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In and Out of Unemployment - Labour Market Dynamics and the Role of Testosterone

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IN AND OUT OF UNEMPLOYMENT - LABOUR MARKET DYNAMICS AND THE ROLE OF TESTOSTERONE

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Abstract

Biological processes have provided new insights into diverging labour market trajectories. In this paper, we use population variation in testosterone levels to explain transition probabilities into and out of unemployment. We follow individual employment histories for 1,771 initially employed and 109 initially unemployed British men from the UK Household Longitudinal Study ("Understanding Society") between 2009 and 2015. To account for unobserved heterogeneity, we apply dynamic random effect models. We find that individuals with high testosterone levels are more likely to become unemployed, but they are also more likely to exit unemployment. Based on previous studies and descriptive evidence, we argue that these effects are likely driven by personality traits and occupational sorting of men with high testosterone levels. Our findings suggest that latent biological processes can affect job search behaviour and labour market outcomes, without necessarily relating to illness and disability.

Keywords: labour market dynamics, unemployment, testosterone, random-effects probit

JEL classification: I10, J64, C23

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1 Introduction

'Joblessness leaves permanent scars on individuals' (Arulampalam, 2001, p. 585), partly because unemployed individuals might be perceived (and might perceive themselves) as violating a social norm. On the other hand, it can also be a rational decision to remain unemployed for a period to hold out for a better job offer and improve the job match. The economic literature has shown that there are various factors which explain why individuals become unemployed or stay in unemployment. However, the focus has been on observable factors, such as individual and household characteristics or the past unemployment experience and duration (see, e.g., Gregg, 2001). More recent evidence points to personality traits and non-cognitive skills as influential factors of job search behaviour and unemployment duration. Studies have investigated, e.g., the locus of control (Caliendo et al., 2015; Heckman et al., 2006; Schurer, 2017), impatience (DellaVigna and Paserman, 2005), the Big 5 personality traits (Viinikainen and Kokko, 2012), or self-efficacy and interpersonal skills (Uysal and Pohlmeier, 2011).

Hormones have been linked to a number of non-cognitive skills and personality aspects. In particular, testosterone is prominently linked to risk-attitude and aggression (Dabbs, 1992; Dabbs et al., 2001; Hughes and Kumari, 2019), but also to skills such as motivation, pro-social behaviour, persistence, or numerical ability (Apicella et al., 2008; Carré and McCormick, 2008; Dabbs et al., 2001; Welker and Carré, 2015). Likely related to these attributes, testosterone has also repeatedly been found to predict men's labour market performance (Dreher et al., 2016; Gielen et al., 2016; Nye et al., 2017). Moreover, testosterone also seems to affect occupational choices (Dabbs, 1992; Greene et al., 2014). Yet, surprisingly testosterone has not been investigated as an explanatory factor of unemployment, something we seek to address in this paper.

We investigate whether differences in serum testosterone levels of men can explain transitions in and out of unemployment. We use data from *Understanding Society (UKHLS),* a longitudinal household survey covering about 40,000 households from the United Kingdom, and link it with the *Health and biomarkers Survey*, which holds a range of biomarker data, including the circulating level of testosterone. We examine two samples of initially employed or initially unemployed men aged 20 to 60, and we standardise their testosterone levels for age and time of the sample.

Taking advantage of the longitudinal nature of the data, we apply dynamic probit random-effects models to estimate labour market transitions. Primarily, we measure the effect of testosterone levels on the likelihood to move into a different labour force status while taking into account the prior employment trajectory. We apply a range of random-effects models, including an extension of the Mundlak-Chamberlain approach to account for unobserved heterogeneity as well as the initial conditions (Wooldridge, 2005).

We contribute to the literature by providing novel evidence on latent biological mechanisms which affect labour market trajectories. Previous studies have only considered inflammation markers in relation

to unemployment but not hormones such as testosterone (Sumner et al., 2020). Moreover, unlike previous studies we examine actual testosterone levels measured in a recent blood sample rather than 2D:4D ratio, which is a prominent marker for prenatal exposure to testosterone (see, e.g., Gielen et al., 2016). The closest study to ours is Hughes and Kumari (2019), who examined the impact of testosterone on the likelihood of being in work for a single time point and did not take advantage of the panel structure of the data. In contrast to our study, they did not explicitly model labour market transitions, nor did they account for state dependence.

Findings from our preferred regression specification indicate that for unemployed men, the risk of remaining unemployed significantly declines in the level of testosterone. In contrast, for employed men, the risk of becoming unemployed is higher for those with high testosterone levels. These findings are robust against different functional specifications for testosterone and different approaches to account for unobserved heterogeneity.

These findings might be explained in part by cognitive and non-cognitive skills that high testosterone levels are associated with, such as numerical skills or logical reasoning. In line with previous studies, our descriptive evidence shows that men with high testosterone levels indeed performed better in these areas. In addition, we find suggestive evidence that individuals with higher testosterone search differently for a job.

Our findings highlight how latent biological processes (beyond illness and disease) affect labour market outcomes. For example, when designing job search assistance programs, it is crucial for policymakers to be aware that differences in job search behaviour can be driven by biological mechanisms. Thus, due to their inherent personality traits, some individuals might require specific forms of assistance to thrive (e.g., individual training rather than group sessions). This study contributes to our understanding of such mechanisms by providing comprehensive evidence on the role of testosterone.

We proceed in Section 2 with a review of the literature on biomarkers, and we derive hypotheses based on this literature how testosterone could translate into diverging employment histories. Section 3 presents our data, and Section 4 outlines our empirical estimation strategy. In Section 5, we show descriptive evidence, and in Section 6, we present the results from our regression specifications. Section 7 discusses further possible mechanism and descriptive evidence for these potential pathways. Section 8 concludes.

2 Testosterone and the labour market

2.1 Existing literature

As biological indicators of physiological processes, biomarkers have proven invaluable for clinical practice. For example, glycated haemoglobin (HbA1c) has become a standard for the diagnosis and

management of (pre-)diabetes. In recent years, the availability of biomarkers for social science research has improved considerably due to data collection efforts of large-scale household surveys, such as the UK Household Longitudinal Study (UKHLS). Unsurprisingly, biomarkers have become an essential source of data for social and behavioural research (see Harris and Schorpp (2018) for a literature review). This includes measures such as fibrinogen, cholesterol, or c-reactive proteins that indicate (potentially undiagnosed) illnesses (e.g., Dowd et al., 2009), markers such as allostatic load which measure body reactions to chronic stress (Chandola and Zhang, 2018), and hormone levels, e.g., cortisol, insulin-like growth factor I (IGF-I) or testosterone, which influence physiological functioning and shape individual characteristics and (consequently) social behaviour (e.g., Bann et al., 2015; Kandasamy et al., 2014).

Testosterone, in particular, has been related to different forms of health issues, e.g., cardiovascular disease (Elagizi et al., 2018), but the evidence has not been very conclusive and causal pathway not fully understood (Bann et al., 2015; Hughes and Kumari, 2019). More convincingly, among men, testosterone seems to affect risky health behaviours and thus, different forms of health hazards (Booth et al., 1999).

Testosterone also plays a role for demographic outcomes, such as fertility, divorce and mating (e.g., Bütikofer et al., 2019), fitness and sport (e.g., Hsu et al., 2015), but also for labour market outcomes (e.g., Coates et al., 2009; Dabbs, 1992; Dabbs Jr. et al., 1990; Parslow et al., 2019).[1] For example, in a twin study on Dutch men, more prolonged prenatal testosterone exposure led to higher earnings during the working life (Gielen et al., 2016). [2] Other studies found education to be lower among people with low testosterone levels (Bann et al., 2015; Nye et al., 2017). Coates and Herbert (2008) followed the daily business of 300 traders in London and found that high levels of testosterone lead to higher profits on that day. Testosterone also affects the choice of occupation. Low testosterone individuals seem to choose more people-oriented jobs, whereas high testosterone individuals choose more things-oriented jobs (Dabbs Jr. et al., 1990; Hell and Päßler, 2011; Nye and Orel, 2015).[3] Typical jobs that have been related to high testosterone are sportsmen, sales men, actors, or politicians (Dabbs Jr. et al., 1990). The evidence is not conclusive, though. A more robust finding is that individuals with high testosterone levels have a higher probability to be self-employed (Greene et al., 2014; Nicolaou et al., 2017; Sapienza et al., 2009).

[1] While testosterone is present in both sexes, most of the experimental studies in the literature have focused on men. Important exceptions looked at both sexes (Dabbs et al., 2001; Gielen et al., 2016; Nye et al., 2017; Sapienza et al., 2009) or exclusively at women (Bütikofer et al., 2019; Parslow et al., 2019).

[2] Among women, high testosterone levels are expected to be associated with higher earnings as well, as women with higher testosterone levels tend to work in male-dominated occupations, which tend to be better paid. However, recent empirical evidence found the opposite or no effect (Bütikofer et al., 2019; Gielen et al., 2016; Nye et al., 2017).

[3] Women that have higher testosterone levels tend to choose jobs that are male-dominated, whereas women with low levels choose more female-dominated jobs (Nye and Orel, 2015). This observation has been used to explain parts of the gender pay gap (e.g., Gielen et al., 2016).

The findings discussed above are usually attributed to non-cognitive skills and individual characteristics associated with high testosterone levels. Typical characteristics that have been stressed in the literature are, among others, being independent, self-centred, adventurous, achievement-oriented, and focused on personal goals (Greene et al., 2014). Further, high testosterone is associated with risk-taking (Apicella et al., 2008; Coates and Herbert, 2008; Hughes and Kumari, 2019; Stenstrom et al., 2011), dominant behaviour and aggression (Archer, 2006; Chance et al., 2000; Dabbs, 1992; Dabbs et al., 2001; Schaal et al., 1996), but also status-enhancing pro-social behaviour.[4] For example, Dreher et al. (2016) injected testosterone or a placebo to 40 young men and found that in an economic bargaining game, treated individuals were indeed more aggressive towards others. Still, at the same time, they were also more generous when it promoted social status. Similarly, individuals with high testosterone levels show more initiative forming friendships and are, therefore, able to build up larger social networks (Booth et al., 2006; Cheng et al., 2013). In other game studies, men with high testosterone levels were more willing to engage in competitive tasks (Carré and McCormick, 2008) and they showed more persistence solving an undoable task (Welker and Carré, 2015).

