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In and out of unemployment—Labour market transitions and the role of testosterone

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ABSTRACT

Biological processes have provided new insights into diverging labour market trajectories. This paper uses population variation in testosterone levels to explain transition probabilities into and out of unemployment. We examine labour market transitions for 2004 initially employed and 111 initially unemployed British men from the UK Household Longitudinal Study ("Understanding Society") between 2011 and 2013. We address the endogeneity of testosterone levels by using genetic variation as instrumental variables (Mendelian Randomization). We find that for both initially unemployed men as well as initially employed men, higher testosterone levels reduce the risk of unemployment. Based on previous studies and descriptive evidence, we argue that these effects are likely driven by differences in cognitive and non-cognitive skills as well as job search behaviour of men with higher 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.

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 various factors 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 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 survey covering about 40,000 households from the United Kingdom, which also holds a range of biomarker data, including the circulating testosterone level. We examine two samples of initially employed or initially unemployed men aged 25–60, and we standardise their testosterone levels for age and time the survey data was collected.

Taking advantage of the longitudinal nature of the data, we examine the likelihood for unemployed men to exit unemployment as well as the risk of entering unemployment for employed men within the following year. Following Hughes and Kumari (2019), we also use a polygenic

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score derived from three genetic markers as an instrument for testosterone levels in a Mendelian Randomization approach to examine how sensitive our results are to potential endogeneity.

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 the second-to-fourth finger length ratio (2D:4D), 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 risk tolerance, gross earnings, household net income, and socio-economic status. In contrast to our study, they only considered the likelihood of being in work at a single point in time, whereas we consider labour market transitions.

Findings from our preferred regression specification indicate that the risk of remaining unemployed significantly declines in testosterone level for unemployed men. In contrast, testosterone has no significant effect on the unemployment risk of employed men. However, the Mendelian Randomisation analysis suggests that serum testosterone levels might be endogenous, and that testosterone reduces the risk of unemployment in both samples.

Cognitive and non-cognitive skills, such as numerical skills or logical reasoning, might partly explain these findings as these are associated with high testosterone levels. 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, policymakers must be aware that biological mechanisms can drive differences in job search behaviour. Thus, due to their inherent skills, some individuals might require specific forms of assistance to thrive - for example, individual training rather than group sessions. This study contributes to our understanding of such mechanisms by providing comprehensive evidence on the role of testosterone.

The rest of this paper is set out as follows. Section 2 reviews the literature on testosterone, and based on this literature we discuss how testosterone could affect labour market transitions. Section 3 presents our data and Section 4 outlines our empirical estimation strategy. Section 5 contains descriptive statistics. Section 6 documents the results from our regression specifications. Section 7 concludes.

2. Testosterone and the labour market

2.1. Existing literature

Testosterone has been found to play 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 et al., 1990; Parslow et al., 2019).,[1][2] For example, in a twin study on Dutch men, more prolonged prenatal testosterone exposure led to higher earnings during working life (Gielen et al., 2016).[3] 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 testosterone levels lead to higher profits on that day. Testosterone also seems to affect the choice of occupation. Low testosterone individuals choose more people-oriented jobs, whereas high testosterone individuals choose more things-oriented jobs (Dabbs et al., 1990; Hell and Päßler, 2011; Nye and Orel, 2015).[4] Typical jobs that have been related to high testosterone are sportsmen, sales men, actors, or politicians (Dabbs 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).

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.[5] 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. However, at the same time, they were also more generous when it promoted social status. Similarly, individuals with high testosterone levels show more initiative in forming friendships and are, therefore, able to build up more extensive social networks (Booth et al., 1999; 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 in 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

[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] In contrast, evidence on the link between testosterone and health is inconclusive (Bann et al., 2015; Hughes and Kumari, 2019).

[3] 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).

[4] 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).

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

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 (Dabbs et al., 1997; Mazur, 1985). For example, Dabbs et al. (2001) interviewed and filmed male college students and found that individuals with high testosterone levels appeared more forward, independent, focused, restless, and oriented toward action.

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.

As noted above, high testosterone levels are associated with aggression (in the broader sense), which includes competition-seeking and dominant behaviour (Archer, 2006; Chance et al., 2000), but also 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 essential resource for the job search (Ponzi et al., 2016). Moreover, 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 naturally (Dabbs et al., 2001, 1997) and exert 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 testosterone level are more reflective in the decision-making process (Bosch-Domènech et al., 2014). Re-employment, therefore, would take longer for individuals with high testosterone but might result in a better job match. Conversely, 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 due to the perceived social stigma of unemployment.

For individuals in employment, once employers learn about their employees' productivity, competition-seeking and dominant behaviour may become less critical. While these individuals may invest more effort into their work to seek promotions, competition-seeking behaviour might also be 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, e.g., positions with performance-based remuneration and where redundancies are more common, e.g., 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, the existing evidence suggests that testosterone might affect transitions both in and out of unemployment, but the direction of the effect is ambiguous, and it may differ for exits and entries into unemployment.

3. Data

The UK Household Longitudinal Study (UKHLS) *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 individual's and household characteristics. *Understanding Society* is the successor of the British Household Panel Survey (BHPS), which started in 2009, and at the time of writing nine 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 researchers 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').[6] A range of bio-medical measures was collected from over 20,000 adults, including testosterone levels.

