**Wage Regulation and the Quality of Police Applicants**

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Pay structures may not reflect differences in individual productivity and effort; in particular, public pay regulation can distort labour markets. We analyse the impact of nationally regulated pay on the quality of applicants to be police officers across England and Wales, exploiting a unique dataset of individual test scores from the national assessment required of all police applicants, and combining this with data on local labour markets and policing conditions. National wage setting impacts on the quality of police applicants through two channels: first, through spatial variations in the relative wage of policing compared to other occupations, and second, because national wages cannot compensate for local variations in the disamenity of policing. We also provide preliminary evidence on whether police recruit quality is associated with police force performance.

**INTRODUCTION**

Individual wage variation does not always reflect variations in individual productivity and effort. This is particularly true in the public sector where pay rates are often centrally negotiated and heavily regulated—for example, when common scale rates and conditions of employment are applied across local public sector employers. This has a number of important implications. First, national wage setting often leads to spatial variation in public sector pay relative to competitively determined pay in other sectors. Second, national wage setting means that wages cannot adjust to reflect spatial differences in the disamenity of working in a particular occupation. These facts lead to the natural inferences that (all else equal) in areas where regulated public sector pay is low relative to private sector pay, or in areas where the disamenity of the public sector occupation is high, public sector workers are of lower quality (and vice versa). However, there has been some discussion in the literature as to whether public sector workers are wholly incentivised by remuneration and other elements of working conditions as opposed to the intrinsic motivation of public service (see, for example, Heyes 2005; Di Tommaso et al. 2009; De Ree et al. 2015; Ashraf et al. 2016; Deserrano 2017). To the extent that selection effects outweigh the inducements of pay and amenity values, the impact of pay on worker quality will be respectively stronger or weaker.

This paper utilizes a unique dataset to analyse the impact of centrally regulated pay on the quality of a particular group of public sector workers: police officers in England and Wales. The paper is one of the first, to our knowledge, to consider simultaneously both these channels through which nationally set wages may affect quality. Furthermore, the novel data that we use—individual test scores from the national assessment required of all police applicants—provide a direct measure of ‘quality’ pertinent to the occupation in question, and therefore represent an improvement over much of the existing literature (other than perhaps in the education field) that has relied on inference from general skills acquired through prior schooling or indirectly from institutional performance in order to measure workforce quality. Using these data, we show that the quality of applicants to local police forces responds positively to the local police wage relative to the outside wage, and negatively to the local disamenity of policing. Although the effects are not
large, they reject the view that selection effects (e.g. preferences for wages over effort) dominate incentive effects (i.e. the monetary and amenity value of the job) when examining worker quality.

Our work therefore brings together several strands of the existing literature. First, it confirms the proposition of Borjas (2002) and others that lower pay of public sector workers relative to outside options lowers the supply and worsens the quality of employees in the public sector. A number of studies, notably Nickell and Quintini (2002) in the UK and Hoxby and Leigh (2004) and Bacolod (2007) in the USA, use pre-entry educational test scores as measures of ability, and show that temporal and/or spatial variations in public pay relative to private pay affect public sector recruitment. An interesting recent paper by Dal Bó et al. (2013) utilizes a public sector recruitment drive with a degree of randomization of pay offers to show that higher public sector wages and better job attributes attract higher quality workers to the public sector, as measured by IQ, personality and aptitude tests.1

Second, our paper builds on the literature on compensating variation and wage differentials. In the standard approach in competitive labour markets, wage differentials in part compensate for the non-pecuniary (dis)advantages of a particular occupation (Rosen 1986) and for the (dis)advantages of locating and working in a particular geographical area (Roback 1982, 1988). Where wages are centrally regulated, such compensating adjustments do not occur (at least, overtly) and the quality and composition of the workforce is thereby affected by these (dis)advantages. Although in many public sector occupations variation in non-pecuniary characteristics within the occupation may be relatively limited, there is evidence of this variation being a factor in the supply of and retention of workers in public health care (Lum et al. 1998; Di Tommaso et al. 2009).

The implications of differential worker quality on public sector performance have also been noted in studies. Propper and Van Reenen (2010) infer that spatial variations in mortality rates across public hospitals in the UK’s National Health Service reflect differences in worker quality arising from relative pay disparities as a result of centralized pay regulation. Propper and Britton (2016) obtain the same result in terms of regulation of the pay of public school teachers and school performance in England. This reflects similar findings on teacher quality in the USA by Hanushek et al. (2004). However, the inference as to the link between hospital performance and the regulated and centralized pay structure is wholly indirect: the findings may also reflect spatial differences in hospital management quality since the outcome measures apply to the hospital as a whole: see Bloom et al. (2015). In general, there is little agreement in the extensive management literature as to what factors cause spatial variations in hospital performance. Moreover, the direct evidence on the effect of worker quality on outcomes in the public sector is mixed. Rivkin et al. (2005), for example, find strong evidence that improving teacher quality is a more cost-effective means of raising pupil outcomes than reducing class sizes, but the survey by Hanushek and Rivkin (2006) finds very mixed evidence as to the link between measures of teacher quality and student performance. Replicating such findings in the police context is particularly hard given that there are few extant measures of police performance; nevertheless, we also provide some tentative evidence on the relationship between police recruit quality and subsequent police outcomes in the present paper, since this is one dimension in which police quality ‘matters’.

The police labour market has been studied much less in recent years than that of other public sector occupations such as teachers and workers in health professions (notwithstanding the contribution of Mas (2006) on decentralized pay arbitration awards
to police officers in the USA). However, even leaving aside the unique data to which we have access, the police labour market in England and Wales is one that readily lends itself to exploring the implications of centrally regulated wages. Unlike in the USA, pay of police officers in England and Wales is broadly set within a national framework, with little variation in pay (at least, outside London). The result is considerable variation across the country in relative wages between the police and other occupations (see HMSO 2011). Furthermore, there is geographical variation in the non-pecuniary characteristics of policing. For example, inner-city policing is a very different form of police activity from policing a largely rural area. Hence we expect local variations in the nature of policing to play a significant role in spatial differences in recruit type and quality in the police service when wages are centrally regulated.

Our empirical results show that, all else equal, a one standard deviation reduction in the relative wage is associated with police applicants scoring 1.1 percentage points lower on average at the national assessment, while a one standard deviation increase in the proportion of violent crime involving injury (an indicator of the disamenity of local policing) is associated with police applicants scoring 1.6 percentage points lower on average. It is also interesting to note in the police context that the impacts on quality of geographical variation in relative wages and the disamenity of policing offset each other somewhat: the association between outside wages and quality is weaker when disamenity is not separately controlled for.

The paper now proceeds as follows. In Section I we describe the wage structure and recruitment process for the police in England and Wales. In Section II we introduce a simple theoretical model, which produces some testable implications of the impact of national wage setting on applicant quality. In Section III we describe our empirical approach and the data used, while Section IV presents our key results and a range of sensitivity analyses. Section V provides some preliminary evidence as to whether there is a relationship between recruit quality and subsequent police performance outcomes. Section VI concludes, in particular focusing on the implications of the results presented here for some recent policy changes in police recruitment.

I. INSTITUTIONAL CONTEXT

Law enforcement in England and Wales is undertaken by police officers attached to 43 territorial police forces, typically operating at the county or metropolitan level. There is not the ‘layering’ of federal, state and local police forces found in the USA, although there are now some specialist national agencies, including the National Crime Agency. Figure 1 illustrates the geographical boundaries of these territorial police forces.

Police forces are autonomous organizations, with responsibility for their own budgets, staffing decisions, and deployment and policing priorities. However, some aspects of policing are subject to a degree of centralization. These include police remuneration (pay and pensions), minimum standards for police recruits, and qualifying examinations for promotion to the ranks of sergeant and inspector.

