical results and section 6 concludes.

2 Literature Review

This chapter makes several contributions to the literature. We contribute to the body of reduced form work on the impact of health shocks on various labour market outcomes. Our focus is a significantly under-researched outcome: occupation and employer changes. Much of the existing literature focusses on estimating the extensive margin response (Garcia-Gomez, Jones and Rice, 2008), although papers that investigate the impact of health shocks on earnings (Jolly, 2013; Dobkin et al., 2018; Charles, 2003; García-Gómez et al., 2013) and hours (Bound and Burkhauser, 1999; Gannon and Roberts, 2011) are also common. These labour market outcomes are also increasingly examined in the structural literature, often with the purpose of evaluating health-related public policies, such as retirement ages and the retirement decision (French, 2005; Blau and Gilleskie, 2001; Blundell et al., 2021) disability insurance (Low and Pistaferri, 2015), and means-tested health insurance (Keane, Capatina and Maruyama, 2020). In a similar vein, Bound, Stinebrickner and Waidmann (2010) estimate a dynamic programming model of the retirement decision but also include the option of switching to a 'bridge job' that is typically worse paid but may be more flexible or require fewer hours or be lower stress.

To reduce concerns around unobserved heterogeneity, reverse causality and sample selection, the reduced form literature tends to focus on sudden, unpredictable and random shocks that happen to previously healthy people, such as being hit by a car (Dano, 2005; Halla and Zweimüller, 2013), a traumatic injury from playing professional football (Carrieri, Jones and Principe, 2018) or acute sudden health conditions such as strokes, cancer or heart attacks (Jones, Rice and Zantomio, 2020; Tanaka, 2021). The structural literature tends to use a simple index of overall health to reduce computational burden (Brown, 2023). We consider a broader range of health conditions, including mental health conditions, which constitute a significant share of the disease burden affecting labour supply, and also identify differences in the labour suppply impact of different types of health shocks.

In general, the literature finds that following a health shock, the likelihood of leaving the labour force increases, and for those who remain working, there is a decline in hours worked and a highly-persistent decline in hourly earnings (Tanaka, 2021). Notably, changing hours and accepting a lower wage, potentially reflecting a decline in a workers productivity due to poor health (Grossman, 1972), are adjustments available to workers that may allow them to remain in employment rather than having to stop working. Flexibility in hours and work location, often achieved by switching to self-employment, is an additional adjustment available (Harris, Zhao and Zucchelli, 2021). There is some evidence that without these options, exiting the labour force is more likely following a health shock (Simonetti et al., 2022). This chapter examines to what extent changing occupation and/or employer are additional means of adjustment that can be used by workers who suffer a health shock to remain working.

Our interest in occupational choice is based on the idea that different types of health shocks may impact an individual's productivity in different ways depending on the tasks required for that occupation. For example, a physical disability may have a bigger impact on someone in an occupation requiring manual labour compared to an office job, and so switching to an office job could be a helpful adjustment. Hudomiet et al. (2018) investigate an aspect of this relationship. They examine how different types of health shocks that worsen 'large muscle' physical strength, fine motor skills or episodic memory (a cognitive task) affect workers differentially depending on the demands of their occupation, but obtain mixed results. They do find that those who suffer a worsening in large-muscle physical strength and work in a highly physical job are more likely to stop working, report depressive symptoms, and reduce their self-reported likelihood of working after the age of 65 compared to those working in less physical occupations. However, the authors obtain a null result for the other two traits they investigate: fine-motor skills and cognitive skills. Hudomiet et al. (2018) suggest this could be because jobs with high cognitive or fine-motor skill demands are more likely to be more flexible, or that workers in these jobs have better alternative jobs they could switch to.

One of the very few papers that does model the relationship between health shocks and subsequent job choices is Jolivet and Postel-Vinay (2020). They build a structural life-cycle model with mental health shocks, and show that mental health shocks have a bigger impact on subsequent employment and income if a job is high-stress or the worker faces other non-health adverse labour supply shocks. Much of the adjustment is via the extensive margin, where workers quit their job and enter a potentially lengthy period of unemployment. These workers are then more likely to accept a new job that is lower stress, although potentially lower paid. There is also some recent research on the impact of poor mental health on economic decision making (Abramson, Boerma and Tsyvinski, 2024). Harris (2019) estimates a dynamic discrete choice model of occupation choice where body weight affects both the distribution of wage offers and the non-monetary costs of participating in each occupation. Both the wage offers and non-monetary costs are a function of occupation-specific job requirements, which include the intensity of mental, physical and social content, to capture that the cost of obesity is higher for some job tasks than others. They find that obesity imposes barriers to occupational mobility; in particular, it is harder to progress a career and switch to professional and managerial occupations with high social content. Biro et al. (2023) explore the wage penalty from not being able to receive wage offers (internal and external) while off sick due to an unexpected accident. The paper identifies long-term wage losses from short-term absences of 3-12 months, but find that much of the wage penalty is due to missed opportunities to change to a better paying employer, not reduced chances to switch occupation. Finally, there are some papers that consider the related question of the impact of occupation choice on health (Michaud and Wiczer, 2018). While these papers have made some progress in understanding the relationship between task requirements of different jobs, health, and subsequent labour market outcomes, the relationship remains poorly understood.

Outside of the health change context, there is a literature on occupational and job change that this chapter builds on. There are various canonical job and/or occupation change models, which typically situate these labour supply changes in a general equilibrium framework. Such models include island economy models, which are based on the equilibrium search framework of Lucas and Prescott (1974), the search and matching model literature (Mortensen and Pissarides, 1994), extended to occupation choice (Carrillo-Tudela and Visschers, 2023), the Roy (1951) model of worker mobility in the presence of sectoral productivity shocks, and horizontal sorting due to match-specific shock models (McCall, 1990). For example, Busch (2020) extends an island economy framework to occupational switching in the presence of task-specific human capital. Individuals can only imperfectly transfer human capital between occupations, with the amount that can be transferred (a cost of switching) a function of distance in the task space between occupations. While Busch (2020) does not mention health directly, a major cause of negative productivity shocks that this chapter explores are health shocks. His results also support the findings of Groes, Kircher and Manovskii

(2014), who argue that occupational mobility is 'U shaped and directional' so that those at the bottom and top of a wage distribution are more likely to switch occupations. In addition, low-wage earners tend to switch to occupations with lower average wages, relative to their former occupation, while the reverse is true for high-wage earners. Since health shocks are highly correlated with low wage work (Benzeval, Davillas and Jones, 2017), this result is consistent with those in poor health swapping to lower-wage occupations. Occupational changes following health shocks could also be consistent with workers having to gather information about what skills they now have. Sanders (2012) models young workers choosing between transitioning to an occupation with similar multi-dimensional (cognitive, manual) skill requirements to their current occupation, or a more dissimilar occupation, as they weigh up furthering skill-specific capital accumulation, and gathering information about their ability. In a similar spirit, Guvenen et al. (2020) model multi-dimensional skill (mis-)match between workers and occupations which reduces as workers learn from occupation switching until their beliefs converge to their true skill portfolio.

3 Framework

To provide a framework for our empirical analysis, we first outline a model of health and occupation choice in which an individual's productivity and utility cost of work changes after a health shock. We set up a two-stage labour supply decision framework somewhat analogous to a two-stage budgeting model. First, individuals identify the highest-wage occupation available to them, taking into account their task-specific productivity, which is a function of their health. Then, they choose between working in this occupation, or exiting the labour force.[1]

Key variables:

Health: Individuals have a stock of health h, which is the sum of three types of health: physical health, mental health, and internal health: $h = h^p + h^m + h^i$. These three types map onto our health data that we describe in the next section. Individuals suffer shocks to h^p, h^m or h^i. Shocks follow a normal distribution. We focus on scenarios where people respond to large negative health shocks, but our framework could also be applied to health improvements.

Utility: Individuals have a utility function where the utility cost of work is a function of health. We make the following simplifying assumptions: consumption utility is not a function of health, individuals consume all their wage income (w_i) each period and receive no non-wage income so that: $u(c_i, l(h_i)) = u(w_i, l(h_i))$

Occupations & Wages: We model occupations (o) as a bundle of three tasks: cognitive, manual, and interpersonal (C,M,I) that we index to j such that $j = \{C, M, I\}$. The wage for each occupation is the sum of three task-specific wages, scaled by that tasks's intensity in that occupation. A crucial component of our wage equation is that different types of health shocks affect an individual's task-specific productivity in different ways. For example, a large fall in physical health may cause a reduction in an individual's manual task productivity, but have no impact on their ability to perform cognitive or interpersonal tasks. This health shock will only have a large impact on wages if the individual works in a highly-manual occupation. This

[1] Since we focus on labour supply decisions, we abstract from labour demand factors such as hiring discrimination or increased risk of non-voluntary job separation.

mechanism allows identical health shocks to have very different impacts on wages depending on task composition.

Adapting notation by Bachmann et al. (2022), wages of individual i in occupation o take the form:[2]

$$w_{i,o}(z_i, h_i) = \sum_{j=C,M,I} \alpha_o^j \lambda_o^j \theta^j(z_i, h_i^p, h_i^m, h_i^i) \tag{1}$$

α_o^j is the intensity of task j for occupation o, and ranges between 0-1 for each j. For example, if $\alpha_o^C > 0.7$, this would indicate an occupation where cognitive tasks are important. We source this task intensity data for each occupation from Lise and Postel-Vinay (2020). λ_o^j is the occupation-specific wage per efficiency unit of task j. On average, $\lambda_o^C > \lambda_o^I > \lambda_o^M$, but there is large variation between occupations. We can identify λ_o^j by comparing an individual's wage in different occupations with similar task intensities (as $\theta^j(.)$ would be held constant and α_o^j is known). $\theta^j(z_i, h_i)$ represents an individual's productivity in performing task j, which is a function of their health and other factors (z_i), such as skill in performing occupation tasks, which is not a function of current health. Note that $\theta^j(.)$ is not occupation specific; it is an individuals productivity at j tasks in any occupation.

While wages are a crucial component of our framework, we are not able to estimate equation 1 in our subsequent empirical work. This is because the available wage data in our LFS dataset is too limited to do so. We discuss this issue further in section 5.3.2.

Two-stage labour supply decision framework

Stage one: In the first stage, an individual who is currently in the labour force and has recently suffered a health shock identifies the best occupation for them, which we define as the one that offers the highest wage given their current health and productivity levels.[3] Each period, individuals receive a set of job offers from different occupations. We denote the alternate occupation offering the highest wage out of

[2]We do not take the logarithm of wages as this would remove the separability of the remuneration from the three different tasks

[3]While we do not allow the utility cost of work to vary by occupation type in our framework, in reality the correlation between the impact of a health shock on the utility cost of work, and productivity in a particular occupation is likely to be high. Therefore, our framework will still be able to accurately predict most occupation changes.

the set of offers as $\hat{o_i}$ and $\hat{w_{io}}$ respectively, and maintain o_i and w_{io} notation for the individual's current occupation and wage. For given values of an individual's task-specific productivities ($\theta^j(z_i, h_i)$), individuals face a distribution of best alternate occupation wages that we assume follows a normal distribution: $N(\mu_w, \sigma_w)$.[4] We assume that the average wage offer at any level of health is lower than an individual's original occupation wage, otherwise individuals would change jobs too frequently. Increases in σ_w will increase the likelihood of individuals changing occupation; the higher the variance of job offers, the more likely that individuals will receive high wage offers.