3.1. 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 labour market transition between the nurse visit and the next survey wave. We start by trimming the nurse visit sample (when biomarkers are collected) to include only men who provide information on their social and economic circumstances, including the current labour force status.[7] We restrict the sample to 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 mainstage wave of Understanding Society. As noted above, the nurse visit took place shortly after either Wave 2 or Wave 3.[8] The interviews in the primary survey were conducted, on average, virtually one year apart. However, the time difference between the nurse visit and the follow-up interview at the primary survey is less than one year. We restrict our sample to individuals who are either employed or unemployed at the follow-up interview. Our final sample consists of 2115 individuals, out of which 111 (5.25%) were unemployed during the nurse visit, and 2004 were employed (94.75%). For 1562 individuals, the follow-up interview was at wave 3 of UKHLS, and for 553 individuals at wave 4.[9]

3.2. Health and biomarkers survey

To be eligible for a nurse visit, 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,

[6] The nurse health visit was conducted among adult survey participants from the General Population Sample (GPS) which consists 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.

[7] 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.

[8] We drop individuals who have a different labour market status at the wave prior the nurse visit. We introduce this restriction to avoid short-term labour market changes affecting the measured testosterone level.

[9] These 553 individuals are former BHPS participants, which joined the *Understanding Society* study at wave 2.

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.

Testosterone levels show wide variation among men and are considered within a normal range between 9 and 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 Fig. 1). Apart from time and age, differences in testosterone levels are thought to originate from prenatal development, particularly in-utero exposure to testosterone. The sex difference in testosterone is almost non-existent before puberty but up to 20 times higher for men thereafter (e.g., Handelsmann et al., 2018). However, where the variation for testosterone levels among men comes from is not entirely clear. There is evidence from mice that maternal stress alters plasma testosterone levels in fetal males (Ward and Weisz, 1980). Similarly, testosterone levels have been found to interrelate with other hormones like cortisol and hence to stress, but evidence for humans is scarce (Braude et al., 1999). In the Health and biomarkers Survey, there are 3597 men with a plausible level of testosterone in the age range 25–64 who had their interview started between 8 am and 8 pm.[10]

3.3. Genetic data

We draw on genetic data collected during the Health and Biomarker Survey (2015) to assess the robustness of our findings, in particular with respect to reverse causality. Access to the data was granted via METADAC (Murtagh et al., 2018). Specifically, we investigate whether genetic variants that partly explain the variance of serum testosterone affect labour market dynamics in a way that is consistent with our main findings. This method, which uses genetic markers as so-called Instrumental Variables (IV) is known as Mendelian Randomisation (MR) (Burgess and Thompson, 2015) and is outlined in section 4.4.

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

The start time of the interview (hour)	Testosterone (nmol/l)		
	Mean	Std Dev	*N*
8	17.30	5.92	16
9	17.73	5.84	154
10	17.82	5.21	367
11	17.14	5.21	303
12	17.08	5.29	194
13	15.14	5.14	175
14	15.44	5.27	208
15	14.39	5.06	223
16	14.55	5.10	275
17	14.80	4.79	350
18	14.36	4.85	584
19	13.78	4.78	594
20	13.09	4.47	154

Notes: Author's own calculations, using data from the Understanding Society subsample Health and biomarkers Survey. $N = 3597$ men with a positive level of testosterone in the age range 20–64 who had their interview started between 8 am and 8 pm.

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

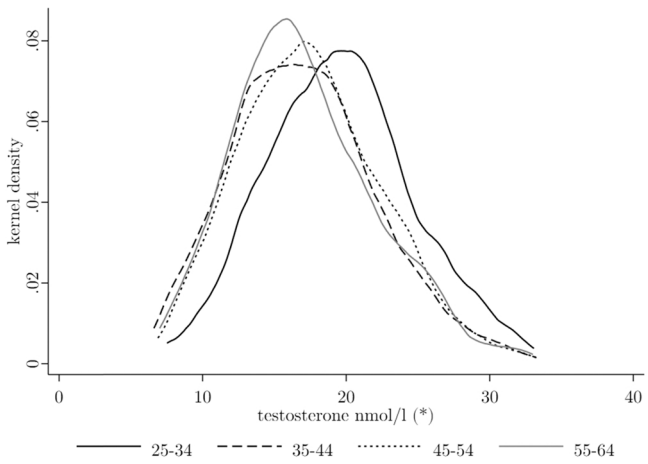

Fig. 1. Level of testosterone (nmol/l) and age. *Notes*: Author's own calculations, using data from the Understanding Society subsample Health and biomarkers Survey. $N = 3597$ men with a positive level of testosterone in the age range 25–64 who had their interview started between 8 am and 8 pm. (*) showing the level of testosterone (nmol/l) corrected by the time of the nurse visit.

Individual's genetic data were genotyped using the Illumina HumanCore Exome and imputation carried out in Minimac 5-12-29 to the European component of 1000 genomes (Hughes and Kumari, 2019). Samples are checked to ensure genetic data is consistent with key information provided, such as gender and ethnicity. Quality control checks removed SNPs with a minor allele frequency of $< 1\%$, call rate threshold $< 98\%$, Hardy-Weinberg Equilibrium $p < 10^{-4}$, or cluster separation score < 0.4 (Hughes and Kumari, 2019).

Three genetic variants are used as instruments for circulating testosterone based on the Genome Wide Association Study (GWAS) of Ohlsson et al. (2011). These are rs12150660 and rs6258 in the SHGB gene on chromosome 17 and rs5934505 near FAM9B on the X chromosome. rs12150660 was imputed, whereas rs6258 and rs5934505 were genotyped (Hughes and Kumari, 2019). Online Appendix A provides further details regarding the genetic data used in this study, including our methodological approach.