Police pay

Police remuneration is negotiated nationally, with a single pay scale forming a series of incremental steps through police ranks. The pay scale effective in September 2010 (which is relevant to the period of our data) for the first three police officer ranks (accounting for virtually all the officer workforce) is set out in Table 1. Scale progression within each
rank is broadly automatic based on years of service, and there is no accelerated progression based on performance. The same pay scale applies across England and Wales, though officers working in the London area are entitled to an additional ‘London weighting’ of £2277, those working in the Metropolitan and City of London police forces may also be entitled to a ‘London allowance’ (COLA) of £4338, and those working in the forces surrounding London may be entitled to additional housing allowances of £2000.
(forces adjacent to London) or £1000 (outer south-east forces). However, these spatial
differentials in police pay are far lower than would be found in the private sector market
for professional workers. London Metropolitan and City of London police officers also
benefit from free travel so long as they are in possession of their warrant card (so
allowing them to ‘keep the peace’ if required during their travel). This is treated as a
benefit-in-kind. The police pension, which constitutes a significant proportion of total
remuneration (on which, see Crawford and Disney 2014), is common to all police
officers. Therefore police remuneration across England and Wales is intended to be
broadly uniform (outside of London). To the extent that any geographical variation in
police wages is observed, this is largely informative about the composition of the
workforce rather than about the wage.

### Police recruitment

The police recruitment process in England and Wales has several stages. It can be
summarized as follows (see also HMSO 2012, pp. 76–88, 661–73). Would-be police
officers apply to their local police force, which operates a screening process to sift out
unsuitable candidates such as those who fail basic standards of physical or financial
fitness, have a criminal record, etc. This first stage can be somewhat ad hoc. HMSO
(2012) (‘The Winsor Review’) notes:

Candidates must apply to a police force using a standard application form. Given the number of
potential applicants, forces will generally apply a practical sift of potential applicants before
deciding those who are to be given an application form as a first stage in the recruitment
process. This can involve requiring potential applicants to attend a familiarisation event …
Other forces may simply limit the number of forms that are printed … [One force] had a small
number of police vacancies, and decided to limit the number of printed application forms to
500. The first 500 people who telephoned the force on an appointed day received the forms.
(HMSO 2012, p. 77)

In addition to filling out the application form, some forces may also require a certain
level of minimum educational achievement (such as a qualification at A level equivalent)
and set additional criteria, such as possession of a clean driving licence. The application form contains a competency-based questionnaire that must be filled in to a satisfactory standard.

Candidates who achieve this standard in the questionnaire are then submitted to the national recruitment assessment process, administered by the National Policing Improvement Agency (NPIA) between 2006 and 2012, and subsequently by the newly established College of Policing. Known as SEARCH (Structured Entrance Assessment for Recruiting Constables Holistically), this assessment process aims to gauge candidates’ performance in seven competency areas through a combination of interactive role play, written exercises, tests of verbal, numerical and logical reasoning, and an interview. Each candidate is given a score for each competency area, as well as an overall score and an indication of whether he or she has passed or failed. These individual scores will be used in this paper as a direct measure of police recruit ‘quality’. The pass scores for these tests are identical across all police forces.

National pass rates have varied over time since the SEARCH process was introduced and have tended to increase as forces improve their strategy in selecting applicants for submission (since the submission of an applicant incurs a direct financial cost for individual police forces), and because information on the assessment tests (including worked examples to actual questions) has begun to be published on websites and in hard copy. However, as we will see, pass rates vary significantly across candidates submitted by individual police forces, and pass scores have also been changed from time to time.

A candidate who obtains at least a pass score may then be appointed to the police force that submitted him or her. If there is a surplus of successful candidates, a force can require a higher test score than the national pass mark or use some other non-discriminatory selection criterion, but it cannot hire below the pass mark—hence, if a police force lacks successful candidates, it may be able to recruit from successful applicants submitted by another force who either choose not to join that force or who, despite passing, were not hired by the force that submitted them to the assessment. Despite this possibility of joining a different force, it should be emphasized that the vast majority of successful candidates accept a job offer from the police force that submitted them for assessment (though they may in subsequent years move to another force). Overall, from 2006 to 2011, the pass rate was over 60%, and 97% of those who passed found a job as a police officer.

II. THEORETICAL MODEL

Before introducing our empirical approach, we set out a simple theoretical model to illustrate how a nationally regulated wage for police officers might result in spatial variation in the quality of police applicants. Consider an economy with two regions, \( r = [H, L] \), in which there are region-specific prices \( P_H \) and \( P_L \), respectively, and (potentially) region-specific wages. In each region there are two occupations, \( j = [P, O] \), where \( P \) is the superscript for policing and \( O \) the superscript for all other occupations. The labour market for policing is regulated such that there is a nationally set wage \( W^P \), while the labour market for other occupations is unregulated and wages potentially vary between the two regions.

Workers come in many skill types, \( k \in K \). ‘Skill’ in this specific context should be interpreted as an aptitude for police work. Utility of workers is given by \( \ln(W^P_{k,r}/P) - d^P_{k,r} \), where the term \( -d^P_{k,r} \) reflects the disutility of working in a particular occupation. Suppose that \( d^P_{k,r} = D_{k,r} \alpha + \epsilon_{k,r} \) and \( d^O_{k,r} = \epsilon_{k,r} \), where \( \epsilon_{k,r} \) is a common local
disutility component, and $D_{k,r}$ is a vector of local disamenity factors relating to policing relative to working in other occupations.

The theory of compensating differentials suggests that wages in the large unregulated sector (or region-specific prices) will adjust to compensate workers for differences in amenities between regions. Equalization of utility suggests that

$$\ln(W^O_{k,H}/P_H) - \varepsilon_{k,H} = \ln(W^O_{k,L}/P_L) - \varepsilon_{k,L}.$$  

In contrast, wages for the police are set nationally: $W^P_{k,H} = W^P_{k,L} = W^P_k$. They cannot adjust to compensate workers for spatial differences in amenities, prices (which can be taken as exogenous to workers in the small police sector) or the disutility of policing. In other words,

$$\ln(W^P_k/P_H) - d_H \neq \ln(W^P_k/P_L) - d_L,$$

or equivalently,

$$\ln(W^P_k/P_r) - D_{k,r} \neq \ln(W^O_{k,r}/P_r).$$

What are the implications of this lack of flexibility in police wages? Suppose, for simplicity, that workers choose between the police and the other occupations conditional on their existing location. (This could be interpreted as workers facing a fixed cost of migration that is greater than the regional variation in the utility from working in the police.) Then a worker of skill type $i$ in region $r$ will want to work in the police if

$$\ln(W^P_k/P_r) - D_{k,r} \alpha > \ln(W^O_{k,r}/P_r).$$

Rearranging equation (4) indicates that a worker of a given skill type will want to work for the police if the relative real wage premium is sufficient to offset the greater disutility of working in the police. Preferences for policing are therefore increasing in the relative wage paid in the police compared to other occupations, and decreasing in the disutility of working in the police compared to other occupations.

Denote the supply of workers of skill type $k$ in region $r$ by $N_{k,r}$, and suppose that a proportion $\theta_{k,r}$ are seeking a job in a given period. The supply of applicants of skill type $k$ to the police is given by $S_{k,r} = \theta_{k,r}N_{k,r}P_{k,r}$, where $P_{k,r}$ is the probability of an individual of skill type $k$ applying to work in the police in region $r$. The total supply of applicants is given by $S_r = \sum_k S_{k,r}$.

This simple model yields straightforward testable implications for spatial variations in the quality of police applicants arising from national wage setting. The quality of police applicants will be greater in regions where the relative real wage paid in the police compared to other occupations is higher, and where the disamenity of working in the police compared to other occupations is lower. Furthermore, the quality of applicants will be greater in areas where there is a greater supply of better-quality workers, and where the probability that such workers are seeking jobs is higher.
III. Empirical Strategy and Data

Our empirical approach for considering the impact of national wage setting on the quality of police applicants is based on data for over 41,000 applicants who were submitted to the police recruitment national assessment in the period 2007–10. Our data contain only those who are submitted to the assessment, rather than all potential applicants in a given local area. In other words, our data arise from a joint decision of an individual to apply to a police force and for that police force to submit the applicant to the national assessment process. We discuss this issue later; for the moment we assume that police forces adopt common selection procedures conditional on the self-selection of individuals to apply to be police officers. Hence we can examine the empirical evidence in support of our theoretical model’s implications using a simple linear estimation strategy, with an estimating equation of the form

\[
Q_{it} = \alpha + \beta \ln\left(\frac{W_{Pr}}{W_{Or}}\right) + D_{rt} \rho + Z_{rt} \gamma + \epsilon_i; \tag{5}
\]

where \(Q_{it}\) is the quality of applicant \(i\) observed at time \(t\), \(W_{Pr}/W_{Or}\) is the computed average relative wage in area \(r\), \(D_{rt}\) is a vector of time-varying area disamenity factors, and \(Z_{rt}\) is a vector of other local time-varying area controls. The implications of the simple theoretical model previously described are that \(\beta\) should be positive and \(\rho\) negative.