Individuals will change occupation if $u(w_{io}, l(h_i)) < u(\hat{w_{io}}, l(h_i))$. In other words, given their current productivity level and skills, $\hat{w}_{i,o}(z_i, h_i) > w_{i,o}(z_i, h_i)$. Conversely, an individual will remain in their current occupation if the opposite inequality condition holds, and $u(w_{io}, l(h_i)) \geq u(\hat{w_{io}}, l(h_i))$. In this case, an individual may have suffered a reduction in their wage due to their health, but their current wage is still higher than or equal to the best alternate occupation offer. Once the individual has determined the occupation that offers them the highest wage, we designate it as o_i^* offering wage w_{io}^*.

Stage two: In the second stage, individuals decide whether to remain in the labour force following a health shock. If they stop working due to poor health, they receive sickness benefit s. We assume that sickness benefits are not very generous, and so $s < w_{io}^* \ \forall i$. We also make a simplifying assumption that the utility cost of work is a function of health but not occupation. Therefore, for a given best available wage w_{io}^* for individual i, there exists a 'reservation' level of health k, such that if $h_i < k$, due to some combination of shocks to h^p, h^m or h^i, an individual's disutility cost of work is too high relative to their consumption utility from their wage income if they work. If $k = h_i$, an individual is indifferent between the two options:

$$u_i(w_i^*, l(k) = \text{work}) = u_i(s, l(k) = \text{not work})$$

We are able to observe some of these choices in our data; we observe whether an

[4]While the overall distribution of wage offers is unlikely to be normally distributed, once we control for an individual's productivity, imposing a normal distribution on the residual components of the wage function is a more reasonable assumption.

individual remains in their original occupation, changes occupation or stops working following a health shock. However, we do not observe an individual's best alternate occupation if they choose to remain in the same occupation or stop working.

4 Data

Our analysis is performed using a UK longitudinal panel data set. We choose to focus on the UK because of the current heightened policy interest in reversing the recent large increase in the share of the British working age population out of work due to illness and disability (HM Treasury, 2023). Not using US data also allows us to abstract from the complex labour supply incentives around obtaining or preserving health insurance access following a health shock. Our data set is constructed using the Labour Force Survey (LFS), a quarterly data set that contains data on individuals for five consecutive quarters, where the fifth (final) survey is administered one year after the first. We supplement this LFS data with data from the Annual Population Survey (APS), which itself is based on LFS data but also includes additional boosts to achieve better geographic coverage. We use the LFS because it captures both rich labour market data, and data on longer-term health conditions that are most likely to impact labour supply. It is also the largest household study in the UK and therefore provides sufficient cross-sectional variation to study different labour market transitions. Unfortunately, the wages data available from the LFS is limited. While it does include an hourly pay variable, this is only reported for the first and fifth waves (if the individual remains in the sample for the full five waves). In addition, answering this question is voluntary and around 1/3 of the sample chooses not to do so. Non-response rates are higher among lower-skilled, lower-paid occupations. As a result, we restrict our analysis to focussing on the relationship between health changes and occupation changes, rather than the impact of health on wages directly.

We restrict our sample to 2010–2019 due to a change in some survey questions in 2010 and to avoid the impact of Covid-19. We focus on individuals who suffer a health shock while working, therefore we drop all individuals from the sample who report that they do not work for all periods they are observed. Our dataset includes 1,115,013 observations of 302,513 unique individuals who are surveyed 2-5 times.

4.1 Health data

The LFS reports two types of health data. Individuals can report a ‘health limit’ meaning that health problems affect the kind of paid work they could have done that quarter. Individuals can also report whether they have any of 16 longer-term health conditions.[5] We make use of both types of health data in our analysis. Table 1 reports the 16 conditions, their prevalence by gender, as well as the share of individuals with each health condition who report that their health limits the type of work they can do.

Table 1: Summary of health data

Condition	Incidence		Health limits work*	
	share of total sample (%)			
	men	women	men	women
Problems or disabilities connected with:				
(1) arms or hands	3.4	5.2	55.7	66.0
(2) legs or feet	5.6	6.4	51.6	54.2
(3) back or neck	5.2	6.6	56.2	57.2
difficulty in seeing	0.9	0.7	46.6	51.4
difficulty in hearing	1.5	1.1	36.8	40.8
a speech impediment	0.1	0.1	66.0	69.8
severe disfigurement, skin conds., allergies	1.9	2.2	29.7	31.8
chest/breathing problems, asthma, bronchitis	5.1	5.4	27.6	28.2
heart, blood pressure, circulation problems	8.3	5.5	23.9	23.5
stomach, liver, kidney, digestive problems	2.8	3.0	31.9	33.3
diabetes	3.4	2.0	23.0	24.1
depression, bad nerves, anxiety	2.5	4.3	47.0	40.9
epilepsy	0.4	0.4	49.2	45.5
severe or specific learning difficulties	0.6	0.3	64.9	55.4
mental illness, other nervous disorders	0.8	1.1	62.0	52.6
other progressive illness e.g. cancer, MS	0.9	1.2	44.0	52.4
other	2.9	5.5	30.8	27.5

*Share of individuals with diagnosed condition who report that their health limits their work

The prevalence of health conditions are fairly similar between men and women, with the exception of problems or disabilities connected with arms or hands, legs or feet, back or neck, and depression, bad nerves and anxiety, which are more common among women, and heart conditions and diabetes, which are more common among men. The share of individuals who report that their health condition limits the type of work they can do varies significantly by condition, with individuals with mental illnesses, learning difficulties and some rarer conditions being most likely to report this. To make our analysis more tractable we aggregate these 16 health conditions

[5] See Labour Force Survey - Volume 3 - Details of LFS variables for further detail. From 2020, an 18th category was included for autism, which we do not include in our analysis.

(excluding 'other') into three categories which we label as physical disabilities, chronic health conditions, and mental health conditions as described in Table 2. These three categories map fairly well onto the first three components of a principal component analysis of the 16 conditions (Appendix A.1).

Table 2: Classification of health conditions into three categories

Category	Conditions
Physical disability	problems or disabilities connected with: - arms or hands - legs or feet - back or neck difficulty in seeing difficulty in hearing a speech impediment epilepsy
Chronic condition	severe disfigurement, skin conds., allergies, chest/breathing issues, asthma, bronchitis, heart, blood pressure, circulation problems, stomach, liver, kidney, digestive problems, diabetes
Mental health condition	depression, bad nerves, anxiety severe or specific learning difficulties mental illness, other nervous disorders

Our empirical approach is to compare the labour market responses of individuals who are working but then their health worsens, to those who remain healthy. We describe an incident of worsening health between two consecutive survey waves as a 'health shock'. This approach means we do not consider the labour market behaviour of individuals whose health condition began prior to them entering the LFS survey, and is stable while they remain in the survey panel. This is because we do not observe their labour supply choices when healthy.[6] We identify a 'health shock' in the data in two different ways: as a health condition that is newly reported in a later survey wave, or the worsening of a pre-existing health condition. We define the latter case as when an individual with a pre-existing health condition newly reports that their health limits the work they can do. Using diabetes as an example, we would classify an individual as having suffered a chronic health shock in period t if they report having diabetes in period t but not in period $t-1$, or if they report having

[6] We do not consider the reverse situation of individuals recovering from a prior health shock as most suffer long-term conditions and we do not have a long enough sample size to consider recovery

diabetes in both period t and period $t-1$ but report that their health limits the work they can do in period t but not in $t-1$, and do not report any other new health condition in period t. Around 85-90 per cent of the health shocks in our sample are new health conditions. We report summary statistics for those who suffer a disability, mental and chronic health shock, as well as those who remain healthy in Table 3. The correlations between observable traits and health shocks are all as expected, and the sample appears to be well balanced across a wide range of observable variables.

Our chosen method of health shock identification may potentially be vulnerable to justification bias, where people inaccurately report their health to justify their labour market outcomes (Bound, 1991). Individuals who are unemployed or in low-status jobs may be more likely to overstate how bad their health is. We do not think this bias is a major threat to our empirical strategy. The prevalence and magnitude of justification bias remains contested in the literature (Kapteyn, Smith and van Soest, 2011). The strongest evidence for justification bias has been found in cases of unemployment or accessing disability benefits, which typically requires an individual to not work (Black, Johnston and Suziedelyte, 2017). There is much less evidence for justification bias in health reporting to justify occupation or employer changes. Our method of identifying health shocks may also be vulnerable to under-reporting, especially for mental health conditions where individuals may be experiencing symptoms but have not received a diagnosis, or they do not wish to disclose a diagnosis. If this issue is significant, then our estimates are likely to be a lower bound of the impact of mental health shocks on occupation transitions. A related concern is measurement error. Attempts by the literature to estimate the magnitude of measurement error in survey responses to medical questions by comparing them to linked data on hospital admissions has typically found the non-reporting rate of serious health conditions to be surprisingly high (Caraballo et al., 2020). We do not try to adjust for measurement error, which may also bias our results towards zero.

Table 3: Summary statistics: percentage shares by category for each health shock*

	share of total sample split by category and health shock type (%)			
	healthy	physical	mental	chronic
Age				
under 30	20.1	7.8	26.2	12.3
30-39	22.6	12.0	22.3	14.5
40-49	25.4	24.3	25.0	23.4
50-59	21.7	37.5	21.2	34.1
60+	10.3	18.4	5.3	15.7
Sex				
male	50.0	48.3	40.5	48.4
female	50.0	51.7	59.5	51.6
Degree				
degree	66.5	74.9	71.1	70.2
non-degree	33.6	25.1	28.9	29.8
Employment status				
employee	79.1	74.0	74.8	77.3
self-employed	13.3	15.0	9.6	13.1
not working/other	7.6	10.9	15.6	9.6
Hourly pay (2010 prices)				
25th percentile	8.0	7.9	7.2	7.9
median	11.7	11.2	9.8	11.5
75th percentile	14.6	13.9	12.2	14.5
Occupation group				
managers, directors, senior officials	10.8	9.9	7.0	10.4
professional	22.0	18.4	18.4	21.4
associate professional/technical	14.1	13.2	14.2	14.0
administrative/secretarial	11.2	11.2	12.2	11.8
skilled trades	10.1	11.9	7.2	9.1
caring, leisure, other services	8.8	10.7	12.8	9.9
sales/customer service	7.2	7.4	10.9	7.3
process, plant, machine ops.	5.9	6.7	4.3	6.4
elementary	9.9	10.8	13.2	9.8
Hours working				
<10	3.7	3.8	5.1	4.1
10-19	9.2	10.7	14.0	9.7
20-29	12.2	13.9	15.8	13.0
30-39	30.3	29.7	31.6	31.2
40-49	31.2	28.0	23.9	29.0
50-59	8.9	8.8	6.4	8.5
60+	4.6	5.0	3.3	4.5
N	*543,649*	*26,075*	*10,252*	*37,581*

*Excludes wave 1 observations as we need two consecutive observations to classify health status

4.2 Labour market transitions data

We examine two types of labour market transitions, which we label as 'occupational change' and 'employer change'. We define occupational change as whether an individual reports that their job has a different SOC (UK standard occupation classification code) relative to their job in the last sample wave. The LFS data reports 4-level SOC codes, identifying almost 400 separate occupations. The majority of occupation changes we observe constitute small changes in role tasks and responsibilities within an organisation, such as 'hairdressers and barbers' to 'hairdressing and beauty salon management', from 'medical practitioner' to 'medical radiographer', from 'primary and nursery education teaching professionals' to 'teaching assistant'. We define employer change using a variable that reports the duration of time an individual has been with their employer. We identify an employer change if an individual is continuously employed in two consecutive waves and reports that his job in the latter wave commenced in the past six months, and at least six months later than the prior job's reported commencement. This is a conservative approach and may not capture some employer changes, such as if an individual changes employers twice in two consecutive quarters.