Cognitive abilities have also been related to testosterone. While early work reported that young boys with high testosterone levels lack intelligence (Chance et al., 2000; Dabbs, 1992), more recent work showed that individuals with high testosterone levels have higher numeric capabilities and thus perform better in computer science or related occupations (Brookes et al., 2007; Brosnan et al., 2011). Similarly, individuals with more prolonged prenatal exposure to testosterone performed better in the cognitive reflection test (Bosch-Domènech et al., 2014), a test which measures the tendency to override an intuitive incorrect answer, and which has therefore been used as a measure of reflection in decision making (Frederick, 2005). Finally, a series of studies showed that people with high testosterone levels perform better in face-to-face situations (e.g., Dabbs et al., 1997; Mazur, 1985). For example, Dabbs et al. (2001) interviewed and filmed male college students and found that individuals with high levels of testosterone appeared more forward and independent and focused directly on the target. They were also more restless and oriented toward action.

Given the evidence, it appears reasonable that testosterone could also explain employment dynamics. The effect of being out of work has been shown to have severe long-term personal consequences in terms of mental health and well-being (Arulampalam, 2001; Bijlsma et al., 2017; Marcus, 2014). There is a sustained interest in the economic literature in the role of individual factors as explanations for individual differences in unemployment patterns. For example, Heckman et al. (2006) investigated the effects of personality traits and non-cognitive skills on unemployment. One specific personality dimension, the locus of control, has been found to be decisive for the time until an individual return to the labour market after a health shock (Schurer, 2017) or, individual job search strategies (Caliendo et al., 2015).

[4] The effect of testosterone on prosocial status-promoting behavior and risk has been found to be moderated by cortisol (e.g., Mehta and Prasad, 2015).

While the evidence is still scarce, clearly personality and the labour market are interrelated. Testosterone shapes many individual characteristics that, in turn, might affect how individuals search for a job. In the following section, we discuss potential mechanisms through which the hypothesised relationship between testosterone and unemployment may operate.

2.2 Testosterone and employment transitions

There are multiple pathways of how testosterone might relate to unemployment. We focus on differences in job search behaviour and self-selection by occupational choice while distinguishing between entry into unemployment and exit from unemployment, i.e., re-employment.

As noted above, high testosterone levels are associated with aggression (in the broadest sense), which includes competition-seeking and dominant behaviour (Archer, 2006; Chance et al., 2000), or even pro-social behaviour (Dreher et al., 2016). If pro-social behaviour associated with higher testosterone levels leads to larger social networks, then these networks might constitute an important resource for the job search (Ponzi et al., 2016). Moreover, the job search in general, and assessment centres or job interviews in particular, might favour competitive, dominant and pro-social individuals. Thus, individuals with high testosterone might invest more effort into their job search, since adopting the required behaviour comes more natural to them (Dabbs et al., 2001, 1997) and exerts less mental strain than it might for individuals with low testosterone. For similar reasons, individuals with high testosterone might perform better in such situations, and might thus be more likely to receive a job offer. Yet, testosterone might also affect individuals' likelihood to accept a job offer. Individuals with low testosterone, who are less willing to take risks, might accept a job offer earlier. In contrast, high testosterone individuals might be more inclined to take a risk and look for a better position. This is in line with the evidence that individuals' with a higher level of testosterone are more reflective in the decision-making process (Bosch-Domènech et al., 2014). Reemployment, therefore, would take longer for individuals with high testosterone but might result in a better job match. Conversely, due to the perceived social stigma of unemployment, high testosterone individuals, worried about their social status, might be more inclined to take first job offers to move out of an economically disadvantaged position.

For individuals in employment, once employers learn about their employees' productivity competition-seeking and dominant behaviour may become less critical. To some extent, such behaviour might even be considered detrimental, e.g., for the performance in teams. Hence, individuals with high testosterone levels may be at an increased risk of entering unemployment compared to individuals with normal testosterone levels.

In terms of occupational choice, workers with high testosterone levels might select into jobs that are perceived as offering greater rewards at higher risks. For example, positions with performance-based remuneration and where redundancies are more common, like in sales or self-employment. Besides, higher numeric capabilities associated with high testosterone levels (Brookes et al., 2007; Brosnan et

al., 2011) would also imply a selection into certain occupations or sectors. Individuals with low testosterone tend to be more risk-averse and might prefer jobs that offer more stability (e.g., in the public sector). Such occupational sorting would imply that high testosterone individuals are more likely to face unemployment, but are able to find re-employment relatively quickly. In contrast, individuals with low testosterone are less likely to lose their job but stay longer in unemployment if they become unemployed.

In summary, based on the existing evidence, we expect that individuals with high testosterone levels are more likely to leave unemployment than individuals with lower testosterone. Once they are employed, however, it is possible that individuals with high testosterone levels face a greater risk of unemployment than those with lower levels.

3 Data

The UK Household Longitudinal Study *Understanding Society* is one of the few surveys available that collects both data on testosterone levels (among other biomarkers) as well as annual longitudinal data on individuals and households characteristics. *Understanding Society* is the successor of the British Household Panel Survey (BHPS), started in 2009, and at the time of writing 9 waves of data are available. With approximately 40,000 households (at Wave 1) in the United Kingdom, it collects a range of individual- and household-related information that also enables the researcher to trace labour market trajectories. Approximately five months after their Wave 2 or Wave 3 (2010-2013) mainstage interview adult participants received a health assessment visit from a registered nurse ('Health and biomarkers survey').[5] A range of bio-medical measures was collected from over 20,000 adults, including testosterone levels.

[5] The nurse health visit was conducted among adult survey participants from the General Population Sample (GPS) which comprises of households in the UK and BHPS sample only. The nurse visit took place after wave 2 (May 2010-July 2012) for those individuals in the GPS and after wave 3 (June 2011-July 2012) for BHPS sample respondents.

3.1 Health and biomarkers Survey

To be eligible for a nurse interview survey respondents must have completed a full face-to-face interview in the most recent mainstage wave, lived in Great Britain, completed their interview in English and, for women, were not pregnant. Among those eligible, approximately 20,700 (57%) took part, of which 13,107 (68.5%) had at least one biomarker which was successfully obtained and processed (Benzeval et al., 2014). During the nurse visit, blood samples were taken to extract a range of biomarker data, including measures of growth hormones (testosterone, DHEA's, IGF-1). Serum testosterone, the specific biomarker of interest for this study was measured using an electrochemiluminescent immunoassay on the Roche Modular E170 analyser. [6]

Among men, testosterone levels show wide variation and are considered within a normal range between 9-25 nmol/L. Testosterone varies by time of day such that values in the morning are higher than those found in the afternoon or evening (See **Table 1**). The level of testosterone also declines in age (See **Figure 1**). In the Health and biomarkers Survey, there are 4,605 men with a plausible level of testosterone in the age range 16 to 70 who had their interview started between 9 am and 8 pm.[7]

Table 1: Level of testosterone (nmol/l) and interview time

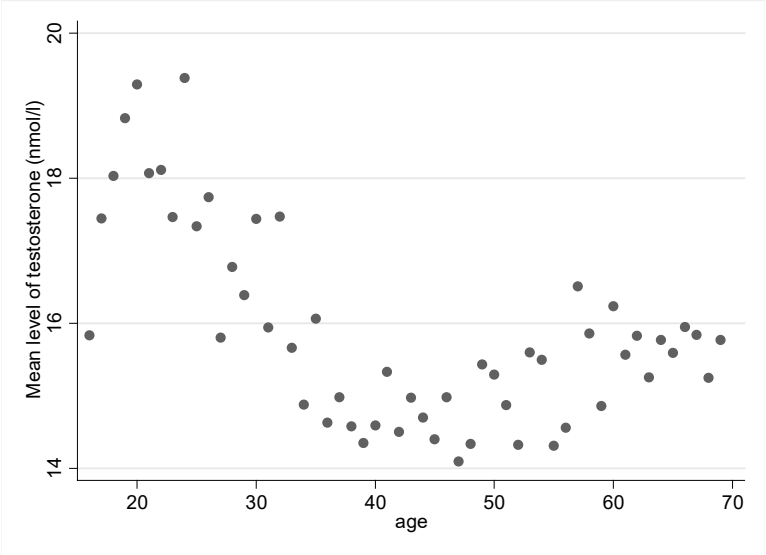
The start time of the interview (hour)	Testosterone (nmol/l)	
	Mean	Std Dev
9	17.50	6.31
10	17.68	5.87
11	17.38	6.25
12	17.31	6.03
13	16.05	6.48
14	16.05	5.76
15	14.49	5.39
16	14.83	5.62
17	15.14	5.21
18	14.64	5.52
19	14.06	4.94
20	13.24	4.42

Notes: Author's own calculations, using data from the Understanding Society subsample Health and biomarkers Survey. $N = 4{,}605$ men with a positive level of testosterone in the age range 16 to 70 who had their interview started between 9 am and 8 pm.

[6] Observational studies typically refer to levels of currently circulating testosterone, but recent studies have used prenatal testosterone levels, approximated by physiological conditions such as the length of the second to fourth manual digits (2D:4D) (Bütikofer et al., 2019; Coates et al., 2009; Gielen et al., 2016; Nye et al., 2017; Parslow et al., 2019; Stenstrom et al., 2011). In contrast to current testosterone levels, prenatal exposure is expected to be independent of early childhood environmental exposures (Nye et al., 2017). The underlying biological mechanism is not fully understood, however.

[7] The number of individuals having their interview outside that time window is negligible.

Figure 1: Level of testosterone (nmol/l) and age



Notes: Author's own calculations, using data from the Understanding Society subsample Health and biomarkers Survey. $N = 4{,}605$ men with a positive level of testosterone in the age range 16 to 70 who had their interview started between 9 am and 8 pm.

3.2 Longitudinal data

In each wave of Understanding Society, survey respondents are asked about their current labour force status. This information is used to estimate the transition into unemployment as well as the degree of persistence. We start by trimming the Health and biomarker Survey to men who are between 20 and 60 during the nurse visit. This survey also holds information about participants' social and economic circumstances, including the current labour force status.[8] We restrict the sample to those men who state being either unemployed or, if employed, an employee. We drop self-employed individuals since this group of individuals is likely to differ from employees on unobservable characteristics (such as personality type) as well as their labour supply behaviour. Also, the sample size is insufficient to include them as a separate group.