We also explore the implications of additionally controlling for a vector of individual characteristics, \(X_i\), when estimating equation (5). We interpret these measured characteristics (age, sex, education, ethnicity and previous experience) as observable indicators of skill type, \(k\), as in our theoretical model. This helps us to unpick the extent to which the impact of local wage conditions and disamenity comes through attracting (or dissuading) applicants with certain observable characteristics that are associated with higher quality.

To allow for unobservables that are correlated across applicants within police force areas, when estimating equation (5), standard errors are clustered at the police force level. Statistical tests are then performed using scaled residuals and critical values drawn from a \(t\)-distribution with \((G - 1)\) degrees of freedom (where \(G\) is the number of forces) in order to account for the relatively small number of clusters (see Brewer et al. (2013), and Cameron and Miller (2015) for a discussion of cluster-robust inference in settings with relatively small numbers of clusters).

The measure of quality of police applicants

Our measure of the quality of police applicants \(Q_i\) is individual-level scores for applicants who took the SEARCH national assessment between 2007 and 2010. The SEARCH assessment involves nine exercises, and each exercise assesses one or more of the seven competency areas on which candidates are judged. Table 2 describes which competency areas were assessed in which exercises in 2008. Each time a competency area is assessed, a candidate receives a score between 0 and 3. His final percentage score for each competency area is then the sum of these scores, divided by the total possible score for that area. (For example, written communication is assessed three times, so candidates can receive ten possible percentage scores: 0, 11, 22, 33, 44, 56, 67, 78, 89 or 100.) His overall percentage score is the sum of all his scores across all competency areas, divided
by 124 (the total possible score across all areas). To pass the national assessment, candidates require an overall score of 50% or more, and at least 44% for written communication, 50% for oral communication, and 50% for respect for race and diversity (RfRD).

In addition to candidates’ overall scores and the binary indicator of whether or not they passed the assessment, we also have data on candidates’ scores for three particular competency areas: oral communication, written communication, and RfRD. Due to the assessment’s structure, there are 10 possible scores for written communication, 16 for oral communication, and 22 for RfRD. Figure 2 illustrates the distribution of candidates’ scores in 2008, which shows that the test of oral communication provides little discriminatory power between candidates, and that very few candidates fail to achieve the required scores for oral communication or RfRD, even though the latter exhibited a wider score variation. There is the greatest variation across candidates in scores for the written assessment, and in 2008, 13% of candidates failed to achieve the 44% pass mark. In the subsequent regression analysis, we convert all these percentage scores into $z$-scores, which we interpret as how many standard deviations above or below the population mean is a particular score.

We also know which force put each candidate forward for assessment, and a number of individual characteristics: age, education, ethnicity, previous employment and prior experience in the police. The scores achieved by candidates vary systematically with these individual characteristics. The regression analysis presented in Table 3 illustrates the characteristics associated with higher scores, and a higher probability of passing overall. On average, women score more highly in all areas than men, those with greater levels of education score more highly than those with lower levels of education, and those with previous experience as a Police Community Support Officer (PCSO) or Special Constable (SC) score more highly than those without such experience. Candidates of white ethnicity score somewhat higher in most areas than those of mixed white ethnicity, but higher across all areas than those of other ethnicities.

Table 2

| Competency areas                        | Interactive | Written | Exercises | Psychometric tests |
|-----------------------------------------|-------------|---------|-----------|--------------------|
|                                         | 1 | 2 | 3 | 4 | 1 | 2 | Interview | Verbal logical reasoning | Numerical reasoning |
| Community and customer focus            | ✓ | ✓ | ✓ | ✓ | ✓ | | | | |
| Effective communication                 | ✓ | ✓ | ✓ | ✓ | | | | | |
| Oral communication                      | ✓ | ✓ | ✓ | ✓ | | | | | |
| Written communication                   | ✓ | ✓ | ✓ | ✓ | | | | | |
| Personal responsibility                 | ✓ | ✓ | ✓ | ✓ | | | | | |
| Problem solving                         | ✓ | ✓ | ✓ | ✓ | | | | | |
| Resilience                              | ✓ | ✓ | ✓ | ✓ | | | | | |
| Respect for race and diversity          | ✓ | ✓ | ✓ | ✓ | | | | | |
| Teamworking                             | ✓ | ✓ | ✓ | ✓ | | | | | |

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The measure of relative wages

A well-known problem facing studies that have explored relative pay between sectors is that we do not simultaneously observe both an ‘inside’ and ‘outside’ wage for any individual. This raises the question of what is the relevant ‘outside wage’ for police applicants. Most police applicants are young adults at the start of their working lives who, if successful, are likely to spend most of their adult career in the police. Indeed, it is not necessarily only starting salaries that motivate career choice in any case. We therefore assume that applicants to be police officers base their career choice on how the average wage of police officers in the local police force compares to the average wage across all other employment in their local area.

Formally, we would ideally estimate

\[ \ln W_{i,r,t} = X_i \beta + \sum_r \vartheta_{1,r} F_{rt} + \vartheta_2 P_i + \sum_r \vartheta_{3,r} F_{rt} \times P_i + \eta_i, \]

where \( W_{i,r} \) is the wage of an individual \( i \) in local area \( r \) at time \( t \), \( X_i \) is a set of demographic characteristics on which wages depend, \( F_r \) is a set of police force area \( \times \) time dummies that allows for time and area variation in the relative wage, and \( P_i \) is an indicator of whether individual \( i \) is employed in the police. The estimated coefficients \( \vartheta_{3,r} \) could then be used in the estimating equation (5) as the measures of geographical variation in relative wages.

Notes

In 2008 the required marks to pass the SEARCH assessment were 50% overall, 44% for written communication, 50% for oral communication, and 50% for respect for race and diversity.

**FIGURE 2. Distribution of candidate test scores, 2008.**
TABLE 3
CHARACTERISTICS ASSOCIATED WITH CANDIDATES’ TEST SCORES