Occupational change is much more frequent than employer change, as shown in Table 4. Less than 20 per cent of occupation changes observed in the data also involve a change in employer, while over 40 per cent of employer changes also involve some change in occupation. This result is in line with other research. Carrillo-Tudela et al. (2016) finds that around half of UK individuals who changed employers also changed occupation or industry. Our analysis excludes individuals who experienced a period of unemployment between jobs, unless that period of unemployment is short so that they are able to report being employed in consecutive survey waves. While occupational change following a period of unemployment is common (Carrillo-Tudela et al., 2016), these labour market outcomes are likely to differ substantially, compared to those who change occupation or employer without suffering a lengthy period of unemployment (Huckfeldt, 2022). In addition, periods of unemployment may worsen health (Picchio and Ubaldi, 2022), complicating an examination of the relationship between health shocks and labour market transitions. In practise, this represents only around 2 per cent of those in our sample who suffer a health shock; the remaining 91 per cent remain working, and 6 per cent cease working in all subsequent surveys they participate in.

Table 4: Occupation and employer change frequency

	Employer change	Employer unchanged	N
Occupation change	14,012	61,934	*75,946*
Occupation unchanged	20,921	595,560	*616,481*
N	*34,933*	*657,494*	*692,427*

To make our analysis of almost 76,000 occupation changes more tractable, we model each occupation as a bundle of three key tasks. We adopt a method from Lise and Postel-Vinay (2020), who perform Principal Component Analysis on approximately 200 occupation descriptors from the O*NET database; a popular US-government-funded database of occupation-specific descriptors. They identify three principal components, which they label as cognitive, interpersonal and manual.[7] Each occupation is assigned a score of between 0 and 1 for each component. Since there are differences in the standard occupation classifications used by US and UK statistical agencies, Blundell et al. (2020) map Lise and Postel-Vinay (2020)'s scores onto UK occupation classifications. These are the data we use for our occupation task intensity scores. Table 5 provides examples of low, medium, and high cognitive, manual, and interpersonal content occupations. Low, medium, and high classifications correspond to the first, second and third terciles of the cognitive, interpersonal and manual score distributions. The distributions are quite similar for the three traits and are approximately normal with a standard deviation of around 0.2 units.[8]

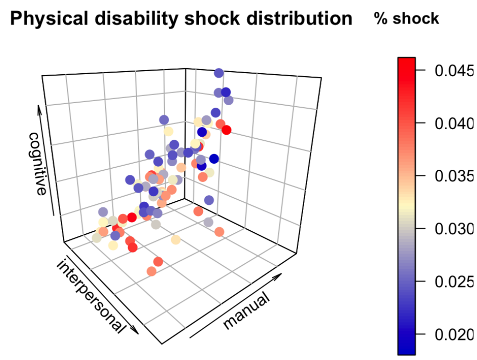
Finally, we map the probability of suffering health shocks onto the distribution of occupations by cognitive, manual, and interpersonal intensity. We graph each occupation as a function of their cognitive, manual, and interpersonal intensity, with the dots shaded according to the share of individuals in that occupation who suffer a health shock. Each dot represents one occupation at the 3-digit SOC level, which equates to around 90 unique occupations. The clustering of dots at certain points of the cube reflects the correlation of cognitive, manual, and interpersonal task intensity in occupations. These plots also illustrate clear differences in the average cognitive,

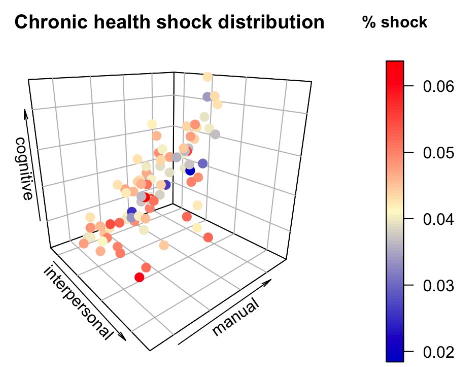
[7]'Cognitive' is defined as the component containing the mathematics skills descriptor, 'manual' is defined as containing the mechanical knowledge descriptor, and 'interpersonal' is defined as containing the social perceptiveness descriptor

[8]Changes to task intensity are also approximately normal; see Appendix A.2 for details

manual, and interpersonal content of occupations with higher and lower rates of health shocks. Those who suffer a physical disability or mental health shock are more likely to cluster in low-cognitive and low-interpersonal work. There does not appear to be a clear correlation between an occupation's manual content and health shock likelihood. The occupations where individuals are least likely to report a physical health shock are white collar professional jobs, while individuals working in 'elementary cleaning occupations' are the most likely to report a physical disability. Mental health shocks are least likely to be reported by pilots, chief executives and senior officials, senior police and military officers (there is potentially under-reporting by this group), and are most likely to be reported by caring personal services jobs such as care workers and nursing assistants, and customer services roles such as call centre operators. Chronic health shocks are more similarly distributed across occupations.

Figure 1: Share of individuals who suffer a health shock, by occupation





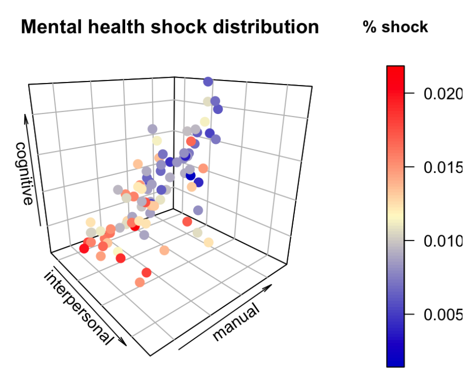


Table 5: Examples of occupations by task intensity

low cognitive occupations			
	low interpersonal	**medium interpersonal**	**high interpersonal**
low manual	Bank/post office clerks	Care workers, home carers	Social workers
	Receptionists	Teaching assistants	Welfare/ housing associate professionals
	Waiters and waitresses	Sales and retail assistants	Probation officers
	Retail cashiers/check-out operators	Musicians	youth/community workers
medium manual	Shelf fillers	Bar staff	Prison service officers
	Cleaners and domestics	Pharmacy/dispensing assistants	Undertakers, mortuary/crematorium assistants
	Cooks	Security guards	-
	Postal workers, mail sorters, couriers	beauticians	-
high manual	Farm workers	(none)	(none)
	Bus and coach drivers, van drivers	-	-
	Food, drink, tobacco process operatives	-	-
medium cognitive occupations			
	low interpersonal	**medium interpersonal**	**high interpersonal**
low manual	Book-keepers, payroll managers, wages clerks	Authors, writers and translators	Primary/secondary/higher education teachers
	Finance officers	Personal assistants and other secretaries	Clergy
	Financial accounts managers	Journalists, newspaper and periodical editors	Psychologists
	-	School secretaries	Insurance underwriters
medium manual	-	Chefs	Nurses
	-	Office managers/supervisors	National government administrative occupations
	-	Sales supervisors	Physiotherapist
	-	Hairdressers and barbers	Sports coaches, instructors, officials
high manual	carpenters and joiners	Farmers	Restaurant/catering managers/proprietors
	gardeners/landscape gardeners	Medical and dental technicians	Police officers (sergeant and below)
	large goods vehicle drivers	Cleaning and housekeeping managers/supervisors	Veterinarians
	Vehicle technicians, mechanics, electricians	Health and safety officers	Paramedics
high cognitive occupations			
	low interpersonal	**medium interpersonal**	**high interpersonal**
low manual	-	chartered and certified accountants	solicitors/barristers/judges
	-	tax experts	HR managers and directors
	-	-	finance and investment analysts and advisors
medium manual	-	business sales executives	medical practitioners
	-	IT project and program managers	property, housing and estate managers
	-	graphic designers	sales account and business development managers
	-	actuaries, economists, statisticians	management consultants and business analysts
high manual	electricians and electrical fitters	civil engineers	chief executives and senior officials
	metal working production and maintenance	production managers and directors in manufacturing	biological scientists and biochemists
	programmers and software development	R&D managers	architects
	laboratory technicians	chartered surveyors	publicans and managers of licensed premises

5 Empirical Results

This section describes our key empirical findings. Referring back to our theoretic framework, we proceed backwards and start with evaluating the data that maps onto the second stage of our decision framework: whether an individual stays in the workplace in their best available occupation (either by retaining the same occupation or switching to a different one), or drops out of the labour force. We establish that suffering a health shock increases an individual's likelihood of both changing their occupation or employer, and stopping work. We then identify how an individual's best available occupation may differ from their previous one. This is an approximation of the first stage of our decision framework as we cannot observe the best available occupation for individuals who choose to stop working in stage two.

We find that following a health shock, people switch to less complex occupations that have lower task intensity across multiple domains. In particular, we observe declines in cognitive task intensity, which can proxy for overall occupation task complexity. Second, we highlight the importance of modelling health as a multi-dimensional variable when analysing labour market mobility, as individuals suffering different health conditions display different occupation mobility patterns. Individuals who do not hold a degree and suffer a mental health shock appear to be particularly vulnerable; we observe the largest declines in task intensity across multiple domains in this group. Finally, we find no evidence that suffering a health shocks leads individuals to change the interpersonal task intensity of their occupation. This is a puzzling null result, and we consider various explanations.

5.1 Occupation and employer transition probabilities

We find that individuals who suffered a health shock are one-to-two percentage points more likely to change occupation or employer in the subsequent three-to-six months, depending on regression specification used. In our entire sample, around 11 per cent change occupation and 5 per cent change employer each quarter. Therefore, our findings represent a 10-20 per cent increase in the likelihood of occupation or employer transition among those who recently suffered a health shock. We report estimates from three different estimation strategies: OLS, fixed effect models and fixed-effect multinomial logits. The latter specification allows us to control for selection bias from some individuals stopping work when they get sick. We estimate the β coefficients of the following equation:[9]

$$\text{transition likelihood}_{i,t} = \beta_1 h^p_{i,t} + \beta_2 h^m_{i,t} + \beta_3 h^i_{i,t} + X_{i,t} + \gamma \text{job traits}_{i,t-1} \quad (2)$$

The outcome variable for this regression is a binary indicator of whether an individual transitions job or occupation, and therefore the estimation sample is conditioned on remaining in employment or self-employment.[10] These β coefficients capture the difference in likelihood of occupation and employer change for those who suffered a health shock over the past six months, compared to the healthy. Our OLS and fixed effect (FE) estimates are reported in Table 6. Once we strip out time-invariant heterogeneity, those who suffered a physical disability shock are one percentage point more likely to change occupation, and those who suffered a chronic health shock are one percentage point more likely to change occupation or employer. We also observe interesting occupational change likelihood patterns by prior occupation and health shock type. Figure 2 illustrates the β coefficients estimated using OLS as reported in Table 6, but estimated separately for each pre-shock occupation group. We report the equivalent graph reporting differences in job change likelihood by prior occupation in Appendix figure 5, and report the raw data of occupation and job change likelihood by prior occupation in Appendix table 12

Our preferred specification is the fixed-effect multinomial logit, as reported in Table 7. We model individuals choosing between stopping working (which does not include going on sick leave) and reporting no longer being employed, changing employer and/or occupation, or remaining working in the same occupation with the same employer. Those who suffer a physical disability shock, mental health shock, or chronic health shock are 18, 12 and 16 per cent more likely respectively to change occupation relative to the healthy.[11] Those who suffer health shocks are similarly more likely to change employer, and both change occupation and employer in the next six months. The most notable difference between these results and our prior OLS and

[9] h_p, h_m and h_i represent physical, mental and internal/chronic health shocks as described in our theoretic framework

[10] If an individual switches from working for an employer to being self-employed (or visa versa), we would count that an employer/job change.