In the next step, we merge this sample to the primary survey of Understanding Society. As noted above, the nurse visit took place either after Wave 2 or Wave 3. Labelling the nurse visit as the reference time-point $t = 0$, we can include information on two pre-periods (see also column one and two of **Table 2**). Although the interviews in the primary survey were conducted, on average, virtually one year apart (see column three of **Table 2**), the time difference to the interview in the primary survey prior to the nurse visit $(t = -1)$ is, on average, about five months. There are only a small number of individuals who have a different labour market status between the nurse visit and the first pre-period. To facilitate our identification strategy, we keep those individuals who have not changed their position (this also reduces short-

[8] Possible answers are: (1) self employed, (2) paid employment(fulltime/parttime), (3) unemployed, (4) retired, (5) on maternity leave, (6) family care or home, (7) full-time student, (8) long-term sick or disabled, (9) government training scheme, (10) unpaid, family business, (11) on apprenticeship, (12) doing something else.

term impacts of labour market status changes on the level of testosterone). For $t = -2$, we allow the individuals to be either employed or unemployed but allow the status to be different from the succeeding waves. Because we want to see whether someone was long-term or short-term (un)employed during the nurse visit, we exclude observations with missing information on the labour force status,

Table 2: Database and number of days between consecutive interviews

		Days until the next interview	
Database of *Understanding Society*	Period t	Mean	Std Dev
Primary survey	-2	366	23
Primary survey	-1	151	25
Health and biomarkers survey (Nurse visit)	0	217	30
Primary survey	1	369	36
Primary survey	2	377	82
Primary survey	3	-	-

Notes: Author's own calculations, using data from the Understanding Society subsample Health and biomarkers Survey. $N = 1{,}880$

To analyse the labour market trajectories of our sample members, we observe individuals for up to three waves following the nurse visit. The focus of our study is the transition between unemployment and employment (and vice versa), and therefore we only include these two states. We allow an individual to exit the panel but not to re-enter. As shown in **Table 3**, our final sample consists of 1,880 individuals who contribute 5,460 observations, out of which 309 (5.7%) were unemployed during the nurse visit, and 5,151 were employed (94.3%).

Table 3: Sample size

	Number of individuals	Number of observations
Employed during nurse visit	1,771	5,151
Unemployed during nurse visit	109	309
Total	1,880	5,460

Notes: Author's own calculations, using data from the Understanding Society subsample Health and biomarkers Survey.

4 Methodology

To estimate labour market transitions, we follow the economic literature by utilising dynamic non-linear models (e.g., Arulampalam, 2001; Bhuller et al., 2017; Biewen and Steffes, 2010; Stewart, 2007). The idea is that the labour market dynamics follow a first-order Markov process, which means that the status in the previous period has a *genuine* effect on the position in the subsequent period. Moreover, if individual effects are persistent over time, not accounting for unobserved heterogeneity will lead to an overestimation of state dependence (Stewart, 2007). The dynamic reduced-form model to estimate state dependence in unemployment can be written as follows:

$$y_{it} = \mathbf{1}(\alpha_1 y_{it-1} + x'_{it=0}\beta + v_i + \varepsilon_{it} > 0) \quad (1)$$

where the subscripts $i = 1, \ldots, N$ are individuals and $t = 1, \ldots, T$ refer to the waves of the dynamic sequence (thus the three waves following the nurse visit, which are labelled as the post-period). The dependent variable (y_{it}) equals 1 if i was unemployed at wave t and 0 otherwise. Following the assumption of a first-order Markov process, y_{it} is explained by its lagged outcome y_{it-1} and the coefficient α_1 reveals the magnitude of state dependence in unemployment. Furthermore, $x_{it=0}$ is a vector of explanatory variables which were collected during the nurse visit at $t = 0$. As covariates, we include: age (linear and second order polynomial), highest qualification, self-rated health, region, urban identifier, household size, long-term disability and legal marital status. To ensure that the explanatory variables refer to the same time point as the measurement of testosterone, in our main specification, the explanatory variables are not time-varying. Lastly, v_i is an individual-specific time-invariant shock and ε_{it} is an idiosyncratic shock. Note, that we make the assumption that $v_i \sim$ iid $N(0, \sigma_v^2)$ and $v_i \perp x_{it=0}, \varepsilon_{it}\ \forall\ i, t$. i.e., the individual-specific effects are randomly distributed across individuals and independent of observable characteristics. As part of our robustness checks and discussed further below, we follow Mundlak (1978) and Chamberlain (1992) and relax this assumption by including time-varying covariates and their means for the period $t > 0$ (see also Wooldridge, 2005).

As explained in section 3.3, we trim the sample to individuals who were either employed or unemployed in the two waves before the nurse visit ($t = -1$ and $t = -2$). However, the time-invariant error-term might be correlated with the outcome in these periods, discussed as the 'initial conditions problem' (Wooldridge, 2005). As $y_{it=0} = y_{it=-1}$, we have four possible combinations of employment sequences in the pre-periods:

- Continuously employed $\left(y^1_{it=0}\right)$: $y_{it=-2} = y_{it=-1} = 0$
- Short-term employed $\left(y^2_{it=0}\right)$: $y_{it=-2} = 0$ and $y_{it=-1} = 1$
- Continuously unemployed $\left(y^3_{it=0}\right)$: $y_{it=-2} = y_{it=-1} = 1$
- Short-term unemployed $\left(y^4_{it=0}\right)$: $y_{it=-2} = 1$ and $y_{it=-1} = 0$

The individual-specific error term takes the following form when we condition on the initial period values (see Wooldridge, 2005):

$$v_i = \sum_{r=2}^{4} \lambda_r y^r_{it=0} + a_0 + \alpha_i \quad (2)$$

Plugging (2) into the original specification (1) results in:

$$y_{it} = \mathbf{1}(\alpha_1 y_{it-1} + \sum_{r=2}^{4} \lambda_r y^r_{it=0} + x'_{it=0}\beta + a_0 + \alpha_i + \varepsilon_{it} > 0) \quad (3)$$

Kroft et al. (2013) provide evidence that the probability of exiting unemployment depends on the unemployment duration. To account for this aspect, we interact the lagged dependent variable with the

variables referring to the labour market status in the pre-period.[9] Our model takes the following form for the full sample:

$$y_{it} = \mathbf{1}(\sum_{r=2}^{4} \gamma_r y_{it=0}^{r} (y_{it-1} = 0) + \sum_{r=1}^{4} \delta_r y_{it=0}^{r} (y_{it-1} = 1) + x'_{it=0}\beta + a_0 + \alpha_i + \varepsilon_{it} > 0) \quad (4)$$

with being employed in the previous period $(y_{it-1} = 0)$ and continuously employed in the pre-period $\left(y_{it=0}^{1}\right)$ as the reference category. We assume that both error terms follow a normal distribution, e.g., $\alpha_i \sim N(0, s_\alpha^2)$ and $\varepsilon_{it} \sim N(0, s_\varepsilon^2)$ and that ε_{it} is iid. As α_i is time-invariant, the composite error term $u_{it} = \alpha_i + \varepsilon_{it}$ is correlated over time and the correlation between two (different) time points is constant and takes the following equi-correlation structure:

$$\rho = corr(u_{it}, u_{is}) = \frac{s_\alpha^2}{s_\alpha^2 + s_\varepsilon^2} \quad (5)$$

with $t \neq s$ and $t, s = 1,2,3$. As the outcome variable is dichotomous, a normalisation of ε_{it} is required. We take $\varepsilon_{it} \sim N(0,1)$ and the outcome probability is:

$$P_{it}(\alpha^*) = \mathbf{\Phi}[(\sum_{r=2}^{4} \gamma_r y_{it=0}^{r} (y_{it-1} = 0) + \sum_{r=1}^{4} \delta_r y_{it=0}^{r} (y_{it-1} = 1) + x'_{it=0}\beta + a_0 + s_\alpha^2 \alpha^*)(2y_{it} - 1)] \quad (6)$$

Note that $\mathbf{\Phi}[\cdot]$ refers to the cumulative standard normal distribution. The likelihood function is the product of all time-point specific probabilities across all individuals. Namely,

$$L = \prod_{i=1}^{N} \int_{\varphi^*} \{\prod_{t=1}^{T} P_{it}(\alpha^*)\} \mathrm{d}F(\alpha^*) \quad (7)$$

where F is the distribution function of $\alpha^* = \alpha / s_\alpha$. Equation (7) does not have a closed-form, and therefore α has to be integrated out. As we assume that α is normally distributed, the integral can be evaluated using Gaussian-Hermite quadrature. All the equations are estimated using Gauss-Hermite quadrature (Butler and Moffitt, 1982).

4.1 Subsample estimations

As we outlined in section 2.2, we expect different (potentially conflicting) effects for those who are initially employed compared to those who are initially unemployed. Therefore, we also estimate separate regressions based on the labour force status at $y_{it=-1}$. For those initially employed, Equation (4) changes to:

$$y_{it} = \mathbf{1}\left(\gamma_2 y_{it=0}^{2} (y_{it-1} = 0) + \sum_{r=1}^{2} \delta_r y_{it=0}^{r} (y_{it-1} = 1) + x'_{it=0}\beta + a_0 + \alpha_i + \varepsilon_{it} > 0\right) \quad (8)$$

Where the reference category is the continuously employed $\left(y_{it=0}^{1}\right)$ who were employed at $t-1$ $(y_{it-1} = 0)$ is. For those initially unemployed it changes to:

[9] Note that our findings on the effect of testosterone are robust to various specifications of including the initial labour market status (e.g., interacting with the lagged labour market position, no interaction, not accounting for the initial labour market status).

$$y_{it} = \mathbf{1}\left(\gamma_3 y^3_{it=0}(y_{it-1}=0) + \sum_{r=3}^{4} \delta_r y^r_{it=0}\,(y_{it-1}=1) + x'_{it=0}\beta + a_0 + \alpha_i + \varepsilon_{it} > 0\right) \quad (9)$$

Where the reference category is the short-term unemployed $\left(y^4_{it=0}\right)$ who were employed at $t-1$ $(y_{it-1}=0)$.