|                | Pr(pass)   | Overall score | Written score | Oral score | RfRD score |
|----------------|-----------|---------------|---------------|------------|------------|
| **2008**       |           |               |               |            |            |
|                | −0.036*** | −0.081*       | −0.171***     | −0.035     | 0.047      |
|                | (0.010)   | (0.042)       | (0.045)       | (0.043)    | (0.069)    |
| **2009**       |           |               |               |            |            |
|                | −0.124*** | −0.358***     | −0.503***     | 0.153***   | 0.146**    |
|                | (0.011)   | (0.051)       | (0.045)       | (0.049)    | (0.067)    |
| **2010**       |           |               |               |            |            |
|                | 0.010     | 0.072         | −0.085**      | 0.222***   | −0.019     |
|                | (0.016)   | (0.067)       | (0.040)       | (0.046)    | (0.082)    |
| Age            |           |               |               |            |            |
|                | 0.038***  | 0.118***      | 0.054***      | 0.070***   | 0.114***   |
|                | (0.006)   | (0.013)       | (0.011)       | (0.009)    | (0.014)    |
| Age squared    |           |               |               |            |            |
|                | −0.001*** | −0.002***     | −0.001***     | −0.001***  | −0.002***  |
|                | (0.000)   | (0.000)       | (0.000)       | (0.000)    | (0.000)    |
| Male           |           |               |               |            |            |
|                | −0.062*** | −0.231***     | −0.108***     | −0.143***  | −0.247***  |
|                | (0.004)   | (0.013)       | (0.018)       | (0.013)    | (0.024)    |
| GCSEs          |           |               |               |            |            |
|                | 0.012     | 0.047         | 0.081**       | 0.153***   | 0.019      |
|                | (0.013)   | (0.040)       | (0.031)       | (0.036)    | (0.038)    |
| A levels       |           |               |               |            |            |
|                | 0.098***  | 0.304***      | 0.262***      | 0.245***   | 0.198***   |
|                | (0.019)   | (0.062)       | (0.037)       | (0.034)    | (0.052)    |
| Graduate       |           |               |               |            |            |
|                | 0.168***  | 0.569***      | 0.432***      | 0.336***   | 0.361***   |
|                | (0.017)   | (0.048)       | (0.030)       | (0.034)    | (0.057)    |
| Experience: PCSO |       |               |               |            |            |
|                | 0.132***  | 0.507***      | 0.119***      | 0.283***   | 0.427***   |
|                | (0.008)   | (0.018)       | (0.025)       | (0.030)    | (0.016)    |
| Experience: SC |           |               |               |            |            |
|                | 0.092***  | 0.363***      | 0.138***      | 0.208***   | 0.293***   |
|                | (0.011)   | (0.029)       | (0.038)       | (0.026)    | (0.022)    |
| Mixed white    |           |               |               |            |            |
|                | −0.031**  | −0.065*       | −0.150***     | −0.023     | 0.015      |
|                | (0.014)   | (0.038)       | (0.031)       | (0.030)    | (0.031)    |
| Asian          |           |               |               |            |            |
|                | −0.209*** | −0.481***     | −0.677***     | −0.395***  | −0.240***  |
|                | (0.009)   | (0.027)       | (0.026)       | (0.032)    | (0.034)    |
| African        |           |               |               |            |            |
|                | −0.288*** | −0.689***     | −0.868***     | −0.657***  | −0.200***  |
|                | (0.011)   | (0.032)       | (0.022)       | (0.046)    | (0.032)    |
| Chinese        |           |               |               |            |            |
|                | −0.103*** | −0.308***     | −0.451***     | −0.560***  | −0.177***  |
|                | (0.026)   | (0.077)       | (0.050)       | (0.165)    | (0.067)    |
| Other          |           |               |               |            |            |
|                | −0.269*** | −0.748***     | −0.883***     | −0.743***  | −0.272***  |
|                | (0.017)   | (0.035)       | (0.045)       | (0.070)    | (0.033)    |
| Missing ethnicity |       |               |               |            |            |
|                | −0.053**  | −0.143**      | −0.174***     | −0.099**   | −0.111***  |
|                | (0.021)   | (0.056)       | (0.052)       | (0.047)    | (0.034)    |
| Constant       |           |               |               |            |            |
|                | 0.176     | 1.779***      | −0.657***     | −1.363***  | −1.894***  |
|                | (0.116)   | (0.287)       | (0.200)       | (0.177)    | (0.259)    |
| R-squared      | 0.078     | 0.159         | 0.108         | 0.062      | 0.080      |

Notes
Sample size is 41,485 individuals. Figures are marginal effects from linear probability model (first column) and linear regressions (final columns). Scores are standardized. Baseline candidate is female, with no qualifications, no previous experience in the police, and of white ethnicity. Standard errors (in parentheses) are clustered at the police force level.

***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively, calculated using scaled residuals and critical t-values to account for the relatively small number of clusters.

The difficulty with this approach is in finding a dataset with sufficient sample size at the local level to enable estimation of equation (6) with a full set of controls in each time period. To deal with these issues, we generally make the simplifying assumption that...
police wages do not vary systematically across the country (after controlling for demographic characteristics). As discussed in Section I, this is broadly the case given national wage setting. Under this assumption $\vartheta_{3,r} = -\vartheta_{1,r}$, so we can simply estimate

$$\ln W_{i,r} = X_i \beta + \sum_r \vartheta_r F + \eta_i$$

and use the negative of the estimated coefficients $\hat{\vartheta}_r$ as the measures of geographical variation in relative wages. Given sample size issues, we also restrict the computed relative wage to be an average across the four years of data with the addition of time dummies in equation (7). We do not believe that there are significant variations in the relative wage over short time intervals, although with structural change in the economy, this would be a more contentious issue in the long run.

We estimate this simplified equation (7) using data from the Labour Force Survey (LFS). The LFS is a quarterly household survey that contains information on individuals’ earnings, and demographic information on which we can condition wages. The data do not contain identifiers for the police force area in which an individual lives, but do contain local authority identifiers that can be exactly aggregated up to police force areas. We pool LFS data from 2005 to 2010, and estimate $\vartheta_r$ across 276,170 observations, controlling for sex, age, age squared, education, ethnicity, interactions between the quadratic in age and education, and time dummies (in addition to the police force area dummies). The resultant distribution of estimated area fixed effects in log hourly wages is shown in Figure 3 (the standard deviation is 0.09). Unsurprisingly, the relative wage of the police to the outside wage is estimated to be lowest (i.e. the fixed effect is most negative) in London, followed by many of the surrounding police force areas (Hertfordshire, Surrey and Thames Valley). In contrast, relative wages are highest in predominantly rural areas such as Dyfed Powys and Devon and Cornwall.

To test our assumption that police wages do not vary systematically across the country—in other words, that variation in the relative wage is driven by variation in ‘outside’ wages—we use data from the Annual Survey of Hours and Earnings (ASHE). ASHE is an employer survey that collects panel data on the earnings and hours worked of a 1% sample of employees in the UK. It has a larger sample size than the LFS, and by pooling ASHE data from 2006 to 2009, we have 495,080 observations, with between 23 and 669 junior officers (those of rank sergeant and below) observed per police force. This allows us to estimate the full equation (6), with controls for sex, age, age squared and time dummies. The estimated geographical variation in average log hourly wages in the police (i.e. $\hat{\vartheta}_{1,r} + \hat{\vartheta}_{3,r}$) is low: the standard deviation of the fixed effect is 0.05 across all police forces, and 0.03 when we exclude the London and Kent police forces. This therefore lends support to our maintained assumption that there is little systematic geographical variation in police wages in contrast to the large variation in police wages relative to outside wages. In Section IV, however, we also explicitly test the sensitivity of our main results to using the estimate of relative wages ($\hat{\vartheta}_{3,r}$) from estimation of equation (6) using the ASHE data.

**Measuring the disamenity of policing**

One of our main contributions in this paper is that we explore the relationship between relative pay and workforce quality while simultaneously allowing for spatial variation in
the disamenity of policing. There is little direct information on what aspects of policing may constitute a ‘disamenity’ to higher-quality applicants. The Winsor Review cites a Home Office review from 2000 that was established to consider barriers perceived by black and minority ethnic communities to applying to join the police force, and comments:

The report found more similarities than differences between ethnic communities and age groups. Most respondents believed that, when choosing a job, career prospects and colleagues were more important than pay. Whilst some saw policing as an attractive career, offering challenges, excitement, financial security and respect within the community, this tended to be outweighed by the obvious drawbacks. These included a belief that racism, and sexism in the case of women, would be experienced from both colleagues and the public, and that individuals would feel isolated in a white culture. Concerns were expressed about the potential dangers of the role, and there were reported fears of negative reactions from friends and family … Personal safety was also a concern. (HMSO 2012, Sec. 3.1.61)

This quotation is illuminating in a number of respects as to the features of policing that deter applicants: (1) these were common responses across all groups and not just ethnic minorities; (2) the disamenities of the job could be more important than relative pay; (3) personal safety and ‘danger’ were explicit concerns among those who are deterred from applying (though other applicants might select into the police precisely for these reasons); and (4) forms of institutional discrimination including racism, sexism, ageism (by inference) and potentially being from a different background antithetical to ‘police culture’ (e.g. a graduate) could be deterrent factors.