[11] For example, if the log-odds coefficient is 0.1673, that equates to $e^{0.1673} = 1.1821$, which is an 18 per cent increase in likelihood relative to the baseline choice

Table 6: Probability of changing occupation or employer

	occupation change		job change	
	OLS	FE	OLS	FE
physical disability shock	0.0219***	0.0148***	0.0075***	0.0047**
	(0.0027)	(0.0032)	(0.0020)	(0.0024)
mental health shock	0.0266***	0.0053	0.0171***	0.0057
	(0.0045)	(0.0055)	(0.0036)	(0.0044)
chronic health shock	0.0192***	0.0128***	0.0175***	0.0138***
	(0.0022)	(0.0027)	(0.0017)	(0.0021)
R^2	0.0153	0.0051	0.0090	0.0027
N	668,474	668,474	665,296	665,296

Clustered standard errors in parentheses, * p<0.1, ** p<0.05, *** p<0.01
health shocks over past 3 months, additional controls: lagged C,M,I intensity, lagged hours, age, sex, ethnicity, education, time dummies, pay, region

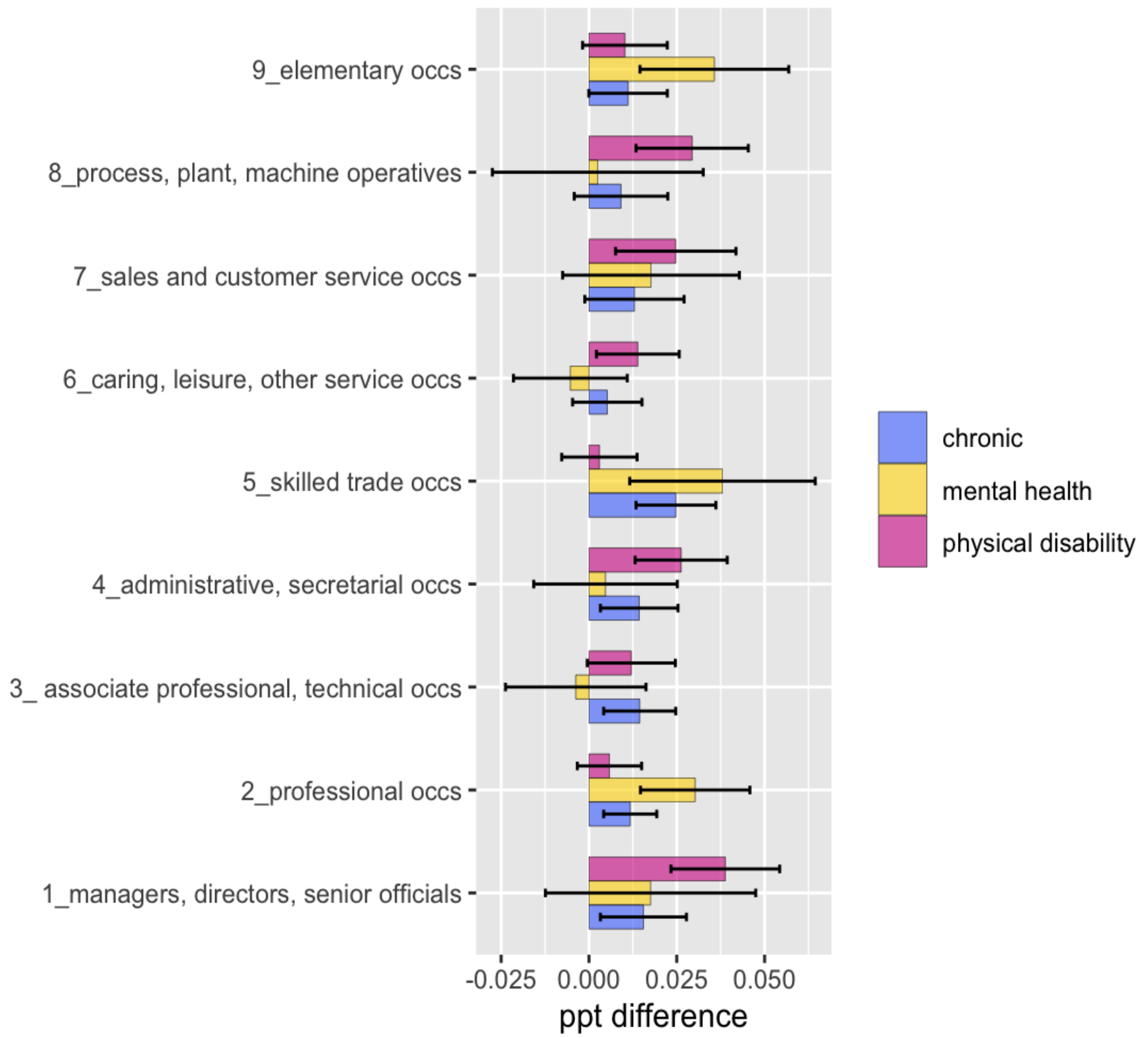
fixed effect results is that the β coefficient on the mental health shock dummy is now significant. This is unsurprising, as those who suffer mental health shocks have the highest probability of stopping work, so not accounting for this likely biases the former estimates downwards.

5.2 Changes to hours worked

Changing hours have been documented in several papers as another common labour supply response to health shocks (Gannon and Roberts, 2011). While the literature typically finds a negative relationship between suffering a health shock and hours worked, the relationship is theoretically ambiguous as some individuals may increase their hours in an attempt to mitigate the decline in hourly wages associated with poor health. There also may be demand-side effects as employers reduce the hours of unwell employees. The share of individuals who report changes to their weekly working hours over a three month period is high; a little under half of our sample report different average weekly hours in consecutive survey waves. Both increases and decreases in weekly hours worked are more commonly observed among individuals who report a recent health shock relative to those who remain healthy.

We estimate a conditional fixed effect multinomial logit that models individuals choosing between: stopping work, a reduction of five hours worked per week or more, small changes in hours worked that range from -4 to 4 hours, and an increase of

Figure 2: Occupation change likelihood by prior occupation
difference from healthy individuals†



† Estimated β coefficients from OLS regression estimates of equation 2, estimated separately by occupation group

five hours or more. A little under 50 per cent of those who report a change in weekly hours between survey waves report a change of at least five hours per week, so our specification captures most larger changes in hours. We include health shock dummies as regressors, as well as age and previous job traits, and estimate the model separately for men and women, as well as those who worked full-time and part-time in the prior quarter. We estimate the model separately for men and women because previous research has shown that hours worked by men and women can respond very differently to shocks (Attanasio et al., 2018). We estimate the model separately

Table 7: Fixed effects multinomial logit - log odds ratio

0: baseline (work unchanged)	
1: stop working	
physical disability shock	0.1345*
	(0.0729)
mental health shock	0.4272***
	(0.1014)
chronic health shock	-0.0012
	(0.0643)
2: change occupation	
physical disability shock	0.1673***
	(0.0354)
mental health shock	0.1128*
	(0.0579)
chronic health shock	0.1518***
	(0.0296)
3: change employer	
physical disability shock	0.0801
	(0.0565)
mental health shock	0.2277***
	(0.0856)
chronic health shock	0.3086***
	(0.0446)
4: change occupation and employer	
physical disability shock	0.1772**
	(0.0727)
mental health shock	-0.0990
	(0.1007)
chronic health shock	0.2506***
	(0.0578)
N	198,969

Standard errors in parentheses, * p<0.1, ** p<0.05, *** p<0.01
Additional controls: age, age quadratics, hours worked pre-shock

by prior full or part time work status to partially control for lagged hours[12] Our specification takes into account time-invariant heterogeneity as well as selection bias from individuals suffering a health shock being more likely to stop working.

Men and women who suffer a health shock are more likely to decrease their hours by at least five, but also increase their hours by at least five, relative to those who remain healthy. These results are fairly broad-based by type of health shock, although

[12]We can include lagged hours as an independent variable in the multinomial logit results on occupation transitions reported in Table 7 without risking dynamic panel bias, which is not the case here.

Table 8: Fixed effect multinomial logit: Changes in weekly hours - log odds ratio

	men		women	
	full time	part time	full time	part time
0: stop work				
physical disability	-0.0510	0.3659	0.0481	0.1491
	(0.1392)	(0.2376)	(0.1778)	(0.1268)
mental health	0.7938***	0.0379	0.3981*	0.4083**
	(0.2130)	(0.2926)	(0.2374)	(0.1795)
chronic	0.0521	0.1102	-0.1467	-0.0392
	(0.1260)	(0.1868)	(0.1518)	(0.1156)
1: ≥ 5hr decline				
physical disability	0.0834*	0.0923	0.1134*	0.0871
	(0.0484)	(0.1296)	(0.0672)	(0.0770)
mental health	0.2858***	0.0652	0.0810	0.0075
	(0.0942)	(0.2162)	(0.1026)	(0.1136)
chronic	0.1178***	0.2067*	0.1222**	0.0427
	(0.0397)	(0.1103)	(0.0550)	(0.0667)
2: baseline (hours stable)				
3: ≥ 5hr increase				
physical disability	0.2185***	0.0906	0.2390***	0.1642**
	(0.0581)	(0.1267)	(0.0847)	(0.0786)
mental health	0.1945*	-0.1118	0.1259	0.2285**
	(0.1126)	(0.1888)	(0.1281)	(0.1120)
chronic	0.2379***	0.0449	0.2334***	-0.0079
	(0.0481)	(0.1081)	(0.0698)	(0.0663)
N	99,250	17,648	47,112	45,803

Multinomial logit: choices (0,1,2,3) = health shock + X_{it} + age + pre-shock job traits
Standard errors in parentheses, * p<0.1, ** p<0.05, *** p<0.01

men who suffer a mental health shock are most likely to stop working or decrease their hours by at least five. We conclude that while the average response of individuals who suffer a health shock but remain in the labour force is to work fewer hours than comparable individuals who do not suffer a health shock, this result obscures significant heterogeneity across multiple dimensions.[13]

5.3 Occupation changes

As well as the increased propensity to change occupations, we also find that the new occupations selected into by those who suffered a health shock differ from those selected into by individuals who remained healthy. Our empirical approach compares the new and old occupations of those who suffered health shocks, using the occupation changes of healthy individuals as a comparison baseline. This strategy requires us to assume that if individuals working in a specific occupation and with specific observable traits who suffered a health shock had instead remained healthy, they would have followed the same occupational mobility patterns as those who remained healthy. We compare occupations by comparing their cognitive, manual, and interpersonal task intensity. We first detail our empirical strategy, before presenting and discussing our key results and performing heterogeneity analysis.