4.2 Including testosterone as a covariate

To ensure comparability across groups, we adjust the circulating testosterone levels for age and time of the day when the blood sample was taken. We use two different approaches to that end:

a. In the regression model, we include the absolute level of testosterone (nmol/l) as a covariate and control for the hour of the nurse visit (Model 1). In a further specification, we include the absolute level of testosterone as a second-degree polynomial (Model 2)

b. We use the Health and biomarkers Survey to construct a sample of men with a positive level of testosterone in the age range 16 to 70 who had their interview started between 9 am and 8 pm ($N = 4{,}605$). We utilise an OLS model to estimate the deviation from the time- and age-corrected mean.[10] We order the distribution of the deviation and form three groups: (i) low level of testosterone if the deviation belongs to the lowest decile, (ii) medium level of testosterone if the deviation is in 2nd to 9th decile, and (iii) high level of testosterone if the deviation belongs to the highest decile (Model 3).

In a robustness check, we re-estimate our regression specifications adjusting the cut-point defining low, medium and high levels to ensure our results remain stable and are not driven by these definitions.

4.3 Observable characteristics and individual-specific effects

Based on our modelling setup, two potential sources of bias may affect our results: (i) unobserved heterogeneity caused by individual-specific differences and (ii) the correlation of the unobserved heterogeneity with the initial conditions (Heckman, 1981). If unobserved heterogeneity is present and persists over time, this will lead to an overstatement of true state dependence (Stewart, 2007). The modelling framework outlined in section 4.1 controls for unobserved heterogeneity, which we assume follows a specific distribution.

In order to address the initial conditions problem, we follow the approach of Wooldridge (2005). By construction, the model in section 4.1 assumes that the covariates used in the regression analysis and the random effect error term are uncorrelated. For example, we rule out a correlation between testosterone and (unobserved) ability (which would be captured in the error term). Wooldridge (2005) addresses the initial conditions by extending the so-called Mundlak-Chamberlain approach. In this case, one specifies an approximation for the individual unobserved time-invariant heterogeneity *given* the initial conditions, where we also condition on exogenous variables likely to be correlated with the unobservable

[10] We include time as a categorical variable on the full hour. Age is included in a linear version (in a robustness check, we included age as a second degree polynomial, but results remain similar).

component. This then allows for correlation between the initial observation (labour force status in our case) and the unobservable individual effects. This approach hinges on the auxiliary conditional distribution for the unobserved heterogeneity to be correctly specified (Wooldridge, 2005). In our case, the individual level (time constant) unobserved effect is a function of the initial labour force status, the mean of time-varying covariates and an individual specific error term. Thus, the specification changes to:

$$y_{it} = \mathbf{1}(\alpha_1 y_{it-1} + x'_{it}\beta + \theta_i + \varepsilon_{it} > 0) \quad (10)$$

Note that in order to provide sufficient variation within an individual, we use up to 5 observations per individual (therefore, the number of time-points we consider is larger than in the base specification). To account for the Mundlak specification, we specify:

$$\theta_i = \sum_{r=2}^{4} \lambda_r y_{it=0}^{r} + \bar{x}'_i a + a_0 + \eta_i \quad (11)$$

Where $\bar{x}_i$ refers to the time-mean of the observable characteristics of the dynamic sequence ($t \geq 1$) (see also Akay, 2012; Rabe-Hesketh and Skrondal, 2013). Inserting Equation (11) into Equation (12) leads to:

$$y_{it} = \mathbf{1}(\alpha_1 y_{it-1} + x'_{it}\beta + \sum_{r=2}^{4} \lambda_r y_{it=0}^{r} + \bar{x}'_i a + a_0 + \eta_i + \varepsilon_{it} > 0) \quad (12)$$

Following the concept in the basic specification, we extend Equation (12) by interacting the lagged labour market position with the initial period position. This leads to our final specification:

$$y_{it} = \mathbf{1}(\sum_{r=2}^{4} \gamma_r y_{it=0}^{r}\,(y_{it-1} = 0) + \sum_{r=1}^{4} \delta_r y_{it=0}^{r}\,(y_{it-1} = 1) + x'_{it}\beta + \bar{x}'_i a + a_0 + \eta_i + \varepsilon_{it} > 0) \quad (13)$$

It is important to note that if the estimation results following this approach are similar to those based on our basic specification, then this implies that by not accounting for time-varying means of the covariates the random effects assumption is likely to hold. Put another way, the basic framework controls for much of the individual level heterogeneity and therefore the approach of Wooldridge (2005), which primarily deals with the residual heterogeneity between covariates and the error term by incorporating the mean of particular covariates (relative to our basic framework), should not change the main conclusions drawn from our baseline estimates.

5 Descriptive statistics

The economic literature has shown that unemployment risk is influenced by factors like the qualification, age, health etc. In our study, we test the explanatory power of testosterone. When we split the sample into initially unemployed and employed (column three and four of **Table 4**), we can see that these groups differ with respect to observable characteristics. For example, among the initially unemployed is a significantly higher share of individuals with no qualification or in poor health. However, we also find that there are significant differences in the distribution of testosterone. The sample of initially unemployed has, on average, a higher level of testosterone, and the difference is statistically significant. One

explanation is that due to time restriction of work, employed individuals provide their blood sample later in the day (not shown), and as levels naturally decrease over the days, they have a lower level of testosterone, on average. However, we still find a higher share of individuals with a testosterone level in the 10th decile (as well as a higher share of individuals in the 1st decile).

Table 4: Descriptives at nurse visit

	Full Sample	Initially unemployed	Initially employed	t-test (p-value)
Testosterone (nmol/l)	15.24	16.67	15.15	0.0057
	(5.60)	(6.89)	(5.50)	
Testosterone (categorical)				
1st decile	10.59	14.68	10.33	0.1525
2nd – 9th decile	80.16	70.64	80.75	0.0102
10th decile	9.26	14.68	8.92	0.0441
Age	43.71	43.13	43.75	0.5279
	(9.95)	(11.75)	(9.83)	
Highest qualification				
Degree	29.95	16.51	30.77	0.0016
Other higher degree	11.76	10.09	11.86	0.5787
A-level etc	23.62	17.43	24.00	0.1173
GCSE etc	22.07	28.44	21.68	0.0988
Other qualification	8.4	11.93	8.19	0.1722
No qualification	4.2	15.60	3.50	0.0000
General Health				
excellent	17.82	9.17	18.35	0.0151
very good	40.59	32.11	41.11	0.0634
good	28.94	33.94	28.63	0.2350
fair	11.28	20.18	10.73	0.0024
poor	1.38	4.59	1.19	0.0031
Region of residence				
England	84.52	95.41	83.85	0.0012
Wales	6.7	2.75	6.95	0.0894
Scotland	8.78	1.83	9.20	0.0083
Rural area	22.18	13.76	22.70	0.0293

	Full Sample	Initially unemployed	Initially employed	t-test (p-value)
Number of people in household				
1	13.35	30.28	12.31	0.0000
2	28.14	23.85	28.4	0.3056
3	20.96	16.51	21.23	0.2405
4+	37.55	29.36	38.06	0.0688
Long-standing illness or disability	24.84	30.28	24.51	0.1762
Legal marital status				
single	26.81	54.13	25.13	0.0000
married	61.60	28.44	63.64	0.0000
separated, divorced, widowed	11.60	17.43	11.24	0.0500
N	1,880	109	1,771	-

Notes: Author's own calculations, using data from the Understanding Society subsample Health and biomarkers Survey. $N = 1{,}880$.

One way to assess labour market dynamics is to consider transition matrices. In **Table 5**, the probability of being (un)employed at t, conditional on the labour market position at $t-1$ is presented. The first number in each cell shows the conditional probability for the full sample, and unsurprisingly there is a high level of state dependence. This means that the chances to stay employed are higher for someone who was already employed in the previous period, and similarly for the unemployed. However, these probabilities differ substantially with respect to the initial labour market position. For example, the risk to stay unemployed is 75 per cent for the initially unemployed, but only 32 per cent for those initially employed.

Table 5: Transition matrix of labour market status

	$employed_t$	$unemployed_t$	$Total_{t-1}$
$employed_{t-1}$	98.14	1.86	94.49
	(90.48)	(9.52)	(27.18)
	[98.27]	[1.73]	[98.52]
$unemployed_{t-1}$	36.21	63.79	5.51
	(25.33)	(74.67)	(72.82)
	[68.42]	[31.58]	[1.48]
$Total_t$	94.73	5.27	
	(43.04)	(56.96)	
	[97.83]	[2.17]	

Notes: Author's own calculations, using data from the Understanding Society subsample Health and biomarkers Survey. $N = 5{,}460$. Numbers in ( ) / [ ] refer to the sample of initially unemployed / initially employed.

As the focus of our study is to identify the effect of testosterone on the unemployment risk, we differentiate the transition matrix further according to the testosterone groups (see **Table 6**). On the one hand, we find that for initially unemployed men the conditional probability of staying unemployed is highest in the first decile (86 per cent) – especially with respect to the 2^{nd} – 9^{th} decile (70 per cent). For initially employed men, we find that those in the top decile have the highest conditional probability of entering unemployment (3.6 per cent). A general pattern in Table 6 is that low testosterone is associated with higher persistence of unemployment, while high testosterone seems to be associated with a higher risk of entering unemployment.

Table 6: Unemployment risk differentiated according to testosterone level

Testosterone (categorical)	Full Sample	Initially unemployed	Initially employed
$unemployed_t \mid unemployed_{t-1}$			
1st decile	74.42	86.49	-*
2nd – 9th decile	59.90	70.00	33.33
10th decile	70.59	81.58	38.46
$unemployed_t \mid employed_{t-1}$			
1st decile	1.30	12.50	1.13
2nd – 9th decile	1.73	8.70	1.61
10th decile	3.78	14.29	3.61

Notes: Author's own calculations, using data from the Understanding Society subsample Health and biomarkers Survey. $N = 5{,}460$. * Due to the short panel, we do not observe individuals who stay unemployed with a low testosterone level for those initially employed.

6 Results

6.1 Base regression

Our base model controls for the labour market position in the initial periods, i.e., the nurse visit and the two waves before it, the labour market position in the previous period, and additional covariates. Furthermore, we include the level of testosterone in three different alternative specifications. **Table 7** shows only the effect of testosterone and unemployment risk (complete output tables are available on request).