Since higher-quality applicants (in terms of test scores) are typically older, better educated and female (see Table 3), this gives a guide to some disamenity factors that should be included. In particular, we control for area-reported crime (the proportion of crime accounted for by 11 encompassing categories: theft, criminal damage and arson,
domestic burglary, non-domestic burglary, drugs offences, public order offences, shoplifting, vehicle offences, violence without injury, violence with injury, and other). We anticipate that a higher crime rate, and a greater proportion of crime being accounted for by ‘harder’ crimes such as violence with or without injury, would imply a greater disamenity of policing than a lower crime rate and a greater proportion of crime being accounted for by ‘softer’ forms of crime. These variables are constructed from data on reported crime published by the Home Office, and population figures collated by the Chartered Institute of Public Finance and Accountancy. The level and composition of reported crime vary annually, and the variables are lagged one year, on the basis that individuals’ decisions to apply to the police force are most likely affected by recent observation of the level and composition of crime.

An additional disamenity that we consider is workload. Although measures such as overtime worked capture the external margin of workload, this issue has typically been raised by police officers and other public sector workers at the intensive margin—that is, in relation to a perceived increasing intensity of work. In our baseline regressions, therefore, we control for the crime rate per member of the local police force, as an indicator of workload.

Other controls

In estimating equation (5), we include a dummy for London since there is a cost of living adjustment made to the wage of police officers in London. We also include time dummies to control for time trends in the quality of the national workforce (or apparent quality, if over time candidates learn how to ‘game’ the assessment), and annual variation in the difficulty of the national assessment (the exact exercises involved typically change annually).

Other controls for local area characteristics are also important to reduce concerns that there are unobservable area characteristics that make it more likely that higher- or lower-quality individuals would apply to the police in a given area (i.e. selection effects). We include controls for the local unemployment rate, and the availability of skilled labour in the local area, as measured by the proportion of the local population aged 25–55 (inclusive) who have a degree, the proportion whose highest qualification is A levels (or equivalent), and the proportion whose highest qualification is below GCSEs (or equivalent). These time-varying local area controls are estimated using the LFS.

The theoretical model in Section II also predicted that higher-quality individuals would apply to the police in a given area if living costs were lower (since then a given wage premium for working in the police would result in a greater increase in purchasing power). A lack of suitable data means that we are unable to control for local area differences in the general level of prices (let alone the price of a basket of goods that police applicants may on average purchase). However, we can include as a control the local area average house price, as an indicator of spatial variation in the general level of prices. We construct a measure of police force area average house price using Land Registry data on median house prices by local authority area, and aggregate these to police force areas by weighting according to the geographical distribution of households in the LFS. It should, however, be noted that insofar as house prices also capture spatial differences in local amenity values, the association between house prices and police quality cannot be signed \textit{a priori}.\footnote{15}
IV. Results

Table 4 describes the distribution of pass rates and average (mean) candidate scores across police forces and time. There is considerable variation in pass rates across force and time: on one-quarter of occasions the annual pass rate was less than 70.8%, while on one-quarter of occasions the annual pass rate was more than 83.7%. Underlying this, there is variation in the average scores achieved by a force’s candidates for oral communication, written communication, respect for race and diversity, and overall. The largest variation in average scores achieved is for written communication, as might be expected given that this was the competency area with the largest variation in scores across candidates (shown in Figure 2).

The demographic composition of candidates put forward for assessment also differs across forces, and this could drive some of the differences in the average scores achieved by candidates (given that, as described in Table 3, some individual characteristics are associated with higher scores). Variation in the composition of candidates is summarized in Table 4. There is relatively little variation in the average age of candidates put forward by forces, but the proportion of male candidates varies from less than 62.6% for one-quarter of forces’ annual submissions, to over 71.1% for one-quarter of forces’ annual submissions. Notably, in the vast majority of cases this proportion is over 50% (despite women performing better on average in assessment—see Table 3). There is also considerable heterogeneity across forces in the average educational qualifications of their candidates, and the proportion of their candidates who have prior experience as a Special Constable or Police Community Support Officer.

The question that we seek to answer by estimating equation (5) is whether this variation in the average quality of candidates across forces is associated with variation in the relative wage and/or variation in the spatial disamenity of policing. Our first estimates of equation (5) appear in Table 5, which illustrates the association between relative wages and applicant quality when we control for time, whether applicants were put forward by the London Metropolitan Police, the availability of skilled labour in the local area, the local unemployment rate, and local average house prices. Note that all non-binary variables are standardized as $z$-values, and therefore coefficients are interpreted as the standard deviation increase in the outcome variable affected by a one standard deviation increase in the independent variable. In line with our model, a higher relative wage for policing is associated with applicants performing better. A 1 standard deviation increase in the log relative wage is associated with a 0.2 standard deviation increase in the overall score. The pass rate is, however, unaffected.

The final two columns of Table 5 include the controls for the disutility of policing in the local area. Including these controls has little impact on the size of the estimated effect of relative wages on applicant quality. Turning to the association between applicant quality and the disamenity of policing itself, we find that a higher level of crime per head of police force in the local area in the year prior to application is associated with a lower pass rate. There is a strong statistical relationship between a higher proportion of crime being accounted for by violent crime involving injury and both a lower score of applicants and a lower pass rate. This is consistent with our prior that a higher crime rate and a higher proportion of ‘hard’ crime are disamenities of policing that would (all else equal) deter higher quality individuals. The magnitude of the effects is also in some sense larger than the effect of the relative wage: a 1 standard deviation increase in the proportion of crime that is violence involving injury is associated with a 0.4 standard deviation decrease in the overall score.
In terms of the other covariates, once we control for the disamenity of policing, we find that these are largely insignificant: local supply constraints in the quality workforce do not appear to be a factor limiting the supply of applicants of higher quality to the police force. House prices, however, are found to have a positive association with scores and pass rates. At first sight this result is perhaps surprising, since, all else equal, a higher local price level would mean that a given wage premium for working in the police would imply lower additional purchasing power, and therefore might be expected to have a

| Table 4 | Distribution of Average Candidate Performance, Candidate Composition, Local Area Characteristics, and the Disamenity of Policing Across Forces and Time |
|---------|---------------------------------------------------------------------------------------------------------------|
|         | Mean | Standard deviation | 25th percentile | Median | 75th percentile |
| **Candidate performance** | | | | | |
| Pass rate | 75.6 | 14.9 | 70.8 | 77.5 | 83.7 |
| **Mean score:** | | | | | |
| Written communication | 64.8 | 8.5 | 60.3 | 66.1 | 69.5 |
| Oral communication | 95.8 | 2.2 | 94.9 | 96.0 | 97.2 |
| Respect for race and diversity | 66.7 | 4.2 | 64.9 | 67.0 | 68.5 |
| Overall | 57.3 | 2.9 | 55.4 | 57.3 | 59.0 |
| **Candidate characteristics** | | | | | |
| Mean age | 26.6 | 2.1 | 25.9 | 26.7 | 27.3 |
| % male | 68.0 | 11.1 | 62.6 | 66.7 | 71.1 |
| % with only A levels | 38.8 | 14.8 | 34.5 | 39.2 | 43.3 |
| % with degree | 27.8 | 16.4 | 21.2 | 28.1 | 32.1 |
| % with experience | 27.0 | 18.8 | 17.1 | 25.0 | 33.0 |
| % white | 86.0 | 15.5 | 82.9 | 90.8 | 94.6 |
| **Local area characteristics** | | | | | |
| % of population with degree | 33.6 | 9.5 | 28.3 | 31.1 | 36.9 |
| % of population with only A levels | 20.1 | 3.4 | 19.3 | 20.6 | 21.9 |
| % of population with only GCSEs | 22.8 | 4.2 | 21.6 | 23.6 | 25.4 |
| Unemployment rate (%) | 4.3 | 2.1 | 3.0 | 4.0 | 4.9 |
| Median house price (£000s) | 158.1 | 52.6 | 119.3 | 145.0 | 175.0 |
| **Disamenity of policing** | | | | | |
| Crime per police force employee | 20.7 | 4.4 | 18.1 | 20.7 | 23.7 |
| Crime per 1000 population | 7.3 | 1.8 | 6.2 | 7.2 | 8.3 |
| % crime: theft | 17.5 | 4.4 | 15.7 | 16.9 | 18.4 |
| % crime: criminal damage | 22.0 | 4.4 | 20.5 | 22.4 | 24.6 |
| % crime: domestic burglary | 5.2 | 1.7 | 4.2 | 5.2 | 6.3 |
| % crime: drugs offences | 4.4 | 2.3 | 3.2 | 3.9 | 4.5 |
| % crime: non-domestic burglary | 6.7 | 1.1 | 6.1 | 6.6 | 7.4 |
| % crime: public order offences | 4.4 | 1.2 | 3.5 | 4.2 | 5.1 |
| % crime: shoplifting | 6.9 | 1.5 | 5.9 | 6.9 | 7.8 |
| % crime: vehicle offences | 12.2 | 2.8 | 10.6 | 12.2 | 14.2 |
| % crime: violence without injury | 9.9 | 1.8 | 8.8 | 9.7 | 11.0 |
| % crime: violence with injury | 1.1 | 0.9 | 0.6 | 0.8 | 1.3 |