5.3.1 Empirical strategy

We use general method of moments (GMM) estimation to identify whether the cognitive, manual, and interpersonal intensity of occupations newly selected by those who suffered a health shock differ from occupations newly selected by those who did not suffer a health shock, controlling for pre-shock occupation and fixed effects. We use GMM estimation as it allows us to account for unobserved heterogeneity, as well as the cognitive, manual, and interpersonal content of occupations pre-shock without risking dynamic panel bias. We estimate equations that follow the below

[13]See Appendix A.3 for additional analysis of hours data

form (replacing cognitive with manual or interpersonal as required):

$$\text{cognitive}_{i,t} = \beta_1^p h_{i,t}^p + \beta_1^m h_{i,t}^m + \beta_1^i h_{i,t}^i + \beta_2^p h_{i,t-1}^p + \beta_2^m h_{i,t-1}^m + \beta_2^i h_{i,t-1}^i + \gamma_1 \text{cognitive}_{i,t-1} + \gamma_2 \text{cognitive}_{i,t-2} + \upsilon_1 \text{manual}_{i,t-1} + \upsilon_2 \text{interpersonal}_{i,t-1} + X_{it} + \varepsilon_{it} \quad (3)$$

We once again focus on estimating and interpreting the β coefficients, which capture the average impact of suffering a health shock on the cognitive, manual or interpersonal intensity of occupations held in period t. We include two lags of each type of health shock to account for both health shocks that occur in the same quarter as a potential occupation change and the quarter before a potential occupation change, as well as two lags of the dependent variable and one lag of the other two tasks. We report results from both Arellano-Bond 'Difference-GMM' and Blundell-Bond 'System GMM' estimation, and additionally report estimates using OLS as a robustness check in Appendix A.4.[14] We report two sets of results; one estimated only using the sub-sample who report changing occupations, the other estimated using our entire sample, many of whom do not change occupation. This allows us to directly compare the occupation transitions of the healthy to the sick, as well as observe broader compositional changes.

We use a conservative set of specifications for our GMM estimations: two-step estimator, time dummies, robust standard errors clustered at the individual level, and an unadjusted initial weighting matrix with the Windmeijer correction to correct for finite-sample bias (Windmeijer, 2005). To prevent over-proliferation of the instruments, we collapse the instrument set. All our specifications do not fail to reject the null of the Hansen J test for overidentifying restrictions (Hansen, 1982), a check of instrumental validity. In addition, we believe our results are reasonably robust to the threat of selection bias from those stopping work following a health shock and therefore not being captured in our estimates of occupation change. Our use of difference GMM (although not selection GMM) is robust to some forms of selection

[14] The additional initial moment restriction of $\mathbb{E}(\varepsilon_{it}\text{task}_{i1}) = 0$ that is required for System GMM estimation is not a particularly onerous restriction for the majority of individuals in my data. task_{i1} refers to the first occupation held by the individual; for the majority this is many years before the health shock I observe in my dataset. Blundell and Bond (2023) note that this additional moment restriction holds automatically if the data generating process begun long enough before the start of the sample period.

bias (Baltagi et al., 2023), although the differences between our difference and system GMM results are small. The key form of selection bias to which our estimation approach would not be robust, is cases where the lagged dependent variable is part of the selection equation. We run regression to check whether the lagged occupation intensity variable is correlated with likelihood of stopping work, and do not find much evidence that this is the case (see Appendix A.6 for further details).

5.3.2 Key results

We report our key results in Table 9. For each of the three tasks, we report four sets of regression results that estimate equation 3 by using the sub-sample of individuals who changed occupation or the full sample, and by using difference or system GMM.

Table 9: Changes in occupation task intensity

	cognitive				interpersonal				manual			
	occ change subsample		full sample		occ change subsample		full sample		occ change subsample		full sample	
	diff-GMM	sys-GMM	diff-GMM	sys-GMM	diff-GMM	sys-GMM	diff-GMM	sys-GMM	diff-GMM	sys-GMM	diff-GMM	sys-GMM
physical	-0.169**	-0.122***	-0.009*	-0.008*	-0.068	-0.043	-0.002	-0.002	-0.125	-0.165**	-0.007	-0.008
	(0.069)	(0.049)	(0.005)	(0.005)	(0.066)	(0.035)	(0.005)	(0.005)	(0.099)	(0.071)	(0.006)	(0.006)
L.physical	-0.0681	-0.016	-0.007**	-0.007**	-0.036	-0.021	-0.002	-0.002	-0.059	-0.087*	-0.006*	0.005
	0.044	(0.021)	(0.003)	(0.003)	(0.047)	(0.016)	(0.003)	(0.003)	(0.063)	(0.048)	(0.003)	(0.003)
mental	0.0068	-0.138	-0.018**	-0.019**	-0.038	-0.067	0.004	0.003	0.044	0.083	-0.019**	-0.020**
	(0.0833)	(0.129)	(0.009)	(0.009)	(0.085)	(0.075)	(0.008)	(0.008)	(0.078)	(0.065)	(0.009)	(0.009)
L.mental	-0.007	-0.063**	-0.007	-0.008	-0.017	-0.003	0.001	0.001	0.056	0.063	-0.005	-0.006
	(0.080)	(0.028)	(0.005)	(0.006)	(0.057)	(0.023)	(0.005)	(0.005)	(0.065)	(0.059)	(0.005)	(0.005)
chronic	-0.033	-0.027	0.008*	0.009**	-0.011	0.002	0.005	0.005	-0.077*	-0.092**	0.002	0.002
	(0.044)	(0.036)	(0.004)	(0.004)	(0.039)	(0.029)	(0.004)	(0.004)	(0.041)	(0.040)	(0.004)	(0.004)
L.chronic	-0.004	0.006	0.006*	0.006**	0.006	0.014	0.003	0.003	0.028	-0.030	0.002	0.001
	(0.026)	(0.014)	(0.003)	(0.003)	(0.025)	(0.012)	(0.003)	(0.003)	(0.027)	(0.023)	(0.002)	(0.003)
L.cognitive	-0.405***	-0.390***	0.596***	0.696***	0.008	0.019	0.023	0.011	0.053	0.059	-0.012	-0.019
	(0.080)	(0.063)	(0.061)	(0.016)	(0.056)	(0.046)	(0.049)	(0.013)	(0.057)	(0.050)	(0.047)	(0.028)
L2.cognitive	0.175**	0.114***	0.047***	0.067***								
	(0.070)	(0.034)	(0.016)	(0.010)								
L.interpersonal	0.041	-0.052	-0.005	-0.020	-0.446***	-0.521***	0.595***	0.555***	0.017	-0.001	0.007	0.008
	(0.089)	(0.073)	(0.065)	(0.016)	(0.099)	(0.060)	(0.084)	(0.018)	(0.071)	(0.063)	(0.056)	(0.027)
L2.interpersonal					0.136*	0.067**	0.048***	0.060***				
					(0.078)	(0.033)	(0.017)	(0.011)				
L.manual	0.005	-0.053	0.018	-0.013	-0.020	-0.041	-0.054	0.011	-0.292***	-0.483***	0.611***	0.733***
	(0.072)	(0.061)	(0.056)	(0.013)	(0.058)	(0.047)	(0.049)	(0.013)	(0.103)	(0.057)	(0.080)	(0.035)
L2.manual									0.317***	0.091***	0.020	0.048***
									(0.104)	(0.035)	(0.018)	(0.011)
L3.manual									0.236***		-0.004	
									(0.077)		(0.014)	
Hansen J test	0.529	0.399	0.813	0.752	0.605	0.781	0.8985	0.9798	0.728	0.134	0.3601	0.6648
N	13,850	13,850	148,803	148,803	13,850	13,850	148,803	148,803	13,360	13,850	145,107	148,803

Standard errors in parentheses, * p<0.1, ** p<0.05, *** p<0.01, Include 3rd lag for (9) and (11) to ensure Hansen J test valid

We find that individuals who suffered a physical disability shock switched to occupations with an average cognitive and manual intensity of 0.1-0.2 units lower than the healthy. A one standard deviation reduction in task intensity is equivalent to around 0.2 units, therefore the effect size we observe is substantial. We also find some evidence that those who suffered a mental health shock switched into occupations with less cognitive and manual intensity. These results vary a little by specification, possibly because our mental health shock sub-sample is much smaller than our chronic or physical health shock sub-sample. Our results for chronic health shocks are more mixed; our estimates using the occupation change sub-sample indicate that they switched into occupations with lower manual intensity than the healthy, while our estimates using the full sample suggest that chronic health shocks are associated with switching to more cognitively-intense occupations. We interpret the latter result as a compositional effect. On average, previous research has found that individuals switch to occupations with increased cognitive intensity (Lise and Postel-Vinay, 2020), and we do not find any evidence that those who suffered a chronic health shock behaved differently from the healthy in this respect. Since those who suffer a chronic health shock are more likely to change occupation than the healthy, a combination of these two effects would result in the coefficient on chronic health shocks for the cognitive regression being insignificant when the sample just consists of those who change occupation, but positive and significant when the whole sample is used.

Our most consistent result across our various specifications, is that individuals select into occupations with lower cognitive intensity following a physical or mental health shock, relative to the healthy. Highly cognitive jobs are typically more complex jobs with higher levels of responsibility that command higher salaries. 'Cognitive' is also the first principal component identified by the principal component analysis run by Lise and Postel-Vinay (2020) on all job tasks, and can be considered a proxy for overall occupation task intensity. Individuals may switch to less cognitive jobs to seek less-demanding jobs that they can better manage while in poor health. However, the gap between the average cognitive intensity of the new occupations of the healthy and the sick may also reflect the latter group missing out on the 'upside' of labour market transitions such as promotions. The reduction in cognitive intensity maps onto individuals selecting occupations that offer lower pay on average. Cognitive intensity is the task that has the strongest relationship with pay (see Appendix A.5 for details).

We re-estimate our preferred System-GMM specification using the average wage and standard deviation of an occupation as the dependent variable, but otherwise following the structure of equation 3.[15] We find that if an individual switches occupations following a new physical disability or worsening in mental health, the new occupation chosen has lower average pay, as well as lower standard deviation of pay, relative to the new occupations of those who remain healthy.[16]

Ex ante, the relationship between health shocks and manual task intensity is theoretically ambiguous. The onset of a physical disability may have a large impact on an individual's productivity to perform manual tasks (θ^M in our model) but not cognitive or interpersonal tasks, so individuals will switch to a less manually-intense job (lower α^M) to seek higher wages. On the other hand, individuals who suffer a health shock and are forced to leave their occupation may have to switch to a low-skilled occupation with low entry conditions. These types of occupations often have medium-to-high manual content, such as bus drivers, gardeners, warehouse workers, shelf-fillers, cleaners, and cooks. We do not model the occupation offer distribution, but this outcome could be more likely if a health shock also has a large impact on cognitive or interpersonal productivity (θ^C and θ^I). We find strong evidence that those who suffer a physical disability reduce the manual intensity of their occupation relative to the healthy, while our evidence is more mixed for mental and chronic health shocks. This suggests that physical health shocks have the biggest impact on θ^M.