The first regression uses the full sample (see the first three columns of **Table 7**) and includes the level of testosterone in a linear trend (1), a second-degree polynomial (2), and as a categorical variable (3). In all three specifications, we find that the unemployment risk increases with the level of testosterone[11]. However, the magnitude is always small, and estimates are not significantly different from zero.

In section 2, we outlined potential reasons why we might expect the effect of testosterone to differ between the initially unemployed and initially employed. Once we condition on initial labour force status (columns four to nine of **Table 7**), we see that the direction of the effect and the magnitude change substantially. For those who are initially unemployed **Table 7** (column 4-6) indicates that the risk of staying unemployed declines in the level of testosterone. This finding is independent of the specification and significantly different from zero.

[11] In the case of specification (2), when looking at a range of 5-30 nmol/l testosterone, there is in the beginning a reducing effect but the slope turns positive from around 10 nmol/l.

Table 7: *Effect of testosterone on unemployment risk*

	Full Sample			**Initially unemployed**			**Initially employed**		
Model	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
testosterone nmol/l	0.0167	-0.0273		-0.0843*	-0.274*		0.0270*	-0.00565	
	(0.0127)	(0.0502)		(0.0443)	(0.165)		(0.0138)	(0.0521)	
(testosterone nmol/l)^2		0.00123			0.00524			0.000908	
		(0.00136)			(0.00417)			(0.00141)	
testosterone									
1st decile			*reference category*						
2nd – 9th decile			-0.132			-2.027**			0.162
			(0.242)			(0.812)			(0.274)
10th decile			0.355			-2.331**			0.622*
			(0.299)			(1.001)			(0.339)
Observations	5,460	5,460	5,460	309	309	309	5,151	5,151	5,151
LogLikelihood	-556	-555.6	-559.7	-93.76	-92.90	-98.25	-435.9	-435.6	-438.8

Notes: Author's own calculations, using data from the Understanding Society subsample Health and biomarkers Survey. $N = 5{,}460$. All models include controls for the labour market status in the initial periods (prior to the nurse visit) as well as the previous period (i.e., lagged labour market status). Model 1 includes a linear trend in circulating testosterone, Model 2 models testosterone with a quadratic polynomial, and Model 3 includes testosterone as a categorical variable.

We also find a significant impact of testosterone on the risk of becoming unemployed for the sample of initially employed. In contrast to the sample of initially unemployed, there is a positive sign, indicating that higher levels of testosterone increase the risk of becoming unemployed. Model (3) suggests that this effect is largest among individuals with a very high level of testosterone – no significant difference is observed between the low and the medium levels of testosterone. Independent of the sample we use, we do not find any support for a second-degree polynomial relationship of testosterone and the unemployment risk.

For the two subsamples, we also calculate the average partial effects (APE) for Model (3) at the individual level. The partial effect for the initially unemployed is the difference (in percentage points) of becoming unemployed if the person was unemployed at $t-1$ and had a testosterone level in the 2nd to 9th decile, resp. 10th decile, compared to the first decile.

Table 8: *Average partial effects*

	Initially unemployed	**Initially employed**
1st decile	*reference category*	
2nd – 9th decile	-0.254*	0.004
	(0.137)	(0.007)
10th decile	-0.300*	0.022
	(0.168)	(0.016)
Individuals	109	1,771

Notes: Author's own calculations, using data from the Understanding Society subsample Health and biomarkers Survey. ***,**,* refers to statistically significant at 1%, 5% and 10% level respectively

Compared to the lowest category, the unemployment risk is reduced by 25.4 percentage points for the medium category and by 30 percentage points by the higher category. In the case of the initially employed, the previous labour market status is set at being employed. The magnitude of the APE is positive but much smaller and not detectable for the 2nd to 9th decile. For the highest decile, we find an elevated unemployment risk of, on average, 2.2 percentage points.

6.2 Robustness checks

In order to assess the sensitivity of our main results for each subsample, we carry out a number of robustness checks.[12] Our primary focus is to understand the link between testosterone and labour market dynamics among working-age men. One concern, therefore, is that our results are driven by the age restriction (20-60) we imposed when choosing our initial sample. However, for those at the bottom and the tail of the sample, labour market decisions might be influenced by external factors. For example, individuals might consider delaying entry to the labour market due to attending university or reducing

[12] Additional robustness estimations which are not described in detail here include dropping covariates. However, none of the tests lead to qualitatively different findings.

labour supply prior to entering retirement. We first narrow the age window by iteratively dropping the youngest and oldest age, until the age range includes those between 25 and 55. The respective coefficients for the categorical testosterone variable are shown in **Figure A 1**. For the group of initially unemployed, we find a stable level for both coefficients, and in all iterations, the coefficients are significantly different from zero at the 10 per cent level (in most cases also at the 5 per cent level). These findings also hold if we instead estimate a specification where testosterone is included as a linear term. Turning to the results for those who are initially employed, the findings are also relatively stable with respect to the highest decile, though we note that in two out of five cases, the effect is insignificant. If we include testosterone as a continuous variable, we find in all specifications a significant effect. Moreover, we find no significant difference between the medium and low-level testosterone groups.

We next consider our categorisation of the variable defining the low, medium and high-level groups. In our main specification, we use the bottom and top decile as cut-off points to determine the three categories. We re-run the model and use as cut-off points between the bottom (top) five to 20 per cent, moving in one percentage points (see **Figure A 2**). For the initially unemployed, we find in line with our expectations that the coefficients for both groups are declining marginally. However, with very few exceptions, the coefficients are statistically significantly different from zero at the five per cent level. For the group of the initially employed, the coefficient for those with a high level of testosterone stays rather stable, but significance increases.

In order to address the correlation between observable characteristics and individual-specific effects, we apply the Mundlak-Chamberlain approach as outlined in section 4.3. A subset of these results can be found in **Table A.3** in the appendix. Once again, we estimate the model conditional on initial labour force status and classify individuals into three groups based on their testosterone level. The results support the findings in **Table 7**, namely that relative to the low testosterone group, individuals with medium and high levels of testosterone are significantly less likely to remain unemployed (APEs of 35 and 28 percentage points, respectively).[13] Moreover, the magnitude of these effects is larger than our main results. Turning to the initially employed group, consistent with our main findings we find those individuals with high levels of testosterone are significantly more likely to become unemployed (APE: 2.1 percentage points) in line with the results reported in **Table 7**.[14]

6.3 Continuous (un)employment

To integrate out the random-effects error terms, we have to impose an assumption on the distribution of the individual-specific unobserved effect ('auxiliary distributional assumption'). However, if the auxiliary distributional assumption is not valid, the random-effects estimator is not consistent. One option to circumvent this issue is to consider dynamic linear probability models, which impose no assumption on

[13] Both are significant at the 1% level.
[14] Significant at the 5% level.

the individual-specific effects. Due to time-differencing, it does not impose any assumption on the distribution for the individual-specific effects. One example is the Arellano and Bond (1991) GMM estimator, which uses (among others) lags of the dependent variable as instruments. A crucial restriction is that there is no second-order serial correlation in the idiosyncratic shocks (there will be first-order correlation due to including the lagged dependent variable). However, to test this assumption, the dynamic sequence of the panel data set must hold at least four periods, and in our basic specification, our panel does not exceed three periods. Furthermore, due to differencing individual-specific time-invariant characteristics (e.g., testosterone level) are excluded.

To run a specification where we do not have to make any assumption about the distribution of the individual-specific effects, we use a simple probit model to estimate the probability of being unemployed in the first three periods after the nurse visit. For those initially unemployed, we run three different specifications, depending on whether the individual was unemployed in (1) one or more waves, (2) two or more waves, or (3) in all three waves. For those initially employed, we are only able to control for one or more wave of unemployment in the first three periods after the nurse visit. We use the same covariates as in the basic specification, which were collected at the nurse visit, and account for the level of testosterone in a categorical way. **Table 1Table 9** presents the marginal effects of the level of testosterone. In line with our previous findings, we see for the initially unemployed that those individuals with a medium level of testosterone are significantly less likely to experience unemployment. For those individuals with a high level of testosterone, the findings indicate that they are significantly less likely to be unemployed in all three waves. However, we do not find any significant effect on experiencing some unemployment spells. These findings are robust to changes in the cut-off point.

When turning to the initially employed, we find that individuals with a high level of testosterone are more likely to experience a spell of unemployment, though the effect is not significant. When changing the cut-off point to the top two deciles, individuals with a high level of testosterone are 4.1 percentage points more likely to experience at least one wave of unemployment compared to individuals with a low level of testosterone, and the effect is significant at the 5% level.

Table 9: *Marginal effects*

	Initially unemployed			Initially employed
Waves unemployed	≥1	≥2	3	≥1
1st decile	*reference category*			
2nd – 9th decile	-0.267***	-0.286**	-0.285**	0.001
	(0.080)	(0.114)	(0.121)	(0.016)
10th decile	-0.169	-0.160	-0.313**	0.035
	(0.140)	(0.158)	(0.145)	(0.026)
Individuals	91	91	91	1,609

Notes: Author's own calculations, using data from the Understanding Society subsample Health and biomarkers Survey. ***,**,* refers to statistically significant at 1%, 5% and 10% level respectively

7 Mechanisms

We showed that testosterone affects men's transitions in and out of employment. Now we examine whether these transitions can be explained by observed behaviour among individuals and personality traits. In section 2.2, we discussed potential channels through which testosterone may affect an individual's employment status. Although we cannot provide conclusive evidence for these mechanisms in this study due to data limitations, we consider several potential channels in a descriptive analysis to examine whether the associations in our dataset are consistent with the literature.

For example, the numerical ability was related to testosterone in experimental studies (Brosnan et al., 2011), and it was also collected during wave 3 in the UKHLS mainstage interview.[15] Survey respondent's practical numerical knowledge is assessed by testing whether they can understand percentages and fractions in typical real-life settings. Such ability measures have been shown to be highly related to wealth (McArdle et al., 2009; McFall, 2013). Individuals are presented with three initial problems, and if none are answered correctly a further (simple) question is asked. On the other hand, if all questions are answered correctly, then an additional (more difficult) question is asked; if this was also answered correctly, a further final question is asked.[16] Thus, an individual's final score is between zero (no correct answers) and five (all correct answers) and a clear ordering exists. Regression results (see **Table A.4** in the appendix) show that relative to individuals with a low testosterone level, the log odds of reporting a higher test score are 1.29 times higher (significant at the 5% level) among those with a medium level of testosterone.[17]

[15] This is approximately 7 months after the wave 2 nurse visit and 5 months before the wave 3 nurse visit, and hence relatively close to the date circulating testosterone is measured.
[16] This test was adopted from the English Longitudinal Study of Ageing and some parts have also been included in the US Health and Retirement Study and Survey of Health Ageing and Retirement in Europe.
[17] Low level is defined as bottom quintile of deviation from mean, medium level is between second and fourth quintile and high level is top quintile.