**Notes**

Distributions are calculated over 133 force–time observations (42 forces, observed between once and four times).
Table 5
Association of Applicant Quality with Relative Wage and Disutility of Policing

| Overall score | Pr(pass) | Overall score | Pr(pass) |
|---------------|---------|---------------|---------|
| \( \ln \left( \frac{W^p}{W^o} \right) \) | 0.176* | (0.097) | 0.210* | (0.108) |
| 2008 | -0.031 | (0.050) | -0.092 | (0.064) |
| 2009 | -0.280*** | -0.100*** | -0.444*** | -0.167*** |
| 2010 | 0.143 | (0.095) | -0.054 | (0.106) |
| London | -0.111 | (0.159) | 0.335* | (0.175) |
| % with degree | 0.005 | (0.093) | 0.068 | (0.101) |
| % with A levels | 0.012 | (0.090) | 0.046 | (0.083) |
| % with no qualifications | -0.011 | (0.062) | 0.065 | (0.062) |
| Unemployment rate | 0.003 | (0.019) | 0.041 | (0.035) |
| Average house price (£000s) | 0.227* | (0.125) | 0.331** | (0.123) |
| Proportion of crime | Theft | -0.020 | (0.114) | -0.001 | (0.031) |
| Criminal damage | -0.011 | (0.152) | -0.038 | (0.050) |
| Domestic burglary | 0.132* | (0.075) | 0.042** | (0.017) |
| Drugs offences | 0.026 | (0.064) | -0.007 | (0.020) |
| Non-domestic burglary | 0.064 | (0.055) | 0.009 | (0.014) |
| Public order offences | -0.011 | (0.039) | -0.005 | (0.010) |
| Shoplifting | 0.039 | (0.061) | 0.004 | (0.017) |
| Vehicle offences | 0.008 | (0.068) | 0.009 | (0.016) |
| Violence without injury | 0.027 | (0.051) | -0.001 | (0.014) |
| Violence with injury | -0.357*** | (0.105) | -0.123*** | (0.029) |
| Crime per head police force | 0.008 | (0.043) | -0.022* | (0.012) |
| R-squared | 0.036 | 0.017 | 0.043 | 0.021 |

Notes
Sample size is 41,485. Scores and non-binary explanatory variables are standardized as z-scores. Standard errors (in parentheses) are clustered at the police force level. ***,**, * indicate statistical significance at the 1%, 5%, 10% level, respectively, calculated using scaled residuals and critical t-values to account for the relatively small number of clusters.

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negative impact on the quality of applicants. However, not only are house prices an imperfect measure of local differences in the cost of living, but, as mentioned previously, they could be indicative of other aspects—for example, areas with higher house prices might be more pleasant and be easier to police, and so have a lower disamenity of policing than other areas.

In Table 6 we present the results of the same full empirical specification, but where the measure of applicant quality is taken to be the score for the three competencies on which we have separate data. As was the case for the overall score and the probability of passing, we find that scores for written communication and respect for race and diversity are positively associated with the relative wage, and negatively associated with the disamenity of policing, as measured by ‘violence with injury’. However, the opposite association with the relative wage emerges for oral communication. The latter is somewhat surprising, although it is worth noting that since all, virtually all, individuals achieve the pass mark required for oral communication (see Figure 2), characteristics adversely associated with this competency area would not necessarily be expected to be adversely associated with the probability of passing the assessment.

Overall, the results in Tables 5 and 6 provide broad empirical support for the main predictions of our simple model: applicant quality is positively associated with higher relative wages, and is negatively associated with the local disamenity of policing (which cannot be compensated for given the national wage structure).

An interesting question is whether these associations are driven by effects at the top or the bottom of the applicant quality distribution. In other words, do higher relative wages improve average quality by encouraging more high-quality applicants to apply or by discouraging worse-quality applicants? We seek to answer this question using quantile regression, estimating the association between the 10th, 25th, 50th, 75th and 90th percentiles of the distribution of overall scores on the same factors as our full specification. (A similar exercise for the individual competencies is inhibited by the relative discreteness of the distributions shown in Figure 2.) The main coefficients of interest from this regression are reported in Table 7. Interestingly, we find that the draw from relative wages and disincentive from disamenities act at different parts of the distribution. As one would perhaps expect, higher relative wages are associated with higher scores in the top half of the distribution—in other words, they attract more better-quality applicants. The disamenity of a higher proportion of crime being violence with injury, however, is stronger towards the bottom of the quality distribution.

Sensitivity analysis

Alternative definitions of the relative wage The analysis presented so far has used a measure of the geographical variation in relative police wages that assumed that police wages do not vary nationally. We test the sensitivity of our results to this assumption as follows. First, we illustrate how our results are affected by using the same assumption, but estimating relative wages using the ASHE data. Note that these differ from those estimated using the LFS (used throughout the rest of the analysis in this paper) not just because the data source is different, but also because with the ASHE data we can estimate the spatial variation in wages conditional on age and sex only, and not on education. In Appendix Table A1 we show that this yields results that are qualitatively similar, but quantitatively slightly smaller and less precisely estimated than our main results. This suggests, as we would expect, that educational attainment is an important determinant of the relative wage. Second, we illustrate how our results are affected by
## Table 6
### Association of Applicant Quality with Relative Wage—Component Test Scores

|                          | Written communication score | Oral communication score | Respect for race and diversity score |
|--------------------------|-----------------------------|--------------------------|--------------------------------------|
| ln ($W_p/W_0$)           | 0.131**                     | -0.188***                | 0.273**                              |
|                          | (0.063)                     | (0.059)                  | (0.122)                              |
| 2008                     | -0.155***                   | -0.099***                | 0.075                                |
|                          | (0.046)                     | (0.034)                  | (0.087)                              |
| 2009                     | -0.493***                   | -0.064                   | 0.128                                |
|                          | (0.076)                     | (0.055)                  | (0.094)                              |
| 2010                     | -0.112                      | 0.053                    | -0.040                               |
|                          | (0.091)                     | (0.077)                  | (0.135)                              |
| London                   | 0.044                       | 0.083                    | 0.446**                              |
|                          | (0.173)                     | (0.110)                  | (0.181)                              |
| % with degree            | -0.126**                    | -0.088                   | 0.042                                |
|                          | (0.059)                     | (0.057)                  | (0.118)                              |
| % with A levels          | -0.073                      | 0.023                    | -0.008                               |
|                          | (0.058)                     | (0.056)                  | (0.109)                              |
| % with no qualifications | -0.081                      | -0.101**                 | 0.021                                |
|                          | (0.054)                     | (0.042)                  | (0.071)                              |
| Unemployment rate        | 0.010                       | 0.009                    | 0.046                                |
|                          | (0.028)                     | (0.019)                  | (0.039)                              |
| Average house price (£000s) | 0.129                      | -0.197***                | 0.230*                               |
|                          | (0.080)                     | (0.060)                  | (0.127)                              |
| Proportion of crime      |                             |                          |                                      |
| Theft                    | 0.096                       | -0.181***                | -0.026                               |
|                          | (0.079)                     | (0.056)                  | (0.115)                              |
| Criminal damage          | 0.070                       | -0.371***                | -0.075                               |
|                          | (0.118)                     | (0.086)                  | (0.121)                              |
| Domestic burglary        | 0.096**                     | 0.004                    | 0.084                                |
|                          | (0.040)                     | (0.038)                  | (0.087)                              |
| Drugs offences           | -0.001                      | -0.043                   | -0.076                               |
|                          | (0.046)                     | (0.034)                  | (0.057)                              |
| Non-domestic burglary    | -0.035                      | 0.013                    | -0.016                               |
|                          | (0.040)                     | (0.043)                  | (0.066)                              |
| Public order offences    | -0.001                      | -0.053**                 | 0.002                                |
|                          | (0.024)                     | (0.021)                  | (0.046)                              |
| Shoplifting              | 0.016                       | -0.103***                | -0.007                               |
|                          | (0.037)                     | (0.044)                  | (0.076)                              |
| Vehicle offences         | 0.040                       | -0.082**                 | 0.038                                |
|                          | (0.040)                     | (0.034)                  | (0.082)                              |
| Violence without injury  | 0.007                       | -0.112***                | -0.042                               |
|                          | (0.032)                     | (0.026)                  | (0.054)                              |
| Violence with injury     | -0.166**                    | -0.171**                 | -0.357***                            |
|                          | (0.076)                     | (0.064)                  | (0.090)                              |
| Crime per head police force | -0.044                      | -0.010                   | -0.008                               |
|                          | (0.038)                     | (0.025)                  | (0.046)                              |
| R-squared                | 0.056                       | 0.024                    | 0.015                                |