Our null result for any relationship between health shocks and subsequent interpersonal task intensity surprised us, as we expected mental health shocks in particular to have a negative impact on an individual's productivity in performing highly-interpersonal tasks. There are several potential explanations for our null result. There may be no relationship between health shocks and an individual's ability to perform in highly interpersonal occupations, perhaps because interpersonal skills are broadly fixed over an individual's working life (Lise and Postel-Vinay, 2020). While we would expect that some mental health conditions such as depression or social anxiety would worsen an individual's interpersonal skills, we cannot find any research specifically

[15]Since our wage data is limited, we restrict our wage analysis to considering occupation averages rather than individual wage trajectories.

[16]See Appendix Table 14 for regression table output

on the relationship between health shocks and interpersonal/social skills. A second possibility is that a more interpersonal job may give individuals more opportunities to advocate for themselves for support in the workplace (Szerman, 2024), and that individuals employed in more interpersonal jobs are also likely to have better interpersonal skills that enable this advocacy to be successful. There is increasing evidence that, relative to other skills, social skills are particularly crucial for labour market success (Noray, 2020).

While we cannot test these hypothesis with our data, we can test a third possibility; that occupations with higher interpersonal task intensity are more likely to have other features desired by those who are in poor health. We find evidence of a positive correlation between interpersonal task intensity and job flexibility, which is a key job trait desired by those in poor health (Florisson et al., 2022).

Table 10: Occupation flexibility and task intensity

	hours vary	part time	region match	hours vary	part time	region match
		OLS			fixed effects	
	(1)	(2)	(3)	(4)	(5)	(6)
interpersonal	0.3175***	0.1103***	0.0566***	0.1143***	0.0222***	-0.0038
	(0.0050)	(0.0023)	(0.0033)	(0.0207)	(0.0082)	(0.0100)
cognitive	-0.2110***	-0.1400***	-0.0375***	-0.1042***	-0.0527***	-0.0126
	(0.0048)	(0.0021)	(0.0032)	(0.0200)	(0.0076)	(0.0095)
manual	0.2365***	0.0226***	0.0271***	0.0742***	-0.0070	0.0026
	(0.0042)	(0.0018)	(0.0028)	(0.0177)	(0.0067)	(0.0081)
hours	-0.0087***	-0.0536***	-0.0025***	0.0031***	-0.0450***	-0.0013***
	(0.0002)	(0.0001)	(0.0001)	(0.0005)	(0.0003)	(0.0002)
hours^2	0.0002***	0.0004***	0.0000***	0.0000***	0.0003***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
N	667,830	835,667	835,173	667,830	835,667	835,173

Standard errors in parentheses, * p<0.1, ** p<0.05, *** p<0.01

Additional controls: age, sex, pay, education, ethnicity

Work ‘flexibility’ can refer to a large range of workplace practises, and we do not have direct measures of flexibility in our database.[17] However, we do have several

[17]A possible extension to this work could be to source flexibility data from elsewhere, such as from

variables that could be associated with flexibility: whether hours worked vary week-to-week, which would capture both shift-based work where hours are likely to vary by employer demand as well as jobs where an individual has significant flexibility to set their own weekly working hours, whether an individual works part-time hours, defined as under 35 hours per week, and whether an individual lives in the same region as where they work. The latter variable is a crude attempt to capture commuting time as well as whether the individual works from home. We regress our proxies for flexibility against cognitive, manual, and interpersonal intensity and report our results in Table 10. We find that interpersonal intensity is strongly positively correlated with all our indicators of flexibility, while cognitive intensity is negatively correlated and manual intensity is more weakly positively correlated. Therefore, individuals who report that their work is flexible are more likely to be in occupations with high interpersonal content.

5.3.3 Heterogeneity analysis

We re-estimate equation 3 separately for those with a university degree, and those with a high school education or below, using System GMM and the full sample. We find that declines in cognitive intensity following a health shock are concentrated among those who do not hold a university degree. The effect size is particularly strong for individuals who suffered a mental health shock and do not hold a degree; we observe large declines in both average cognitive intensity as well as average manual intensity for this group. The magnitude of these changes suggest that low-educated individuals who suffer a mental health shock are particularly vulnerable to the labour market consequences of health shocks, and further research into their employment outcomes is recommended.

We also replicate this analysis by sex; we report the full results in Appendix table 15. Men and women respond in a similar way to physical health shocks, but women seem to make larger changes to their occupation task intensity following a mental health shock. In particular, we observe large declines in the average cognitive content of occupations held by women who suffer a mental health shock, relative to healthy women.

recent work by Adams-Prassl et al. (2023)

Table 11: System GMM: Changes in occupation content, by education level

	cognitive		interpersonal		manual	
	no degree	degree	no degree	degree	no degree	degree
	(1)	(2)	(3)	(4)	(5)	(6)
physical disability	-0.0095	-0.0042	-0.0049	0.0061	-0.0047	-0.0144
	(0.0059)	(0.0086)	(0.0058)	(0.0072)	(0.0069)	(0.0109)
L.physical disability	-0.0064*	-0.0078	-0.0028	0.0006	-0.0028	-0.0111*
	(0.0035)	(0.0058)	(0.0037)	(0.0055)	(0.0040)	(0.0064)
mental	-0.0316***	0.0025	0.0083	-0.0086	-0.0309***	0.0009
	(0.0118)	(0.0129)	(0.0103)	(0.0105)	(0.0109)	(0.0153)
L.mental	-0.0146**	0.0051	0.0033	-0.0044	-0.0108*	0.0041
	(0.0073)	(0.0076)	(0.0066)	(0.0058)	(0.0065)	(0.0094)
chronic	0.0096*	0.0081	0.0067	0.0020	0.0015	0.0052
	(0.0058)	(0.0066)	(0.0046)	(0.0066)	(0.0050)	(0.0063)
L.chronic	0.0054	0.0068	0.0026	0.0025	0.0007	0.0032
	(0.0035)	(0.0044)	(0.0031)	(0.0044)	(0.0031)	(0.0043)
Hansen J stat p-value	0.9073	0.7575	0.9909	0.9405	0.8153	0.5880
N	96,025	52,778	96,025	52,778	96,025	52,778

Standard errors in parentheses, * $p<0.1$, ** $p<0.05$, *** $p<0.01$

6 Conclusion

This chapter sought to address a gap in the literature and investigated how suffering a health shock affects subsequent occupational mobility. We found that those who report a new physical disability, worsening of mental health, or new chronic health condition are more likely to change occupation or employer over the subsequent few months, as well as stop working and drop out of the labour force. We also find that the occupations selected by these individuals differ from the occupation choices of comparable individuals who remain healthy. Those who reported a new physical disability switched to occupations with lower cognitive and manual task intensity, those who reported worsening mental health switched to occupations with lower cognitive intensity, and those who reported a new chronic health condition switched to occupations with lower manual intensity, relative to the occupation choices of those who remained healthy. These results are broadly consistent with individuals who suffer a health shock switching to jobs with fewer responsibilities that may be easier to manage with their health condition, as well as switching to jobs with lesser manual requirements if they suffered a physical or chronic health shock. The reduction in cognitive intensity may also reflect individuals with physical disabilities or poor mental health facing additional barriers to being promoted to better paid, more task-intensive work. Better understanding the occupation mobility patterns of individuals who suffer a health shock but remain in the labour force can contribute to policy work in supporting individuals in poor health remain in or return to the labour force, which is currently a UK government policy priority. In addition, our work highlights the importance of separately considering different health conditions rather than relying on a single health variable or index for analysis, as occupation change patterns differ by health condition.

There are many interesting potential extensions to our research. Our finding that individuals do not seek to reduce the interpersonal content of their job following a health shock surprised us. Further research could unpack this result, especially as prior literature has found a positive relationship between interpersonal task intensity and positive labour market outcomes for those with disabilities or low education levels (Aghion et al., 2023). Identifying how different types of health shocks erode task-specific skills, for example determining whether mental health shocks erode interpersonal task productivity, could help explain the mechanisms behind the occupation transitions we describe in this paper, as could a further examination of the relationship between flexibility and task intensity for different occupations. A dataset with much better wage data, such as an administrative dataset with linked health data, could be used to identify the wage consequences of different types of occupation changes following health shocks. Finally, such a dataset could be combined with our theoretic framework and empirical results to build a structural model of occupation choices following health shocks that could be used to support government policy making.

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A Appendix

A.1 PCA analysis for health category classification

C (component) 1 maps onto physical disabilities, C2 maps onto mental health, C3 maps onto chronic health conditions.

Figure 3: Principal component analysis

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
Problems - arms or hands	0.550	-0.178	-0.117	-0.036	-0.005	-0.018	0.047	0.017	-0.006	0.048
Problems - legs or feet	0.565	-0.151	-0.069	-0.045	0.001	-0.025	0.041	0.002	0.001	0.029
Problems - back or neck	0.520	-0.117	-0.112	-0.002	-0.048	-0.009	0.019	0.040	-0.016	-0.022
Difficulty in seeing	0.097	0.102	0.161	0.031	0.263	0.136	-0.593	-0.146	0.373	0.319
Difficulty in hearing	0.145	0.140	0.183	0.096	0.239	0.093	-0.491	-0.039	0.020	-0.440
A speech impediment	0.054	0.106	-0.001	0.124	0.611	-0.112	0.106	-0.198	-0.310	-0.052
Skin conditions, allergies	0.138	0.275	0.197	0.505	-0.232	-0.092	0.077	-0.082	0.082	0.115
Chest/breathing problems	0.110	0.281	0.247	0.470	-0.238	-0.125	0.154	-0.113	0.083	0.129
Heart, blood pressure	0.141	0.205	0.482	-0.367	-0.015	-0.109	0.119	-0.022	-0.002	-0.064
Stomach, liver, kidney, digestive	0.098	0.259	0.175	0.009	-0.131	0.352	0.058	0.174	-0.255	-0.571
Diabetes	0.052	0.134	0.421	-0.500	0.019	-0.253	0.170	-0.141	0.108	0.121
Depression, bad nerves, anxiety	0.086	0.538	-0.364	-0.178	-0.122	0.007	-0.050	-0.038	0.038	0.001
Depression, bad nerves or anxiety	0.009	0.083	-0.019	0.059	0.317	0.123	0.346	0.524	0.668	-0.127
Learning difficulties	0.023	0.210	-0.098	0.153	0.488	-0.238	0.254	-0.018	-0.202	0.075
Mental illness, phobia, panics	0.033	0.479	-0.456	-0.220	-0.080	-0.044	-0.049	-0.113	0.093	0.024
Other progressive illness	0.036	0.051	0.066	-0.051	0.101	0.808	0.294	-0.316	-0.050	0.292
other	0.044	0.193	0.122	-0.041	0.016	0.092	-0.199	0.691	-0.416	0.465
Proportion explained	0.110	0.081	0.071	0.065	0.063	0.059	0.059	0.058	0.058	0.056
Cumulative proportion	0.110	0.191	0.262	0.327	0.390	0.449	0.508	0.566	0.624	0.681

Only report first 10 components, so omit C11-17

A.2 Additional summary statistics

We provide some additional information on the distribution of occupation changes. We graph the distribution of occupation content changes in Figure 4. The correlations between task changes is as follows: the correlation between cognitive and interpersonal is 0.60, cognitive and manual is 0.42 and manual and interpersonal is -0.17.