Alongside numerical ability, Understanding Society assesses an individual's fluid reasoning using logic puzzles (number series). Such measures have been found to be related to individuals financial knowledge (Delavande et al., 2008) and are negatively associated with age (Salthouse, 2010). [18] We, therefore, control for age in the regression analysis. Individuals in households were randomly allocated to a set of questions.[19] Within each 'set', individuals were asked six questions. An individual's final score ranged between zero (no correct answers) and six (all correct answers). Regression results **Table A.5** in the appendix) show that relative to individuals with a low testosterone level, the log odds of reporting a higher test score are 1.28 times higher (significant at the 5% level) among those with a medium level of testosterone. It is important to note that, given our main sample follows individuals aged between 20 and 60 years old when initially observed, one could argue that individuals underlying ability is relatively stable across time (as opposed to ability at very young ages). Indeed, this is one of the underlying assumptions we make when controlling for initial conditions and time-invariant unobserved heterogeneity following Wooldridge (2005). Thus, even though these differences in numerical ability and fluid reasoning are in line with the literature on testosterone, they are unlikely to be the mechanism through which testosterone affects employment status in our base model as we control for such time-invariant unobserved heterogeneity.[20]

A similar line of reasoning applies to occupational class. Given that occupational class is likely to be time-invariant (at least in the short panel considered in this paper), it is unlikely to drive our results. Moreover, in our data, we do not observe an association between occupational class and testosterone levels, which earlier studies have found (Dabbs, 1992).

Research suggests that males with higher levels of testosterone are more likely to express certain personality traits and behaviours in social and professional situations (Green et al. 2014, Dabbs et al. 2001). These same traits may help such individuals overcome adverse situations, such as unemployment. Understanding Society fielded a General Health Questionnaire at wave 3 which included attitudinal questions relating to whether individuals felt they have recently been losing confidence in themselves and, separately, whether individuals feel they have recently been able to face up to problems. In this case, individuals with medium levels of testosterone were significantly more likely to report a response which suggested they were had not lost confidence or the ability to face problems, compared to individuals with low levels of testosterone. We also consider risk-taking, which has been associated with high testosterone levels (Apicella et al., 2008; Coates and Herbert, 2008). Respondents in Understanding Society were asked to rate their willingness to take general risks on a scale between 0 and 10, where higher

[18] This test was developed for use in the US Health and Retirement Study.
[19] We only analyse the relationship between testosterone and responses to 'Set 1' as there was a CAPI coding error in 'Set 2'. See McFall (2013) for further details.
[20] Our robustness checks show that (i) our main results hold even when restricting the sample to those aged at least 25 and (ii) if we assume individual's ability is appropriately captured by the specification described in section 4.3, and hence is time constant then our main findings hold after controlling for such unobserved factors.

values indicate a greater willingness to take risks. In a regression model controlling for age and log earnings, we found a positive and statistically significant association between being in the high testosterone group and reporting a higher score (OR=1.23*).

Individual's behaviour is also strongly correlated to their personality. For example, one might expect that individuals with higher levels of testosterone are willing to search more intensely for a job ceteris paribus. In response to a question about job search in the last 4 weeks and asked to individuals who did not report being in paid work in the last week or having a job, those with medium level of testosterone were more likely to report using the internet to search for a job compared to unemployed individuals belonging to the low testosterone group. In addition, individuals were also asked about whether they used their network to explore employment opportunities. Based on purely descriptive evidence, the data suggest a higher proportion of the high testosterone group mentioned such a strategy, however, this result was not statistically significant. We also examine individuals' self-reported likelihood to lose their job in the next 12 months (very unlikely, unlikely, likely or very likely), and find a strong positive association between those individuals who belong to the high testosterone group and the likelihood of job loss (OR=1.37**, controlling for age and log earnings).

In summary, the associations found in Understanding Society are in line with earlier studies, showing that testosterone is positively associated with numerical ability and cognition as well as personality traits such as risk-taking and self-confidence. Moreover, we also find some descriptive evidence for differences in job search behaviour. While we cannot conclusively prove that these potential mechanisms explain the observed relationship between testosterone levels and unemployment, we interpret our descriptive findings as suggestive evidence that such mechanisms are likely to play a role.

8 Conclusion

This paper examines the relationship between testosterone levels and unemployment dynamics among men in the UK. Based on existing studies on testosterone and individual behaviour, we expect that individuals with higher testosterone levels are more likely to exit unemployment, but employed individuals with high testosterone levels are at a higher risk of entering unemployment. The results from our dynamic random effects labour market model confirm these expectations. Among initially unemployed individuals, those with medium and high testosterone levels are significantly more likely to leave unemployment compared to those with testosterone levels in the lowest decile. In contrast, for our sample of initially employed men, those with testosterone levels above the 9th decile were more likely to enter unemployment than those with medium and low levels of testosterone.

Descriptive evidence suggests that these mechanisms might be driven by differences in personality traits and job search behaviour as well as occupational sorting. While "aggressive" behaviour such as competition-seeking or dominance might put individuals with high testosterone levels at an advantage during

their job search, these same traits might prove detrimental to remain in employment. Moreover, individuals with high testosterone levels tend to choose occupations in which spells of unemployment and re-employment are more common. In contrast, men with lower testosterone levels tend to prefer stable and secure occupations. Our findings have important implications for labour market policy. They demonstrate that latent biological processes can affect job search behaviour and labour market outcomes, without necessarily relating to illness and disability. While it would surely be impractical to determine testosterone levels of unemployed men to improve their labour market outcomes, such differences can still be taken into account. For example, when considering how much assistance should be provided to job seekers (or whether sanctions should be applied), it is important to recognise that some differences in job search behaviour are driven by biological processes outside the control of the job seeker. Hence, some individuals might require more assistance than others. One specific example could be training programmes, where individuals with lower testosterone levels might benefit more from individual coaching rather than group sessions. Our results also suggest that individuals with high testosterone levels are at an advantage during the job search, although such hormonal differences do not necessarily translate into better productivity. Awareness of the impact of personality and behavioural traits on performance during job interviews can potentially improve the quality of the job match.

While our results are robust to a wide variety of specification changes, including approaches to account for unobserved individual heterogeneity and initial conditions, there are nevertheless some limitations. Most importantly, the causality of our findings is not clear. We control for time-invariant unobserved heterogeneity, and the dynamic structure of our models should ensure that testosterone levels were measured before changes in employment status. Nevertheless, our models assume that the levels of testosterone (adjusted for age and time of day) remain broadly stable. Unfortunately, our data does not allow us to test this assumption since only one measurement of testosterone is available for each individual. Repeated measures of testosterone could be used to examine whether this assumption holds, as well as if and how testosterone levels change during labour market transitions. In a future extension of the paper, we plan to draw on genetic predictors of testosterone levels to identify random variation in testosterone levels that remains stable over the life course. These genetic predictors will be used as instrumental variables in a Mendelian Randomization design to assess the causality of the findings from our dynamic labour market model. Moreover, we recommend that future research should examine the long-term cumulative effects of testosterone levels on labour market outcomes. Finally, it would be worthwhile to study the mechanisms for which suggestive evidence was presented in this paper in more detail and determine whether they extend to women as well.

References

Akay, A., 2012. Finite-sample comparison of alternative methods for estimating dynamic panel data models. Journal of Applied Econometrics 27, 1189–1204. https://doi.org/10.1002/jae.1254

Apicella, C.L., Dreber, A., Campbell, B., Gray, P.B., Hoffman, M., Little, A.C., 2008. Testosterone and financial risk preferences. Evolution and Human Behavior 29, 384–390. https://doi.org/10.1016/j.evolhumbehav.2008.07.001

Archer, J., 2006. Testosterone and human aggression: an evaluation of the challenge hypothesis. Neuroscience & Biobehavioral Reviews 30, 319–345. https://doi.org/10.1016/j.neubiorev.2004.12.007

Arulampalam, W., 2001. Is Unemployment Really Scarring? Effects of Unemployment Experiences on Wages. The Economic Journal 111, F585–F606.

Bann, D., Hardy, R., Cooper, R., Lashen, H., Keevil, B., Wu, F.C.W., Holly, J.M.P., Ong, K.K., Ben-Shlomo, Y., Kuh, D., 2015. Socioeconomic conditions across life related to multiple measures of the endocrine system in older adults: Longitudinal findings from a British birth cohort study. Social Science & Medicine 147, 190–199. https://doi.org/10.1016/j.socscimed.2015.11.001

Benzeval, M., Davillas, A., Kumari, M., Lynn, P., 2014. Understanding Society: The UK Household Longitudinal Study. Biomarker User Guide and Glossary. University of Essex, Colchester.

Bhuller, M., Brinch, C.N., Königs, S., 2017. Time Aggregation and State Dependence in Welfare Receipt. The Economic Journal 127, 1833–1873. https://doi.org/10.1111/ecoj.12366

Biewen, M., Steffes, S., 2010. Unemployment persistence: Is there evidence for stigma effects? Economics Letters 106, 188–190. https://doi.org/10.1016/j.econlet.2009.11.016

Bijlsma, M.J., Tarkiainen, L., Myrskylä, M., Martikainen, P., 2017. Unemployment and subsequent depression: A mediation analysis using the parametric G-formula. Social Science & Medicine 194, 142–150. https://doi.org/10.1016/j.socscimed.2017.10.011

Booth, A., Granger, D.A., Mazur, A., Kivlighan, K.T., 2006. Testosterone and Social Behavior. Social Forces 85, 167–191.