**Notes**
Sample size is 41,485. Scores and non-binary explanatory variables are standardized as z-scores. Standard errors (in parentheses) are clustered at the police force level.

***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively, calculated using scaled residuals and critical $t$-values to account for the relatively small number of clusters.

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controlling for an estimate of the relative wage that allows geographical variation in police wages. (In other words, we estimate the full equation (6) rather than equation (7), and use \( \tilde{\theta}_3^{r} \) rather than \( \tilde{\theta}_1^{r} \) as our measure of variation in relative wages.) The results are shown in the bottom panel of Table A1. The results are broadly in line with those estimated just using the outside wage, suggesting that our main results are not affected by our assumption that (conditional) police wages do not vary spatially.

Excluding London from the regression estimates London is arguably very different from the rest of the country. Studies in the context of the labour market for health workers suggest that the intra-London heterogeneity in local wages and local area characteristics is significantly greater than the variation between London and elsewhere. Furthermore, London weightings and allowances mean that the relative police wage is higher for any given outside wage in London compared to the rest of the country. Although all our regressions include a dummy for London, we further test whether the inclusion of London is biasing our results by excluding the London Metropolitan Police. The results, depicted in Appendix Table A2 slightly weaken the wage coefficients but make no difference to the disamenity coefficients.

### Applicant preferences versus force-specific recruitment policy

We now come to a potential problem with our implicit identification strategy. Our dataset contains only candidates who were put forward to the national assessment, and not all the initial applicants to a given police force. If all applicants could put themselves forward to national assessment, or the selection of a subset of applicants to be put forward by a particular police force were random, then it would be perfectly valid to argue that we had identified the direct association between the quality of applicants on the one hand, and the local ‘outside’ wage offer and the local disamenity of policing on the other. However, if each police force shortlisted candidates in some way that is

| **Table 7** | **ASSOCIATION OF APPLICANT QUALITY WITH RELATIVE WAGE—QUANTILE REGRESSIONS** |
|-------------|--------------------------------------------------------------------------------|
|             | 10th percentile | 25th percentile | Median | 75th percentile | 90th percentile |
| \( \ln \left( \frac{W^p}{W^O} \right) \) | 0.087 | 0.180* | 0.295** | 0.233** | 0.244** |
|             | (0.110) | (0.100) | (0.116) | (0.095) | (0.110) |
| Violence    | -0.034 | 0.010 | 0.009 | 0.045 | 0.101* |
| without injury | (0.062) | (0.063) | (0.058) | (0.049) | (0.056) |
| Violence    | -0.498*** | -0.430*** | -0.344** | -0.275** | -0.149 |
| with injury | (0.148) | (0.114) | (0.153) | (0.125) | (0.156) |
| Crime per head | -0.044 | -0.030 | -0.007 | 0.029 | 0.051 |
| police force | (0.047) | (0.047) | (0.060) | (0.056) | (0.053) |
| R-squared   | 0.034 | 0.041 | 0.041 | 0.041 | 0.038 |

**Notes**
Sample size is 41,485. Scores and non-binary explanatory variables are standardized as z-scores. Regressions also control for year dummies, London, educational composition of the local workforce, local unemployment rate, average house prices, and the proportion of crime accounted for by other crime types as in our main specification (all estimated coefficients available on request). Standard errors (in parentheses) are clustered at the police force level.

***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively, calculated using scaled residuals and critical t-values to account for the relatively small number of clusters.
correlated with the local relative wage or the local disamenity of policing, then our empirical estimates of the association of these factors with applicant quality would be biased: we would be observing both the selection decision of applicants and any potential selection among applicants by police forces. Hence the underlying applicant choice model would not be fully identified.

As described in Section I, the overt criteria for individuals to apply to be police officers are pretty general, and clearly some of the criteria used to assess, or ration, applicants by local police forces are ad hoc. We have carefully examined archived versions of the recruitment pages of individual police force websites to search for information on forces’ selection criteria. We found that over the period of our data, six forces conducted explicit pre-national assessment selection by shortlisting candidates based on their initial application forms and/or a fitness test—although it is not clear what the shortlisting criteria are. A further ten forces at one time or another limited the number of initial applicants in some way, most commonly requiring potential applicants to attend an introductory session in order to get the application form.

To check that these force-specific recruitment procedures are uncorrelated with other force-area characteristics that we are interested in, our strategy is to check that our results remain robust to the inclusion of a number of proxies for force selection procedures. Specifically, we test the sensitivity of our results by including dummies indicating whether a force engaged in limiting applicants or shortlisting applicants for the national assessment. We also test sensitivity to controlling for whether a force’s chief constable was female, and the proportion of officers with the rank of superintendent or above who are female—variations in which may be expected to be indicative of selection procedures by the police force. For example, a female chief constable might be particularly keen to broaden the police workforce away from the traditional stereotype of a male-dominated preserve.

The results from adding in additional variables are presented in Table 8. The additional controls indicative of force-specific recruitment procedures are jointly significant in all the regressions. Perhaps surprisingly, forces that limited the number of applications and forces that shortlisted candidates prior to assessment actually fielded candidates who on average did slightly worse overall at the national assessment than forces that did not. This raises policy concerns that we touch on in Section VI. Forces with a female chief constable on average had slightly higher-quality candidates overall (on average overall scores were 0.2 standard deviations higher), though the component scores that we have access to suggest that with a woman chief constable, while scores for respect for race and diversity were on average higher, scores for written communication were on average lower. The proportion of higher-ranking officers who are female is in general associated with lower-quality applicants. These are interesting results but we have no particular explanation for them.