4. Methodology

We aim to understand how the individual's testosterone level impacts labour market changes between the nurse visit and the follow-up interview in the primary *Understanding Society* survey one year later. We distinguish between employed and unemployed men aged between 25 and 64. The reduced form model for unemployment can be written as follows:

$$y_{i(t=1)} = \mathbf{1}(\theta_1 T_{i(t=0)} + \alpha_1 y_{i(t=0)} + X'_{i(t=0)}\beta + u_{i(t=1)} > 0) \quad (1)$$

where the subscripts $i = 1, \ldots, N$ are individuals, and the time indicator $t = 1$ refers to the first post-nurse-visit interview, whereas $t = 0$ refers to the time-point of the nurse visit. The dependent variable $\left(y_{i(t=1)}\right)$ equals 1 if i was unemployed at $t = 1$ and 0 else. $y_{i(t=1)}$ is explained by the testosterone level $T_{i(t=0)}$ as measured during the nurse visit. Testosterone levels vary over the course of the day (Kanabar et al., 2022), and unemployed men might be more likely to participate in their UKHLS interview during working hours than working men. To ensure comparability of testosterone, we adjust the circulating testosterone levels for age and time of the day when the blood sample was taken. We use the Health and biomarkers Survey to construct a sample of men with a positive level of testosterone in the age range 25–64 whose interview started between 8 am and 8 pm ($N = 3597$). We form four age groups,

spanning the following ages: 25–34, 35–44, 45–54, and 55–64. Next, for each age group, we estimate the diurnal change of testosterone by regressing the absolute level of testosterone (nmol/l) and controlling for the time difference of the nurse visit (hour and minute) to 10 am.[11] We use the beta coefficients to correct the individual's testosterone level and standardize them to 10 am. Afterwards, we calculate the deviation by taking the difference between the estimated age-group specific and time-corrected sample mean and the individual's corrected testosterone level. Our first regression model includes the age- and time-adjusted testosterone in nmol/l as a covariate (Model 1). Further specifications include the corrected testosterone level as a second-degree polynomial (Model 2). In our last specification (Model 3), we form three groups based on the distribution of the deviation of individual testosterone levels from the age-group specific and time-corrected sample means within each age group: (i) low level of testosterone if the deviation belongs to the lowest quartile, (ii) medium level of testosterone if the deviation is in the 2nd to 3rd quartile, and (iii) high level of testosterone if the deviation belongs to the highest quartile. In a robustness check, we re-estimate our regression specifications adjusting the cut-off point defining low, medium, and high levels to ensure our results remain stable and are not driven by these definitions.

In addition to testosterone we also account for the labour market status $y_{i(t=0)}$ and a vector of explanatory variables $X_{i(t=0)}$ during the nurse visit. The latter includes: age (linear and quadratic), highest qualification, self-rated health, region, urban identifier, household size, long-term disability, legal marital status, % body fat, smoking behaviour, as well as consumption of beta-blockers or Central Nervous System (CNS) medication. $u_{i(t=1)}$ is an idiosyncratic shock. As the outcome variable is dichotomous, a normalisation of $u_{i(t=1)}$ is required. We take $\sigma_u^2 \sim N(0,1)$ and the outcome probability is:

$$P_{it}\left(y_{i(t=1)}=1\right)=\mathbf{\Phi}\left[\theta_1 T_{i(t=0)}+\alpha_1 y_{i(t=0)}+X'_{i(t=0)}\beta)\left(2y_{i(t=1)}-1\right)\right] \quad (2)$$

$\mathbf{\Phi}[\bullet]$ refers to the cumulative standard normal distribution.

As we outlined in Section 2.2, the effect of $T_{i(t=0)}$ might differ for those who are initially employed $\left(y_{i(t=0)}=0\right)$ compared to those who are initially unemployed $\left(y_{i(t=0)}=1\right)$ during the nurse visit. Therefore, we estimate separate regressions based on the labour force status during the nurse visit. For the sample of initially (un)employed, Eq. 1 takes the following form:

$$y_{i(t=1)}=\mathbf{1}(\theta_1 T_{i(t=0)}+X'_{i(t=0)}\beta+u_{i(t=1)}>0) \quad (3)$$

4.1. Mendelian Randomisation

Mendelian Randomisation (MR) uses genetic variation to shed light on the causal relationships between one or more modifiable risk factors and a particular outcome (Davies et al., 2018). One of the main strengths of this approach is that, under certain conditions, it can resolve the issue of unmeasured confounding by using genetic variation, which is fixed at conception, to help identify causal effects. In this study, we use MR to provide additional support for our main findings based on the probit specification outlined in the previous subsection.

Genetic variants act as so-called instrumental variables and therefore must satisfy four conditions in order to be valid: (i) relevance, (ii) independence, (iii) exclusion, and (iv) monotonicity. In our case, this means that the instruments must be (i) associated with the testosterone, (ii) there must be no unmeasured confounders linking genetic variants and unemployment, (iii) the genetic markers only affect unemployment dynamics via their effect on testosterone, and (iv) the genetic markers should affect testosterone levels in the same direction for all observations. We consider the plausibility of these assumptions in the context of our study using various diagnostic checks (see inter-alia Davies et al., 2018) in section 6.4.

Instead of using the three genetic markers (rs12150660 and rs6258 in the SHGB gene on chromosome 17 and rs5934505 near FAM9B on the X chromosome) separately, following Hughes and Kumari (Hughes and Kumari, 2019), we combine them into a single measure (polygenic score) using the beta values from Ohlsson et al. (2011). This is done to improve their statistical power and reduce the possibility of biased results due to weak instruments. We then use the individual-specific polygenic score to predict testosterone level using a standard IV model.