Booth, A., Johnson, D.R., Granger, D.A., 1999. Testosterone and Men's Depression: The Role of Social Behavior. Journal of Health and Social Behavior 40, 130–140. https://doi.org/10.2307/2676369

Bosch-Domènech, A., Brañas-Garza, P., Espín, A.M., 2014. Can exposure to prenatal sex hormones (2D:4D) predict cognitive reflection? Psychoneuroendocrinology 43, 1–10. https://doi.org/10.1016/j.psyneuen.2014.01.023

Brookes, H., Neave, N., Hamilton, C., Fink, B., 2007. Digit Ratio (2D:4D) and Lateralization for Basic Numerical Quantification. Journal of Individual Differences 28, 55–63. https://doi.org/10.1027/1614-0001.28.2.55

Brosnan, M., Gallop, V., Iftikhar, N., Keogh, E., 2011. Digit ratio (2D:4D), academic performance in computer science and computer-related anxiety. Personality and Individual Differences 51, 371–375. https://doi.org/10.1016/j.paid.2010.07.009

Bütikofer, A., Figlio, D.N., Karbownik, K., Kuzawa, C.W., Salvanes, K.G., 2019. Evidence that prenatal testosterone transfer from male twins reduces the fertility and socioeconomic success of their female co-twins. Proc Natl Acad Sci USA 116, 6749. https://doi.org/10.1073/pnas.1812786116

Butler, J.S., Moffitt, R., 1982. A Computationally Efficient Quadrature Procedure for the One-Factor Multinomial Probit Model. Econometrica 50, 761–764. https://doi.org/10.2307/1912613

Caliendo, M., Cobb-Clark, D.A., Uhlendorff, A., 2015. Locus of Control and Job Search Strategies. The Review of Economics and Statistics 97, 88–103. https://doi.org/10.1162/REST_a_00459

Carré, J.M., McCormick, C.M., 2008. Aggressive behavior and change in salivary testosterone concentrations predict willingness to engage in a competitive task. Hormones and Behavior 54, 403–409. https://doi.org/10.1016/j.yhbeh.2008.04.008

Chamberlain, G., 1992. Comment: Sequential Moment Restrictions in Panel Data. Journal of Business & Economic Statistics 10, 20–26. https://doi.org/10.2307/1391799

Chance, S.E., Brown, R.T., Dabbs, J.M., Casey, R., 2000. Testosterone, intelligence and behavior disorders in young boys. Personality and Individual Differences 28, 437–445. https://doi.org/10.1016/S0191-8869(99)00110-5

Chandola, T., Zhang, N., 2018. Re-employment, job quality, health and allostatic load biomarkers: prospective evidence from the UK Household Longitudinal Study. International Journal of Epidemiology 47, 47–57. https://doi.org/10.1093/ije/dyx150
Cheng, J.T., Tracy, J.L., Foulsham, T., Kingstone, A., Henrich, J., 2013. Two ways to the top: Evidence that dominance and prestige are distinct yet viable avenues to social rank and influence. Journal of Personality and Social Psychology 104, 103–125. https://doi.org/10.1037/a0030398
Coates, J.M., Gurnell, M., Rustichini, A., 2009. Second-to-fourth digit ratio predicts success among high-frequency financial traders. Proc Natl Acad Sci USA 106, 623. https://doi.org/10.1073/pnas.0810907106
Coates, J.M., Herbert, J., 2008. Endogenous steroids and financial risk taking on a London trading floor. Proc Natl Acad Sci USA 105, 6167. https://doi.org/10.1073/pnas.0704025105
Dabbs, J.M., 1992. Testosterone and Occupational Achievement. Social Forces 70, 813–824. https://doi.org/10.2307/2579755
Dabbs, J.M., Bernieri, F.J., Strong, R.K., Campo, R., Milun, R., 2001. Going on Stage: Testosterone in Greetings and Meetings. Journal of Research in Personality 35, 27–40. https://doi.org/10.1006/jrpe.2001.2305
Dabbs, J.M., Strong, R., Milun, R., 1997. Exploring the Mind of Testosterone: A Beeper Study. Journal of Research in Personality 31, 577–587. https://doi.org/10.1006/jrpe.1997.2203
Dabbs Jr., J.M., de la Rue, D., Williams, P.M., 1990. Testosterone and occupational choice: Actors, ministers, and other men. Journal of Personality and Social Psychology 59, 1261–1265. https://doi.org/10.1037/0022-3514.59.6.1261
Delavande, A., Rohwedder, S., Willis, R., 2008. Preparation for Retirement, Financial Literacy and Cognitive Resources. University of Michigan, Michigan Retirement Research Center.
DellaVigna, S., Paserman, M.D., 2005. Job Search and Impatience. Journal of Labor Economics 23, 527–588. https://doi.org/10.1086/430286
Dowd, J.B., Zajacova, A., Aiello, A., 2009. Early origins of health disparities: Burden of infection, health, and socioeconomic status in U.S. children. Social Science & Medicine 68, 699–707. https://doi.org/10.1016/j.socscimed.2008.12.010
Dreher, J.-C., Dunne, S., Pazderska, A., Frodl, T., Nolan, J.J., O'Doherty, J.P., 2016. Testosterone causes both prosocial and antisocial status-enhancing behaviors in human males. Proc Natl Acad Sci USA 113, 11633. https://doi.org/10.1073/pnas.1608085113
Elagizi, A., Köhler, T.S., Lavie, C.J., 2018. Testosterone and Cardiovascular Health. Mayo Clinic Proceedings 93, 83–100. https://doi.org/10.1016/j.mayocp.2017.11.006
Frederick, S., 2005. Cognitive Reflection and Decision Making. Journal of Economic Perspectives 19, 25–42. https://doi.org/10.1257/089533005775196732
Gielen, A.C., Holmes, J., Myers, C., 2016. Prenatal Testosterone and the Earnings of Men and Women. Journal of Human Resources 51, 30–61. https://doi.org/10.3368/jhr.51.1.30
Greene, F.J., Han, L., Martin, S., Zhang, S., Wittert, G., 2014. Testosterone is associated with self-employment among Australian men. Economics & Human Biology 13, 76–84. https://doi.org/10.1016/j.ehb.2013.02.003
Gregg, P., 2001. The Impact of Youth Unemployment on Adult Unemployment in the NCDS. The Economic Journal 111, 626–653. https://doi.org/10.1111/1468-0297.00666
Harris, K.M., Schorpp, K.M., 2018. Integrating Biomarkers in Social Stratification and Health Research. Annu Rev Sociol 44, 361–386. https://doi.org/10.1146/annurev-soc-060116-053339
Heckman, J.J., 1981. The Incidental Parameters Problem and the Problem of Initial Conditions in Estimating a Discrete Time-Discrete Data Stochastic Processs, in: Manski, C.F., McFadden, D. (Eds.), Structural Analysis of Discrete Data with Econometric Applications. MIT Press, Cambridge, Massachusetts, pp. 179–195.
Heckman, J.J., Stixrud, J., Urzua, S., 2006. The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior. Journal of Labor Economics 24, 411–482. https://doi.org/10.1086/504455
Hell, B., Päßler, K., 2011. Are occupational interests hormonally influenced? The 2D:4D-interest nexus. Personality and Individual Differences 51, 376–380. https://doi.org/10.1016/j.paid.2010.05.033

Hsu, C.-C., Su, B., Kan, N.-W., Lai, S.-L., Fong, T.-H., Chi, C.-P., Chang, C.-C., Hsu, M.-C., 2015. Elite Collegiate Tennis Athletes Have Lower 2D: 4D Ratios Than Those of Nonathlete Controls. The Journal of Strength & Conditioning Research 29.

Hughes, A., Kumari, M., 2019. Testosterone, risk, and socioeconomic position in British men: Exploring causal directionality. Social Science & Medicine 220, 129–140. https://doi.org/10.1016/j.socscimed.2018.11.004

Kandasamy, N., Hardy, B., Page, L., Schaffner, M., Graggaber, J., Powlson, A.S., Fletcher, P.C., Gurnell, M., Coates, J., 2014. Cortisol shifts financial risk preferences. Proc Natl Acad Sci USA 111, 3608. https://doi.org/10.1073/pnas.1317908111

Kroft, K., Lange, F., Notowidigdo, M.J., 2013. Duration Dependence and Labor Market Conditions: Evidence from a Field Experiment*. The Quarterly Journal of Economics 128, 1123–1167. https://doi.org/10.1093/qje/qjt015

Marcus, J., 2014. Does Job Loss Make You Smoke and Gain Weight? Economica 81, 626–648. https://doi.org/10.1111/ecca.12095

Mazur, A., 1985. A biosocial model of status in face-to-face primate groups. Social Forces 64, 377–402. https://doi.org/10.2307/2578647

McArdle, J.J., Smith, J.P., Willis, R., 2009. Cognition and Economic Outcomes in the Health and Retirement Survey. National Bureau of Economic Research Working Paper Series No. 15266. https://doi.org/10.3386/w15266

McFall, S., 2013. Understanding Society- UK Household Longitudinal Study: Cognitive Ability Measures (Understanding Society User Manual).

Mehta, P.H., Prasad, S., 2015. The dual-hormone hypothesis: a brief review and future research agenda. Current Opinion in Behavioral Sciences 3, 163–168. https://doi.org/10.1016/j.cobeha.2015.04.008

Mundlak, Y., 1978. On the Pooling of Time Series and Cross Section Data. Econometrica 46, 69–85. https://doi.org/10.2307/1913646

Nicolaou, N., Patel, P.C., Wolfe, M.T., 2017. Testosterone and Tendency to Engage in Self-Employment. Management Science 64, 1825–1841. https://doi.org/10.1287/mnsc.2016.2664

Nye, J.V.C., Bryukhanov, M., Kochergina, E., Orel, E., Polyachenko, S., Yudkevich, M., 2017. The effects of prenatal testosterone on wages: Evidence from Russia. Economics & Human Biology 24, 43–60. https://doi.org/10.1016/j.ehb.2016.11.003

Nye, J.V.C., Orel, E., 2015. The influence of prenatal hormones on occupational choice: 2D:4D evidence from Moscow. Personality and Individual Differences 78, 39–42. https://doi.org/10.1016/j.paid.2015.01.016

Parslow, E., Ranehill, E., Zethraeus, N., Blomberg, L., von Schoultz, B., Hirschberg, A.L., Johannesson, M., Dreber, A., 2019. The digit ratio (2D:4D) and economic preferences: no robust associations in a sample of 330 women. Journal of the Economic Science Association 5, 149–169. https://doi.org/10.1007/s40881-019-00076-y