Figure 4: Histogram of occupational content changes

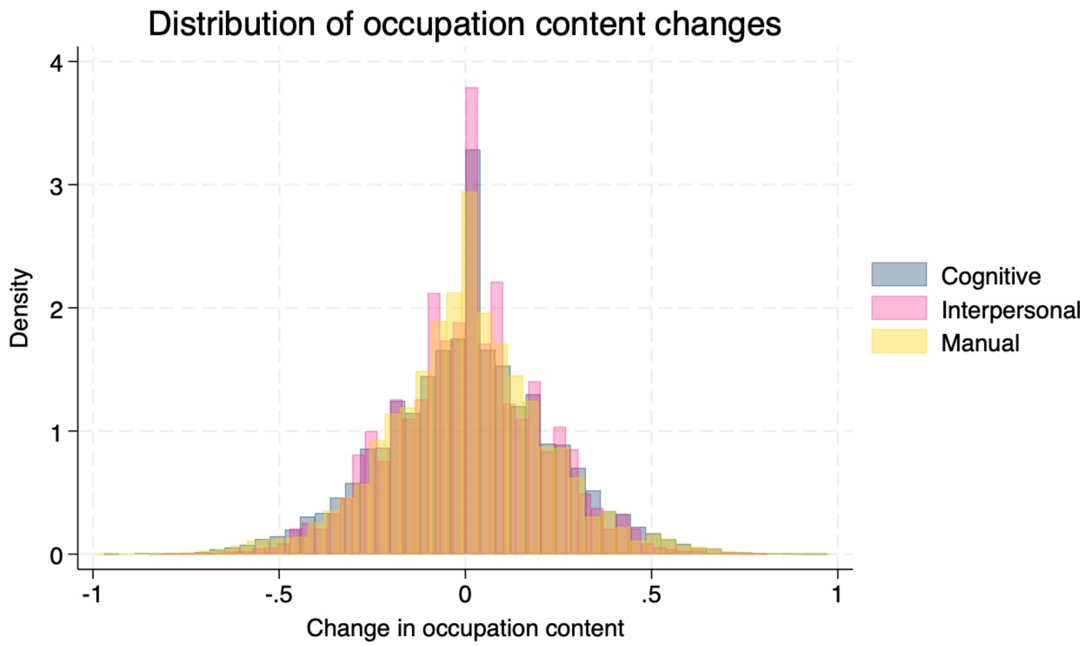
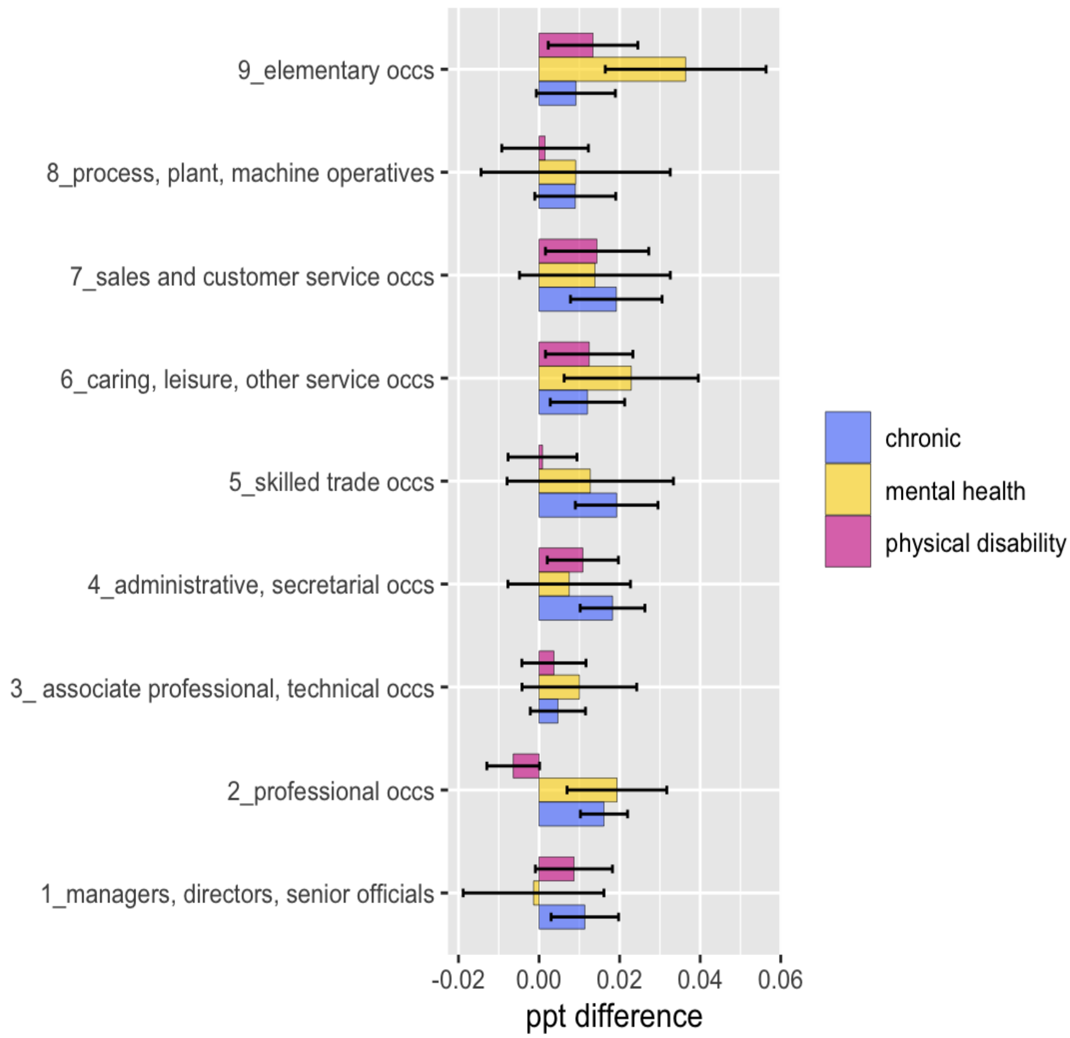


Table 12: Labour market transitions by occupation and health shock type, share of total

	change occupation				change job				stop working			
	Disability	Mental	Chronic	Healthy	D	M	C	H	D	M	C	H
corporate managers and directors	19.2	18.8	17.9	14.2	6.5	6.3	6.2	5.2	2.3	2.0	2.1	1.5
other managers and proprietors	15.1	15.5	13.3	13.3	4.7	5.4	4.8	4.4	3.4	4.3	3.0	2.2
science, research, engineering and tech prof.	16.7	19.6	16.1	14.2	4.4	6.1	6.3	4.9	3.0	4.0	2.1	1.4
health professionals	3.8	4.6	4.1	3.7	4.7	7.0	6.3	4.8	2.4	2.1	2.0	1.2
teaching and educational prof.	10.6	10.4	10.4	8.9	4.2	7.7	5.8	4.4	5.1	3.2	3.7	2.4
business, media and public service prof.	12.8	17.8	12.8	11.6	4.9	6.9	6.2	5.2	2.2	3.3	1.9	1.7
science, engineering and tech. associate prof.	18.8	15.0	18.4	16.3	4.6	6.6	5.4	4.4	2.1	7.5	2.6	1.7
health and social care associate prof.	15.9	11.3	16.5	13.1	4.3	4.4	5.7	4.1	3.2	3.3	3.2	2.2
protective service occupations	6.8	4.8	7.3	5.9	2.6	2.4	2.9	2.6	3.4	2.4	1.7	0.9
culture, media and sports occupations	7.7	5.1	8.2	7.5	4.2	4.4	4.0	4.4	4.6	7.0	4.7	3.4
business and public service associate prof.	14.7	16.7	14.9	13.8	5.1	6.6	4.9	5.2	2.9	3.4	2.7	2.1
administrative occupations	15.5	15.0	14.0	13.2	5.6	5.4	6.0	4.5	3.7	4.3	3.3	2.7
secretarial and related occupations	9.1	8.9	11.0	7.7	4.6	8.6	6.0	4.6	5.0	7.9	4.1	2.4
skilled agricultural and related trades	4.0	6.5	5.0	4.6	1.0	3.2	1.9	2.5	4.2	14.5	5.5	1.6
skilled metal, electrical and electronic trades	12.4	14.3	14.4	10.7	4.4	6.0	5.2	4.5	3.2	7.2	2.6	1.5
skilled construction and building trades	6.4	12.1	7.7	5.9	3.4	5.1	4.4	3.7	3.0	4.7	3.5	1.8
textiles, printing and other skilled trades	8.5	9.9	9.9	7.5	4.6	5.8	6.5	5.3	5.4	7.4	3.3	2.5
caring personal service occupations	9.5	9.4	8.9	8.1	6.2	8.2	6.5	5.3	4.7	5.5	4.3	3.0
leisure, travel and related personal service	9.5	5.6	8.9	7.5	4.0	5.2	5.0	4.6	3.2	4.8	4.0	3.1
sales occupations	11.9	13.2	12.6	11.0	6.6	8.5	6.9	6.1	5.3	8.2	5.6	4.3
customer service occupations	17.4	17.6	17.9	16.5	6.1	6.8	8.6	5.7	3.9	6.5	3.2	3.1
process, plant and machine operatives	17.2	17.3	14.9	14.6	4.4	7.1	4.8	4.7	3.7	7.1	3.2	2.4
transport/mobile machine drivers/operatives	8.0	8.1	7.1	6.7	4.9	6.5	5.1	5.2	2.8	4.2	3.0	1.8
elementary trades and related occupations	17.4	15.8	14.3	14.0	6.0	7.9	7.3	6.8	6.5	15.8	8.9	4.7
elementary administration and service	7.4	10.8	8.7	8.3	5.6	9.3	6.4	6.2	5.2	8.8	4.9	4.6

Figure 5: Jobs change likelihood by prior occupation - difference from healthy individuals

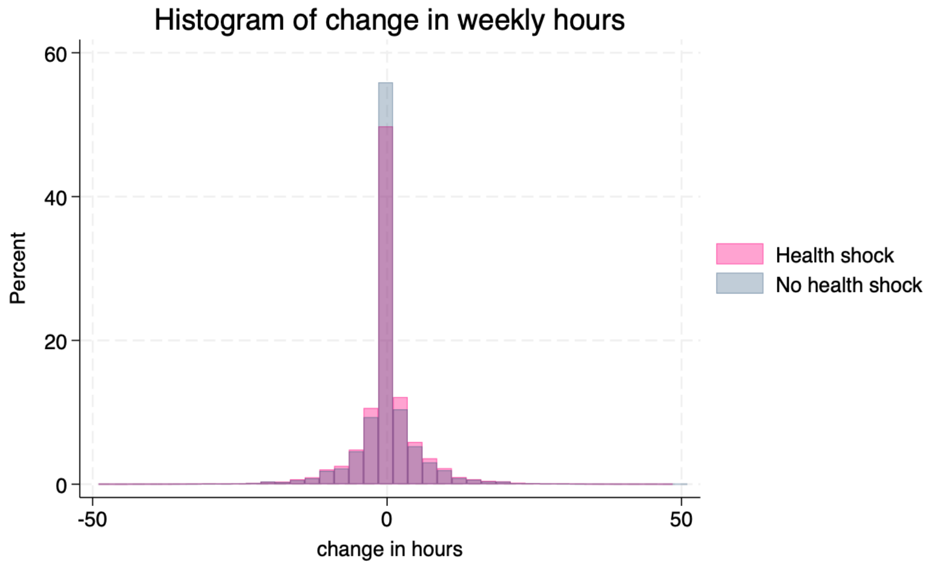


A.3 Additional analysis of hours changes

We firstly graph the distribution of the reported changes in hours between two quarters for those who suffer a health shock and for those who remain healthy in Figure 6. Those who suffer a health shock are more likely to increase or decrease their hours relative to those who remain healthy.