In addition, METADAC provides the first ten principal components (PCAs). PCAs account for population stratification in GWASs, i.e., they refer to the overall genome and hence ancestry, over and above what is included in our polygenic score. Following previous literature (see inter-alia Hughes and Kumari, 2019), we include these first ten principal components in the MR regression analysis.

5. Descriptive statistics

The economic literature has shown that unemployment risk is influenced by factors such as qualifications, age, health, etc. In our study, we test the explanatory power of testosterone. When we split the sample into initially unemployed and employed (columns three and four of Table 2), we can see that these groups differ with respect to observable characteristics. For example, there is a significantly higher share of individuals without a higher qualification or whose health is not good or better among the initially unemployed.

We also find some differences in the distribution of corrected testosterone. The sample of initially unemployed has, on average, a higher level of testosterone, but the difference is not statistically significant. Further, we do not find significant differences when looking at the three testosterone groups described earlier. The kernel density plot shown in Fig. 2 indicates a slightly larger tail at higher levels of corrected testosterone.

One way to assess intertemporal changes in the labour market position is to consider transition matrices. In Table 3, the probability of being (un)employed at $t=1$ (the first interview after the nurse visit), conditional on the labour market position at $t=0$ (the nurse visit) is presented. The largest probabilities are on the main diagonal, which means that individuals either stay employed or unemployed and do not move between different labour market statuses. However, we see that the fraction moving from unemployment into employment is substantially larger than the one entering unemployment after stating being employed at the nurse visit.

We differentiate the transition matrix further according to the testosterone groups to which an individual belongs (see Table 4). We find that for initially unemployed men at $t=0$, the conditional probability of staying unemployed is highest in the first quartile (75 per cent) – especially concerning the 2nd – 3rd quartile (49 per cent). For initially employed men at $t=0$, we find that those in the top quartile have the highest conditional probability of entering unemployment (3.6 per cent). A general pattern in Table 4 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.

6. Results

6.1. Baseline regression

Our baseline model controls for the labour market position and additional covariates collected during the nurse visit. Furthermore, we include the level of testosterone in three different alternative specifications. Table 5 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 columns (1)-(3)

[11] We checked for a non-linear relationship between time of the day and testosterone level but not indications were found.

Table 2
Descriptive statistics measured at nurse visit (measured at $t = 0$).

	Full Sample	Initially unemployed	Initially employed	t-test (p-value)
Testosterone (nmol/l)	17.73 (5.09)	18.35 (5.85)	17.70 (5.04)	0.190
Testosterone (categorical, %)				
1st quartile	24.40	28.83	24.15	
2nd – 3rd quartile	50.35	40.54	50.90	
4th quartile	25.25	30.63	24.95	0.104
Age	44.78 (10.12)	45.05 (10.06)	44.71 (10.13)	0.176
Highest qualification (%)				
Degree	29.74	15.32	30.54	
Other higher degree	12.15	10.81	12.23	
A-level etc	22.98	18.02	23.25	
GCSE etc	21.75	28.83	21.36	
Other/No qualification	13.38	27.03	12.62	0.000
General Health (%)				
excellent	17.45	9.91	17.86	
very good	40.76	26.13	41.57	
goof=d	29.22	32.43	29.04	
fair/poor	12.58	31.53	11.53	0.000
Region of residence (%)				
England	84.78	96.40	84.13	
Wales	6.19	3.60	6.34	
Scotland	9.03	–	9.53	0.001
Rural area (%)	22.46	16.22	22.80	0.105
Number of people in household (%)				
1	12.62	28.83	11.73	
2	30.35	27.93	30.49	
3	20.80	14.41	21.16	
4 +	36.22	28.83	36.63	0.000
Long-standing illness or disability (%)				
	27.00	36.94	26.45	0.015
Legal marital status (%)				
single	23.83	47.75	22.50	
married	63.92	31.53	65.72	
separated, divorced, widowed	12.25	20.72	11.78	0.000
% body fat				
	23.37 (8.41)	24.31(9.60)	23.31(8.34)	0.223
Smoking (%)				
	18.68	47.75	17.07	0.000
Beta blockers (%)				
	3.03	4.50	2.94	0.350
CNS medicine (%)				
	8.98	18.92	8.43	0.000
N	2115	111	2004	

Notes: Author's own calculations, using data from the Understanding Society subsample Health and biomarkers Survey. $N = 2115$.

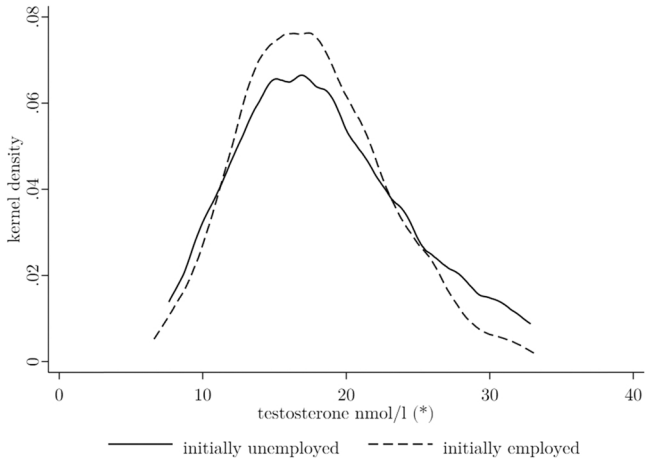

Fig. 2. Level of testosterone (nmol/l) by labour market status at the nurse visit ($t = 0$). *Notes*: Author's own calculations, using data from the Understanding Society subsample Health and biomarkers Survey. $N = 2115$ men with a positive level of testosterone in the age range 25–64 who had their interview started between 8 am and 8 pm and who were either employed (and an employee) or unemployed. (*) showing the level of testosterone (nmol/l) corrected by the time of the nurse visit.