Ponzi, D., Zilioli, S., Mehta, P.H., Maslov, A., Watson, N.V., 2016. Social network centrality and hormones: The interaction of testosterone and cortisol. Psychoneuroendocrinology 68, 6–13. https://doi.org/10.1016/j.psyneuen.2016.02.014

Rabe-Hesketh, S., Skrondal, A., 2013. Avoiding biased versions of Wooldridge's simple solution to the initial conditions problem. Economics Letters 120, 346–349. https://doi.org/10.1016/j.econlet.2013.05.009

Salthouse, T.A., 2010. Selective review of cognitive aging. Journal of the International Neuropsychological Society 16, 754–760. https://doi.org/10.1017/S1355617710000706

Sapienza, P., Zingales, L., Maestripieri, D., 2009. Gender differences in financial risk aversion and career choices are affected by testosterone. Proc Natl Acad Sci USA 106, 15268. https://doi.org/10.1073/pnas.0907352106

Schaal, B., Tremblay, R.E., Soussignan, R., Susman, E.J., 1996. Male Testosterone Linked to High Social Dominance but Low Physical Aggression in Early Adolescence. Journal of the American Academy of Child & Adolescent Psychiatry 35, 1322–1330. https://doi.org/10.1097/00004583-199610000-00019

Schurer, S., 2017. Bouncing back from health shocks: Locus of control and labor supply. Journal of Economic Behavior & Organization 133, 1–20. https://doi.org/10.1016/j.jebo.2016.10.019

Stenstrom, E., Saad, G., Nepomuceno, M.V., Mendenhall, Z., 2011. Testosterone and domain-specific risk: Digit ratios (2D:4D and rel2) as predictors of recreational, financial, and social risk-taking behaviors. Personality and Individual Differences 51, 412–416. https://doi.org/10.1016/j.paid.2010.07.003

Stewart, M.B., 2007. The interrelated dynamics of unemployment and low-wage employment. Journal of Applied Econometrics 22, 511–531. https://doi.org/10.1002/jae.922

Sumner, R.C., Bennett, R., Creaven, A.-M., Gallagher, S., 2020. Unemployment, employment precarity, and inflammation. Brain, Behavior, and Immunity 83, 303–308. https://doi.org/10.1016/j.bbi.2019.10.013

Uysal, S.D., Pohlmeier, W., 2011. Unemployment duration and personality. Journal of Economic Psychology 32, 980–992. https://doi.org/10.1016/j.joep.2011.03.008

Viinikainen, J., Kokko, K., 2012. Personality traits and unemployment: Evidence from longitudinal data. Journal of Economic Psychology 33, 1204–1222. https://doi.org/10.1016/j.joep.2012.09.001

Welker, K.M., Carré, J.M., 2015. Individual Differences in Testosterone Predict Persistence in Men. European Journal of Personality 29, 83–89. https://doi.org/10.1002/per.1958

Wooldridge, J.M., 2005. Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity. Journal of Applied Econometrics 20, 39–54. https://doi.org/10.1002/jae.770

Appendix

Figure A 1: *Robustness check for different age ranges*

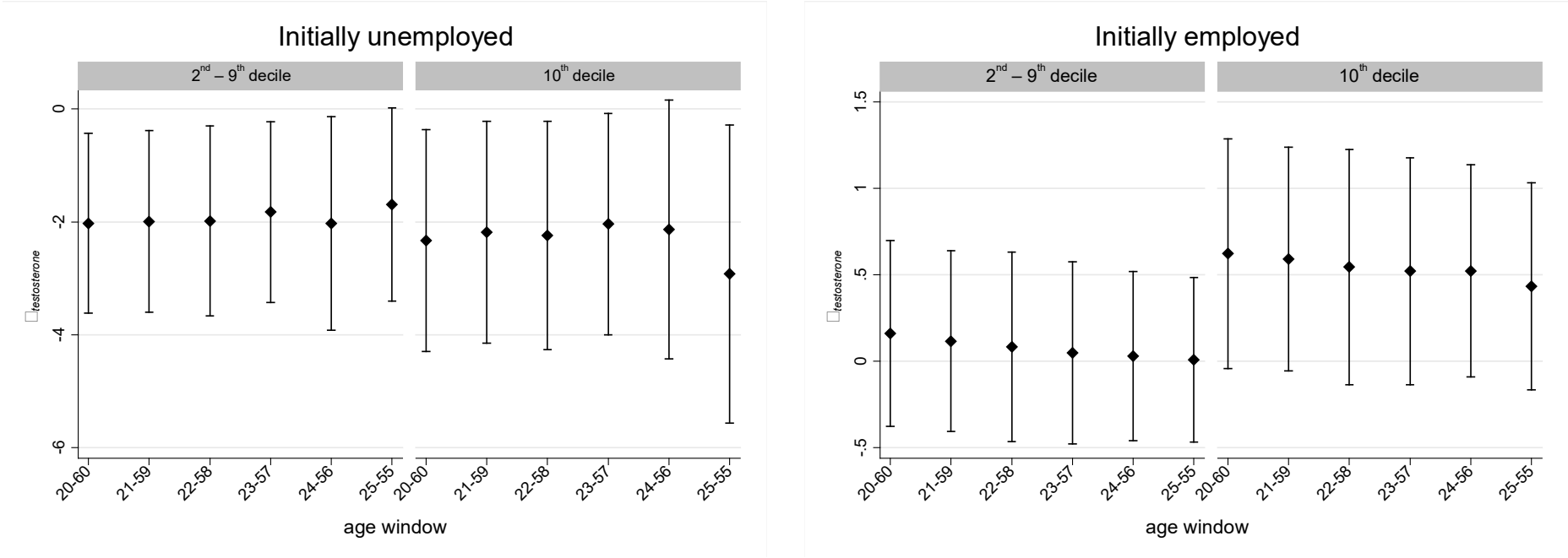


Figure A 2: *Robustness check for different testosterone cut-off points*

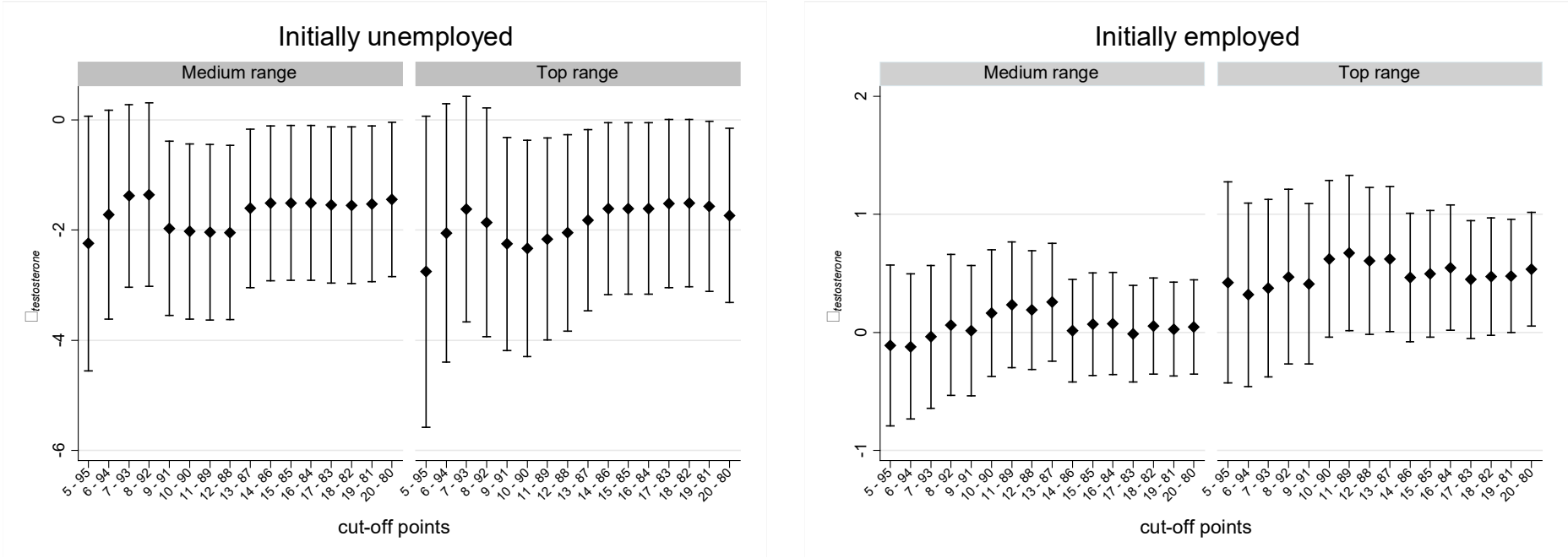


Figure A 3: Effect of testosterone on unemployment risk controlling for initial conditions and unobserved heterogeneity

Specification	**Initially unemployed**	**Initially employed**
testosterone		
1st decile		
2nd – 9th decile	-4.13***	0.4
	(1.47)	(0.43)
10th decile	-3.21**	1.18**
	(1.42)	(0.58)
Observations	371	6,408
LogLikelihood	-50.59	-297.4

Notes: Author's own calculations using data from Understanding Society subsample Health and biomarkers Survey. N= 6,771.
***,**,* refers to statistically significant at 1%, 5% and 10% level respectively

Figure A 4: Numerical ability (proxied by number abilitytest) and testosterone level

Specification	**Total score: numerical ability**
Testosterone group	
Low (1st quintile)	Reference group
Medium (2nd- 4th quintile)	1.29***
	[0.10]
High (5th quintile)	1.01
	[0.003]
Age	1.01***
	[0.003]
Observations	3,123
LogLikelihood	-3844.41

Notes: Author's own calculations using data from Understanding Society
***,**,* refers to statistically significant at 1%, 5% and 10% level respectively. Coefficients refer to odds ratio (exp(β)).

Figure A 5: Fluid reasoning (proxied by logic puzzle test) and testosterone level

Specification	**Total score: fluid reasoning**
Testosterone group	
Low (1st quintile)	Reference group
Medium (2nd- 4th quintile)	1.28**
	[0.14]
High (5th quintile)	1.22
	[0.18]
Age	0.99***
	[0.004]
Observations	1,540
LogLikelihood	-2358.37

Notes: Author's own calculations using data from Understanding Society
***,**,* refers to statistically significant at 1%, 5% and 10% level respectively. Coefficients refer to odds ratio (exp(β)).