We then estimate the mean change in hours worked following a health shock by replicating the system-GMM specification from a prior section of this paper. We estimate the following equation only using the individuals in our sample who change occupation, change jobs, as well as the full sample. We do not use the first lag of

Figure 6



the hours variable as an instrument as including it leads to a strong rejection of the null of the Hansen J-test, while only including the second and later lags does not, suggesting that the errors follow an MA(1) process. We also include a second lag of the dependent variable when we use the full sample for our estimation, as hours are much less persistent for the sub-sample that changes occupation relative to the full sample.

$$\begin{aligned}\text{weekly hours}_{i,t} = \beta_1^D \text{disability shock}_{i,t} + \beta_1^M \text{mental shock}_{i,t} + \beta_1^C \text{chronic shock}_{i,t} + \\ \beta_2^D \text{disability shock}_{i,t-1} + \beta_2^M \text{mental shock}_{i,t-1} + \beta_2^C \text{chronic shock}_{i,t-1} + \\ \gamma_1 \text{weekly hours}_{i,t-1} + \gamma_2 \text{weekly hours}_{i,t-2} + \varepsilon_{it}.\end{aligned} \tag{4}$$

We find that the sub-sample that changed occupation or job following a physical disability shock or mental health shock also, on average, worked fewer hours in their new occupation than those who changed occupation while remaining healthy. When we repeat our estimation using the full sample, only the coefficient on the lagged physical disability shock term continues to be negative and significant. However, there is a risk that this specification is vulnerable to selection bias because our lagged dependent variable is correlated with the selection equation. Those who work fewer hours are more likely to stop working following a health shock. One way to potentially reduce this bias would be estimate full time and part time workers separately; we are not able to do this because our sample becomes too small.

Table 13: Average weekly hours - system GMM

	(1) Occupation change sub-sample	(2) Employer change sub-sample	Full sample
physical disability shock	-1.0684*	–6.6858***	0.0249
	(0.5836)	(2.5892)	(0.1249)
L.physical disability shock	-0.6131***	0.3725	-0.1524**
	(0.2284)	(0.6602)	(0.0665)
mental health	0.0793	2.5348	-0.2490
	(1.2951)	(3.5931)	(0.2388)
L.mental health	-1.0143**	-2.2415***	-0.0075
	(0.4409)	(0.8614)	(0.1567)
chronic	0.2941	1.8911	-0.0135
	(0.4956)	(1.4073)	(0.1067)
L.chronic	0.3050	-0.3354	-0.0624
	(0.2013)	(0.4599)	(0.0554)
L.hours	0.7302***	0.1356	1.1761***
	(0.1046)	(0.1120)	(0.0958)
L2.hours		-0.2424***	
		(0.0596)	
Hansen J-stat p val	0.3162	0.4320	0.0646
N	73405	33097	366768

Standard errors in parentheses, * p<0.1, ** p<0.05, *** p<0.01

A.4 Additional robustness checks

As a robustness check, we re-estimate our main occupation change specification using OLS rather than GMM. We regress cognitive, manual, and interpersonal content of jobs in period t against dummies for suffering a health shock in the past six months, controlling for job characteristics pre-shock. To reduce the risk of dynamic panel (Nickell) bias, we run several specifications that control for job characteristics pre-shock. The three specifications are: do not control for lagged cognitive, manual, and interpersonal intensity (specification 1), include lagged occupation codes at the two digit level (25 categories) instead of lagged dependent variables (specification 2), and include lagged cognitive, manual, and interpersonal intensity as lagged dependent variables (specification 3). These are reported in Table 7.

Figure 7: Occupation content OLS regressions - full sample

	Spec 1	2	3	1	2	3	1	2	3
		cognitive			interpersonal			manual	
disab	-0.0046	-0.0010	0.0001	-0.0001	0.0000	0.0003	0.0041	0.0015	0.0009
	(0.0033)	(0.0020)	(0.0014)	(0.0028)	(0.0018)	(0.0012)	(0.0032)	(0.0022)	(0.0012)
mental	-0.0121**	-0.0104***	-0.0034*	0.0010	0.0004	-0.0014	-0.0163***	-0.0070**	-0.0022
	(0.0048)	(0.0030)	(0.0020)	(0.0042)	(0.0028)	(0.0018)	(0.0047)	(0.0031)	(0.0016)
chronic	0.0004	0.0001	0.0015	0.0039	0.0024	0.0021**	0.0000	0.0007	0.0012
	(0.0029)	(0.0017)	(0.0011)	(0.0026)	(0.0016)	(0.0010)	(0.0030)	(0.0020)	(0.0011)
N	218386	216350	216350	218386	216350	216350	218386	216350	216350

Standard errors in parentheses, * p<0.1, ** p<0.05, *** p<0.01
Controls: age, sex, educ, ethnicity, time, lagged job traits

A.5 Additional specifications

We consider two additional specifications that relate to pay and gender. First, the various channels by which health shocks influence subsequent labour market transitions will also impact pay. Unfortunately, the pay data available in the LFS is quite limited. It only reports an individual's pay in the first and fifth survey wave, and only for a subset of the sample as answering this question is voluntary. Around 1/3 of the sample does not answer this question, and the data is more likely to be missing for individuals in lower-skilled lower-paid occupations. Therefore, we focus on comparing the average salaries of occupations, rather than an individual's wage trajectory following a health shock, and estimate an occupation's average salary and its standard deviation in Table 14. These regressions only includes individuals who changed occupations.

Second, we report our main specification re-estimated by sex in Table 15.

A.6 Selection effects

It is possible that those who stop working bias the estimates of cognitive, manual, content, especially if the lagged dependent variables are correlated with selection in

Table 14: System GMM: average wage and standard deviation of new occupation

	(1) occupation ave. salary	(2) occupation st. dev. salary
disability shock	-0.0556**	-0.0213**
	(0.0229)	(0.0107)
L.disability shock	-0.0289**	-0.0033
	(0.0147)	(0.0032)
mental health shock	-0.0205	0.0072
	(0.0436)	(0.0152)
L.mental health shock	-0.0584**	-0.0108**
	(0.0246)	(0.0050)
chronic health shock	-0.0170	0.0123
	(0.0243)	(0.0098)
L.chronic health shock	0.0159	-0.0002
	(0.0111)	(0.0029)
Hansen J stat p-value	0.5352	0.4316
N	38,294	40,158

Standard errors in parentheses,* p<0.1, ** p<0.05, *** p<0.01
Additional controls: first two lags of dependent variable

our GMM specifications. To assess the significance of this risk, we regress a dummy variable that captures whether an individual stops working in period t on lags of interpersonal, manual, cognitive task intensity, lagged hours worked, as well as my standard demographic controls such as age, sex, and education level and report the results in Table 16. We find that there is no relationship between lagged occupation task intensity and stopping work. This is a good result for our main occupation content change specification. While this finding does not fully absolve us from the risk of selection bias, it does reduce it.

A related concern is attrition rates from the sample following a health shock. We report attrition rates between waves 1-5 of the survey by health shock. We do observe a small uptick in attrition rates for those who suffer a health shock, especially those with mental health conditions.

Table 15: Changes in occupation content, by sex, difference GMM

	(1)	(2)	(3)	(4)	(5)	(6)
	cognitive		interpersonal		manual	
	men	women	men	women	men	women
physical disability	-0.0116	-0.0058	-0.0019	-0.0023	-0.0108	-0.0044
	(0.0078)	(0.0059)	(0.0071)	(0.0062)	(0.0091)	(0.0070)
L.physical disability	-0.0085*	-0.0065*	-0.0017	-0.0026	-0.0037	-0.0071*
	(0.0046)	(0.0039)	(0.0045)	(0.0041)	(0.0057)	(0.0037)
mental	-0.0088	-0.0246**	0.0166	-0.0066	-0.0180	-0.0197**
	(0.0159)	(0.0108)	(0.0150)	(0.0079)	(0.0188)	(0.0083)
L.mental	-0.0043	-0.0099	0.0104	-0.0067	-0.0038	-0.0065
	(0.0096)	(0.0065)	(0.0093)	(0.0047)	(0.0106)	(0.0048)
chronic	0.0155**	0.0020	0.0077	0.0025	0.0019	0.0015
	(0.0072)	(0.0052)	(0.0054)	(0.0053)	(0.0067)	(0.0044)
L.chronic	0.0077*	0.0043	0.0025	0.0021	-0.0007	0.0031
	(0.0044)	(0.0035)	(0.0037)	(0.0035)	(0.0043)	(0.0029)
Hansen J stat p-value	0.9299	0.4068	0.4698	0.9528	0.9077	0.4045
N	74,620	74,183	74620	74,183	74,620	74,183

Standard errors in parentheses, * p<0.1, ** p<0.05, *** p<0.01

Table 16: Likelihood of stopping work

	(1)
L.cognitive	-0.0043
	(0.0038)
L2.cognitive	0.0043
	(0.0053)
L3.cognitive	0.0010
	(0.0045)
L.manual	0.0039
	(0.0035)
L2.manual	0.0007
	(0.0044)
L3.manual	-0.0027
	(0.0036)
L.interpersonal	0.0038
	(0.0042)
L2.interpersonal	-0.0064
	(0.0061)
L3.interpersonal	0.0015
	(0.0051)
L.hours	0.0001**
	(0.0001)
L2.hours	0.0001
	(0.0001)
L3.hours	-0.0001*
	(0.0000)
age	0.0079**
	(0.0031)
age2	-0.0265**
	(0.0111)
age3	0.0408**
	(0.0174)
age4	-0.0243**
	(0.0098)
sex	0.0002
	(0.0005)
education	-0.0018***
	(0.0005)
pay in period 1	0.0027***
	(0.0007)
N	188,966

Standard errors in parentheses, * p<0.1, ** p<0.05, *** p<0.01

Table 17: Attrition rate; by health shock type

	t-1	t (shock)	t+1	t+2	t+3
healthy	100	97.3	95.9	94.9	94.1
new disability at t	100	96.6	94.8	93.6	91.8
new mental health condition at t	100	95.2	93.1	91.4	91.0
new chronic health condition at t	100	96.8	95.2	94.4	93.0