Table 3
Transition matrix of labour market status.

	$employed_{t=1}$	$unemployed_{t=1}$	$Total_{t=0}$
$employed_{t=0}$	97.21 (1948)	2.79 (56)	94.75 (2004)
$unemployed_{t=0}$	39.64 (44)	60.36 (67)	5.25 (111)
$Total_{t=1}$	94.18 (1992)	5.82 (123)	

Notes: Author's own calculations, using data from the Understanding Society subsample Health and biomarkers Survey. $N = 2115$. Numbers in () refer to the sample size.

Table 4
Unemployment risk differentiated according to testosterone level.

Testosterone (categorical)	$unemployed_{t=0}$	$employed_{t=0}$
$unemployed_{t=1}$		
1st quartile	75.00	2.48
2nd – 3rd quartile	48.89	2.55
4th quartile	61.76	3.60

Notes: Author's own calculations, using data from the Understanding Society subsample Health and biomarkers Survey. $N = 2115$.

of Table 5) and includes the age- and time-corrected level of testosterone in a linear trend (1), a quadratic trend (2), and as a categorical variable (3). Model (3) is our preferred specification because it is more robust to outliers than a linear or quadratic trend, and it does not require an assumption on the functional form of testosterone. In the first specification, we find that the unemployment risk increases with the level of testosterone. When moving to Model (2), we find a U-shape relationship, reaching the lowest value around a testosterone level of 18 nmol/l and then increasing again. The latter finding is mirrored by our last specification, where men with a testosterone level in the 2nd or 3rd quartile face a lower risk of becoming unemployed. However, the magnitude is always small in all three specifications, 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 those who were unemployed and those who were employed during the nurse visit. Once we distinguish by the initial labour market status (columns (4)-(9) of Table 5), we see that the direction of the effect and the magnitude change substantially. For those who are initially unemployed, Table 5 (column (4)-(6)) indicates that the risk of staying unemployed declines in the level of testosterone.[12] Although the significant quadratic term in column (5) indicates a non-linear effect of testosterone, column (6) suggests that the difference between the medium and high testosterone groups is rather modest.

In contrast to the sample of initially unemployed, we do not find significant effects in any of the specifications considered for the sample

[12] In the case of Model (2), we see a decline in the unemployment risk until reaching a corrected testosterone level of 25 nmol/l.

Table 5
Effect of testosterone on unemployment risk.

				Labour market position during nurse visit					
	Full Sample			unemployed			employed		
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
testosterone nmol/l	-0.0038	-0.0332		-0.0693**	-0.4633**		0.0047	-0.0023	
	(0.0109)	(0.0585)		(0.0351)	(0.1977)		(0.0122)	(0.0689)	
(testosterone nmol/l)^2		0.0007			0.0096**			0.0001	
		(0.0015)			(0.0047)			(0.0018)	
testosterone									
1st quartile	*reference category*								
2nd – 3rd quartile			-0.1602			-1.3653***			-0.0207
			(0.1345)			(0.4699)			(0.1545)
4th quartile			-0.0268			-1.4097**			0.1257
			(0.1518)			(0.0575)			(0.1721)
Observations	2115	2115	2115	111	111	111	2004	2004	2004
Log Likelihood	-315.590	-315.462	-314.724	-51.355	-49.075	-48.211	-243.558	-243.553	-243.076

Notes: Author's own calculations, using data from the Understanding Society subsample Health and biomarkers Survey. $N = 2115$. All models control for age (linear and quadratic), highest qualification, self-rated health, region, urban identifier, household size, long-term disability, legal marital status, % body fat, smoking behaviour, beta-blockers, Central Nervous System medicine. The Full Sample also controls for the labour market status during the nurse visit. Model 1 includes a linear trend in circulating corrected testosterone, Model 2 models corrected testosterone with a quadratic polynomial, and Model 3 includes testosterone as a categorical variable.

Table 6
Average partial effects.

	Labour market position during the nurse visit	
	unemployed	employed
1st quartile	*reference category*	
2nd – 3rd quartile	-0.2930***	-0.0012
	(0.0832)	(0.0090)
4th quartile	-0.3042***	0.0083
	(0.1049)	(0.0113)
Observations	111	2004

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.

of initially employed men.

We also calculate the average partial effects (APE) for Model (3) for the two subsamples (Table 6).[13] The partial effect is the difference (in percentage points) of staying or becoming unemployed if the person had a testosterone level in the second to the third quartile, resp. the top quartile, compared to the first quartile.

Compared to the lowest category, the unemployment risk for those who were unemployed during the nurse visit is reduced by 29.3 percentage point for the medium category and by 30.4 percentage point (both estimates significant at the 1% level) by the higher category. While these are very large effects, they are overall comparable to the differences in transition probabilities shown in Table 4. In the case of those men employed during the nurse visit, the magnitude of the APE is only positive for the top quartile, and the magnitude is small.

[13] We calculate the predicted probability of staying unemployed for the sample of initially unemployed men for Model (1) and Model (2). We calculate the mean probability for a corrected testosterone level between 6 and 30 nmol/l (with 1 unit increments) and Fig. A1 shows the respective sample means. While both slopes point in the same direction—higher testosterone values go along with a lower risk of staying unemployed— we find a deviation in the probabilities at the tails of the testosterone distribution.

6.2. Robustness checks for the initially unemployed

In order to assess the sensitivity of our main results, we carry out a number of robustness checks.[14] As we only detected strong effects for the group of men who were unemployed during the nurse visit, we restrict discussion to this particular group. Our focus is to understand the link between testosterone and labour market changes among working-age men. First, we want to test whether our findings are driven by a few observations at the top and the bottom of the testosterone level distribution. For this reason, we drop the top and bottom 5% of the corrected testosterone values. The number of observations drops by 13.5%, indicating that men with extreme testosterone values are overrepresented among the unemployed. Table 7 shows the respective marginal effects, and we still find sizeable and highly significant effects of higher testosterone levels reducing the risk of staying unemployed. We further find no indications for a non-linear relationship between testosterone level and unemployment risk (See column (5) of Table A1).

Another concern is that our results are driven by the chosen age restriction (25–64). 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 labour supply prior to

Table 7
Average partial effects of truncated sample.

	unemployed during the nurse visit
1st quartile	*reference category*
2nd – 3rd quartile	-0.2415**
	(0.0947)
4th quartile	-0.3302***
	(0.1211)
Observations	96

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.

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

entering retirement. We first narrow the age window by iteratively dropping the youngest and oldest age until the age range includes those between 30 and 59. The respective marginal effects for the categorical testosterone variable are shown in Fig. 3. For simplicity, we have grouped the two highest testosterone groups together. Thus, the graph shows the marginal effect of belonging to the second or higher quartile compared to the bottom quartile. Across all age groups, we find a strongly significant reduction in unemployment risk for higher testosterone levels. Further, the variation in the magnitude only varies marginally across the different age windows.

Next, we consider our categorisation of the variable defining the testosterone groups. We use the bottom and top quartile as cut-off points to determine the three categories in our main specification. We re-estimate the model and use as cut-off points for the bottom group 20–30 per cent, moving in one percentage points (see Fig. 4 for the marginal effects). We find that a higher testosterone level significantly reduces the risk of future unemployment, independent of the threshold used to distinguish between low and high levels.

6.3. Mendelian randomisation

For the Mendelian Randomisation analysis, we only consider a specification with a linear trend in testosterone levels. Identifying a quadratic trend or separate groups would require additional instruments that predict variation between, e.g., medium and high levels of testosterone. The first-stage estimates shown in Table A2 show that the polygenic score is indeed highly predictive of testosterone levels. The top panel of Table 8 shows estimates of the reduced form regression of the unemployment on the polygenic score as well as the estimates (reported as APEs) from an IV-probit regression using the polygenic score as an instrument for testosterone. Based on the reduced form regression estimates, the lower part of Table 8 reports APEs for the coefficient of interest.

For the sample of unemployed men, we find that in the reduced form regression, a higher polygenic score is associated with a reduced probability of remaining unemployed. This suggests that men with a genetic predisposition towards higher testosterone levels were less likely to remain unemployed. However, the causal effect of testosterone itself in the IV-probit model is imprecisely estimated. For employed men, we find that higher testosterone levels significantly reduce the risk of entering unemployment, both in the reduced form and the IV-probit model.

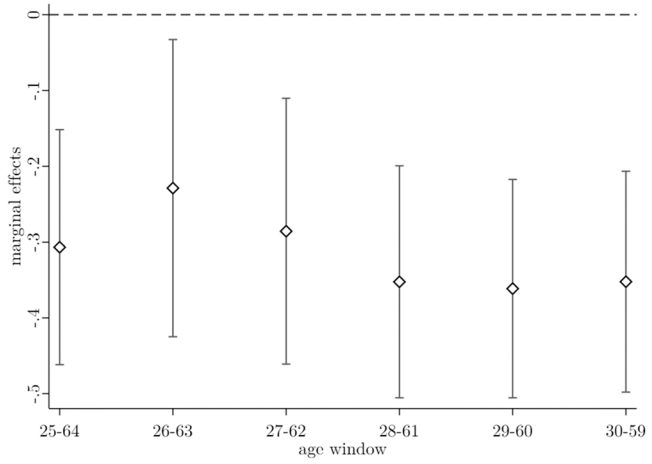

Fig. 3. Robustness on different age-windows, *Notes*: Author's own calculations, using data from the Understanding Society subsample Health and biomarkers Survey. $N = 2115$ men with a positive level of testosterone in the age range 25–64 who had their interview started between 8 am and 8 pm and who were either employed (and an employee) or unemployed. (*) showing the level of testosterone (nmol/l) corrected by the time of the nurse visit.

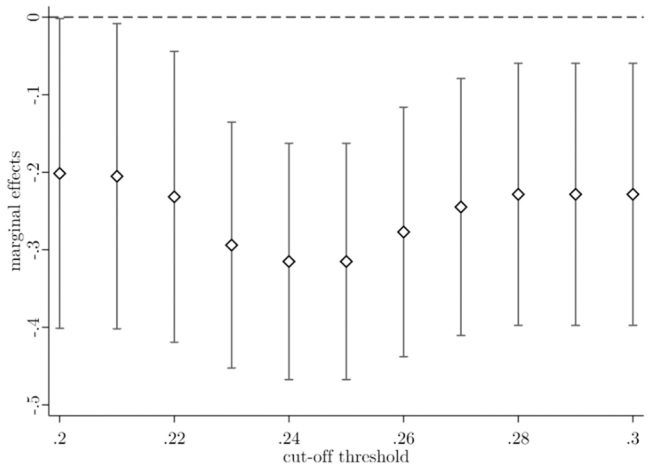

Fig. 4. Robustness on different cut-off thresholds, *Notes*: Author's own calculations, using data from the Understanding Society subsample Health and biomarkers Survey. $N = 2115$ men with a positive level of testosterone in the age range 25–64 who had their interview started between 8 am and 8 pm and who were either employed (and an employee) or unemployed. (*) showing the level of testosterone (nmol/l) corrected by the time of the nurse visit.

Comparing these estimates to the results shown in Tables 5 and 6, we note that the Mendelian Randomisation analysis partly supports our conclusions. For the sample of unemployed men, we find a reduction in the probability of remaining unemployed both for our main specification in Table 5 and the Mendelian Randomisation analysis in Table 8. However, the point estimates in the Mendelian Randomisation analysis are considerably smaller, and the estimate in the IV-probit model is not statistically significant. Both the lack of precision and the smaller point estimate could be due to the limited explanatory power of the polygenic score for variation in testosterone levels. The first stage estimate for unemployed men in Table A2 is relatively small and not statistically significant. This means the polygenic score is only a weak instrument for testosterone in this subsample, likely due to the limited sample size.[15] Moreover, the polygenic score only identifies variation in testosterone levels that is conceptually stable over the life course. It seems reasonable that the effects of such long-term differences on unemployment risk are smaller than the effects of both long-term differences and short-term fluctuations. Nevertheless, we interpret the significant reduced form effect as (partial) support for our conclusions.

For the sample of employed men, the finding of a reduction in the risk of unemployment in the Mendelian Randomisation analysis contradicts the small and insignificant estimate reported in our main specification. There are two possible explanations for this difference: First, we cannot rule out that these estimates reflect the conceptual difference between long-term differences in testosterone levels identified in the Mendelian Randomisation model and short-term fluctuations in testosterone, which may dominate in our main specification. Second, the difference in the estimates might suggest that testosterone levels are indeed endogenous, and that the estimated (insignificant) effect in our main specification is upward-biased. Such upward bias could arise, e.g., from unobserved factors that are correlated with both elevated testosterone levels and a higher risk of unemployment. For example, previous studies indicate that divorce is associated with both elevated testosterone levels (Mazur and Michalek, 1998) and unemployment (Hansen, 2005). Occupational sorting could also explain such an upward bias

[15] Sanderson-Windmeijer F statistics reported in Table 8 confirm this. In addition the test statistic for weak-instrument robust inference (Anderson and Rubin, 1949) has also been provided for each subsample in Table A2. In this case the test statistic strongly rejects the null hypothesis and implies the matrix of reduced form coefficients has the appropriate rank and so is identified.

Table 8
Mendelian Randomisation.

			Labour market position during nurse visit			
	Full sample		unemployed		employed	
Model	Reduced form	IV-Probit	Reduced form	IV-Probit	Reduced form	IV-Probit
testosterone nmol/l		-0.12***		-0.03	-0.007**	-0.12***
		-0.03		-0.93	-0.003	-0.05
Polygenic score	-0.007***		-0.018*			
	-0.002		-0.009			
	Average Partial Effect					
Polygenic score	-0.0008***		-0.006**		-0.0005**	
	-0.0002		-0.0027		-0.0002	
SW F-statistic		6.53		1.14		6.89
AR confidence set		(−0.190, −0.035)		(−0.5,0.5)†		(−0.105,0)
Observations	1681	1647	87	82	1594	1565
Log Likelihood	-380.35	-5215.1	-49.75	-298.6	-205.93	-4799.7

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. Regressions control for first and second degree polynomials in age and the first 10 principal components. SW F-statistic is the Sanderson-Windmeijer F-statistic on the strength of the excluded instrument. AR confidence set reports the Anderson-Rubin confidence set using a confidence level of 95% based on inversion of the Anderson-Rubin test statistic and a numerical grid search †None of the values considered within this interval were rejected as part of the confidence set. We did not extend the search beyond these values, since values above 0.5 were deemed implausible.

either if men with high testosterone levels select into occupations with a high risk of unemployment or if occupational tasks in high-risk occupations lead to elevated testosterone levels (but not if testosterone has a causal effect on occupational choice).

Both of these explanations – conceptual differences between long-term and short-term variation in testosterone vs. endogeneity of testosterone – raise the question of why our estimates differ substantially for the sample of employed men but are more similar for the sample of unemployed men. It is difficult to imagine why the conceptual difference should affect employed men more than unemployed men. On the other hand, it is plausible that unobserved confounders and selection processes affecting the entry into unemployment differ from those affecting persistent unemployment. This suggests endogeneity as the more plausible explanation for the differences in our estimates.

6.4. Assumptions in the Mendelian Randomization analysis

The causal interpretation of these estimates relies on four assumptions: (i) relevance, (ii) independence, (iii) exclusion, and (iv) monotonicity. Considering relevance, the first-stage estimates and the F-statistic on the strength of the excluded instrument (see Table A2) suggest that the polygenic score predicts variation in testosterone levels, but the strength of this association is relatively weak. However, the Anderson-Rubin test suggests that at least in the full sample and for initially employed men we can reject the hypothesis that the true effect is zero. In addition, we construct Anderson-Rubin 95% confidence sets based on test inversion, which show that for the full sample, the effect of testosterone is bounded between − 0.19 and − 0.035, and for the sample of initially employed men, the effect of testosterone is bounded between − 0.105 and 0.[16]

Independence is likely to hold because a person's genome is determined by random recombination of their parent's genes. Moreover, Hughes and Kumari (2019) show that in the UKHLS data, the polygenic score is not significantly associated with many commonly considered confounders, such as self-reported health or marital status (see Table 4 in Hughes and Kumari, 2019). This covariate balance also addresses concerns regarding the exclusion restriction – if the genetic variants associated with higher testosterone levels were also predictive of other characteristics that affect labour market transitions, we would expect to see significant associations between the polygenic score and known confounders of the relationship between testosterone and labour market outcomes.

We also implement a recently proposed test of instrument validity and monotonicity (Mourifié and Wan, 2017), which jointly tests independence, exclusion, and monotonicity. The test only allows for binary instruments and treatments, and we, therefore, implement it using a binary indicator for low testosterone (i.e., values within the first quartile) and a binary indicator for PGS values that are lower than the average value of the PGS in the group of men with low testosterone. The test fails to reject the null hypothesis of joint instrument validity and monotonicity at the 10% level. Although this does not necessarily mean that instrument validity and monotonicity hold, there is no evidence to suggest that these assumptions are violated in our sample. We also note that a violation of monotonicity would imply that for some individuals, the genetic variants used to construct our polygenic score are predictive of lower (rather than higher) testosterone levels, which does not appear to be very plausible.

7. Conclusion

This paper examines the relationship between testosterone levels and unemployment dynamics among men in the UK. Our probit regression model controlling for previously identified confounders suggests that among 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 employed men, we do not find significant effects of testosterone on the risk of entering unemployment. We address endogeneity in testosterone levels in a Mendelian Randomisation analysis, using genetic variants predicting testosterone levels as instruments for serum testosterone. We find a negative effect of testosterone on unemployment risk, both among unemployed men (only significant in the reduced form regression) and among employed men (highly significant in both the reduced form and the IV-probit regression).

Previous studies show that testosterone is associated with cognitive and non-cognitive skills, e.g., numerical ability (Brookes et al., 2007; Brosnan et al., 2011), risk preferences (Apicella et al., 2008), or persistence (Welker and Carré, 2015). Several of these results can be replicated in the UKHLS data. For example, in a descriptive analysis we find that higher testosterone levels are associated with higher numerical ability in our sample. We also find that men with medium and high testosterone levels are more likely to report that they have been able to face their problems lately than men with low testosterone levels, and

[16] In line with the insignificant Anderson-Rubin test statistic shown in Table A2, the confidence set for the initially unemployed men does not exclude any meaningful values.

unemployed men with medium testosterone levels were more likely to report using the internet to search for jobs than men with low testosterone levels. Other correlations (fluid reasoning skills, risk aversion, likelihood of losing job, using one's personal network for job search) have the expected sign but are not statistically different from zero (see online appendix C for details of these analyses). It is plausible that such differences in cognitive and non-cognitive skills as well as job search behaviour might also drive the estimated effects of testosterone on labour market transitions in this study. However, examining these potential pathways in a formal mediation analysis requires a larger sample and is therefore left for future research.

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 we do not advocate determining the testosterone levels of unemployed men to improve their labour market outcomes, such differences can still be taken into account. For example, among unemployed individuals participating in training programmes, profiling individual's personality traits, in order to determine the type and extent of assistance required (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, certain types of men might require tailored assistance. For example, 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. In addition, 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 several specification changes, e.g., the included age range and the choice of cut-off points to define groups for testosterone levels, there are nevertheless some limitations. We control for several important factors that have been shown to affect both unemployment risks and testosterone levels in previous studies. In addition, we conduct a Mendelian Randomisation analysis to address potential endogeneity in testosterone levels by using individual's genetic predisposition towards testosterone levels as an instrument for observed levels. Although we interpret the estimates from the Mendelian Randomisation as causal effects (indicating that testosterone is endogenous in our probit specification), the results should be interpreted with caution. Our sample size is limited, particularly for unemployed men, and our models likely lack statistical power. Moreover, the polygenic score only predicts a limited amount of variation in testosterone levels, which further reduces the precision of the IV estimates. Taken together, these caveats likely explain why we find a significant effect in the reduced form regression of the polygenic score on unemployment risk for the sample of unemployed men, yet the IV estimate of the effect of testosterone is not significant.

Finally, genetic variants identify variation in testosterone levels that is conceptually stable across the life course. However, testosterone levels fluctuate considerably, e.g., with age and even during the day. It is not clear whether we should expect stable differences in testosterone levels to affect the unemployment risk of men or whether short- and medium-term fluctuations in testosterone levels drive these results. Repeated measures of testosterone would be useful to disentangle long-term differences in testosterone levels from short- and medium-term fluctuations. Unfortunately, our data do not allow us to test these differences since only one measurement of testosterone is available for each individual. Studying the mechanisms for which suggestive evidence was presented in this paper in more detail could also shed further light on this question. 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 determine whether the findings extend to women.

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CRediT authorship contribution statement

Peter Eibich: Conceptualization, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Ricky Kanabar:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Alexander Plum:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Julian Schmied:** Conceptualization, Investigation, Methodology, Writing – original draft, Writing – review & editing.

Declarations of Interest

The authors declare no conflicts of interest.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ehb.2022.101123.

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