From the point of view of the central argument of this paper, while these results suggest that there may be some degree of selection by forces that affects candidate quality, it is important to note that the estimated coefficients on the relative wage and indicators of policing disamenity are largely unchanged by the inclusion of these additional controls. This suggests that the main results are not biased by abstracting from any force-specific selection procedures over this period. In the final panel of Table 8, we exclude all forces that report any kind of selection procedure, and estimate the model on the remaining forces—the inference being that we thereby focus on forces where quality seems to be (explicitly at least) largely driven by the choice of applicants. This reduces the sample size considerably and renders some of the relative wage
| Baseline | Overall score | Pr(pass) | Written communication score | Oral communication score | Respect for race and diversity score |
|----------|---------------|----------|-----------------------------|--------------------------|--------------------------------------|
| In ($W^p/W^o$) | 0.210* | 0.035 | 0.131** | -0.188*** | 0.273** |
| | (0.108) | (0.023) | (0.063) | (0.059) | (0.122) |
| Violence without injury | 0.027 | -0.001 | 0.007 | -0.112*** | -0.042 |
| | (0.051) | (0.014) | (0.032) | (0.026) | (0.054) |
| Violence with injury | -0.357*** | -0.123*** | -0.166** | -0.171** | -0.357*** |
| | (0.105) | (0.029) | (0.076) | (0.064) | (0.090) |
| Crime per head police force | 0.008 | -0.022* | -0.044 | -0.010 | -0.008 |
| | (0.043) | (0.012) | (0.038) | (0.025) | (0.046) |
| R-squared | 0.043 | 0.021 | 0.056 | 0.024 | 0.015 |
| Baseline with controls for force selection | | | | | |
| ln ($W^p/W^o$) | 0.190** | 0.031 | 0.115** | -0.172*** | 0.240** |
| | (0.084) | (0.019) | (0.047) | (0.055) | (0.092) |
| Violence without injury | 0.016 | 0.009 | 0.058 | -0.069** | -0.007 |
| | (0.062) | (0.017) | (0.040) | (0.026) | (0.063) |
| Violence with injury | -0.418*** | -0.136*** | -0.208*** | -0.094 | -0.410*** |
| | (0.131) | (0.036) | (0.078) | (0.058) | (0.118) |
| Crime per head police force | -0.013 | -0.014 | -0.001 | 0.002 | -0.014 |
| | (0.039) | (0.011) | (0.030) | (0.024) | (0.045) |
| Limited applicants = 1 | -0.186*** | -0.041** | -0.122*** | 0.082* | -0.181** |
| | (0.068) | (0.017) | (0.039) | (0.045) | (0.088) |
| Shortlisted = 1 | -0.080 | -0.030 | -0.135*** | -0.003 | -0.210** |
| | (0.076) | (0.021) | (0.049) | (0.026) | (0.083) |
| Proportion of high ranks that are female | -0.010 | -0.002 | -0.002 | -0.042*** | -0.016 |
| | (0.018) | (0.005) | (0.016) | (0.012) | (0.025) |
| Female chief constable | 0.158** | -0.009 | -0.090* | -0.056 | 0.171** |
| | (0.070) | (0.019) | (0.052) | (0.044) | (0.079) |
| R-squared | 0.046 | 0.022 | 0.058 | 0.025 | 0.019 |
| Omitting forces that report selection | | | | | |
| ln ($W^p/W^o$) | 0.004 | -0.012 | 0.147* | -0.115 | 0.116 |
| | (0.098) | (0.031) | (0.081) | (0.071) | (0.132) |
| Violence without injury | 0.058 | 0.006 | 0.015 | -0.089*** | 0.060 |
| | (0.060) | (0.018) | (0.044) | (0.031) | (0.058) |
| Violence with injury | -0.487*** | -0.158*** | -0.173* | -0.018 | -0.396*** |
| | (0.106) | (0.031) | (0.088) | (0.077) | (0.131) |
| Crime per head police force | 0.052 | -0.010 | -0.001 | -0.015 | 0.116*** |
| | (0.042) | (0.014) | (0.037) | (0.033) | (0.032) |
| Proportion of high ranks that are female | 0.005 | 0.002 | -0.018 | -0.053*** | 0.008 |
| | (0.016) | (0.006) | (0.023) | (0.012) | (0.030) |
| Female chief constable | 0.275*** | -0.006 | -0.100* | -0.089* | 0.276*** |
| | (0.052) | (0.015) | (0.054) | (0.052) | (0.056) |
| R-squared | 0.062 | 0.026 | 0.051 | 0.036 | 0.031 |

Notes
Sample size is 38,924 (16,197 excluding police forces reporting that they limited applicants and used shortlisting procedures). Scores and non-binary explanatory variables are standardized as z-scores. Regressions also control for year dummies, London, educational composition of the local workforce, local unemployment rate, average house prices, and the proportion of crime accounted for by other crime types as in our main specification (all estimated coefficients available on request). Standard errors (in parentheses) are clustered at the police force level. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively, calculated using scaled residuals and critical t-values to account for the relatively small number of clusters.
coefficients insignificant. Interestingly, however, the disamenity terms remain strongly robust.

Applicant characteristics

One mechanism by which the relative wage effect operates is through the impact on observable quality attributes of applicants, such as educational attainment. As we describe in Section VI, this has become an important issue in recent efforts to reform police recruitment procedures. We therefore test whether the relative wage and disamenity effects are driven by candidates with particular characteristics (observed skill types) being more or less likely to apply.

First, we examine the impact on our headline results from Tables 5 and 6 if we additionally control for candidate characteristics (age, sex, education, ethnicity, and previous experience as a Special Constable or a Police Community Support Officer). Doing so reduces the magnitude of the associations between quality and relative wages, and quality and disamenity, but does not eliminate them, especially in relation to disamenity. The results are given in Appendix Table A3. This reduction should not be surprising; we would expect that part of the effect of national wage-setting on the quality of applicants is to influence the composition of applicants in terms of their observable characteristics, as well as through differences in the unobservable quality of candidates. However, it has an important policy implication, which we discuss in Section VI, whereby raising quality standards of applicants by enforcing selection on observables (such as attaining a certain level of educational attainment) will not necessarily eliminate self-selection of applicants in terms of unobservable quality.

Second, we examine the direct effect of relative wages and disamenities on observable applicant characteristics. Table 9 presents the results of regressions that explore the association between mean age of applicants, the probability of being female, having A levels or higher qualifications, being of white ethnicity, and having previous policing experience, with relative wages and the disamenity of policing. These suggest that a lower relative wage for policing is associated with a lower average age of applicants, and a smaller proportion of applicants who are female. Moreover, these are both characteristics associated with higher test scores (see Table 2). There is little association between the relative wage and the probability that an applicant has previous policing experience. However, variation in the prevalence of previous experience among applicants is likely to be driven by different forces’ decisions regarding the role of Special Constables and Police Community Support Officers in their workforce, rather than a selection effect of whether individuals with such experience go on to apply to be police officers. There is also little association between broad measures of the educational qualifications of candidates and relative wages, or between whether a candidate is white and relative wages. This suggests that the self-selection of applicants arising from the relative wage arises from selection within categories of educational attainment and ethnicity.

In terms of the impact of the disamenity of policing on candidate characteristics, perhaps surprisingly, we do not find that a high proportion of violent crime is associated with a lower proportion of female applicants. However, we do find that it is associated with a lower proportion of white applicants, a lower proportion of applicants with higher qualifications, and a lower proportion of those with previous experience in the police service. In terms of the controls for force-specific selection processes, those forces that shortlist before the national assessment are found to put forward more white candidates.
Table 9
Association of Applicant Characteristics with Relative Wage and Disamenity

|                          | Pr(Female) | Age   | Pr(Experience) | Pr(A levels or above) | Pr(White) |
|--------------------------|------------|-------|----------------|-----------------------|-----------|
| In \( \frac{W^p}{W^O} \) | 0.036**    | 0.857**| 0.017          | 0.009                 | 0.040     |
|                          | (0.018)    | (0.368) | (0.035)        | (0.022)               | (0.025)   |
| 2008                     | 0.011      | 0.305  | 0.044          | -0.012                | 0.027     |
|                          | (0.014)    | (0.243) | (0.034)        | (0.027)               | (0.033)   |
| 2009                     | -0.004     | 0.891**| 0.042          | -0.107***             | 0.022     |
|                          | (0.032)    | (0.342) | (0.064)        | (0.040)               | (0.052)   |
| 2010                     | 0.012      | 0.848* | 0.068          | -0.102**              | -0.011    |
|                          | (0.037)    | (0.439) | (0.083)        | (0.047)               | (0.059)   |
| London                   | -0.022     | 1.699***| 0.203**        | 0.262***              | 0.016     |
|                          | (0.046)    | (0.496) | (0.089)        | (0.058)               | (0.078)   |
| % with degree            | 0.010      | 0.567**| 0.030          | 0.033                 | 0.040     |
|                          | (0.020)    | (0.275) | (0.033)        | (0.029)               | (0.037)   |
| % with A levels          | -0.017     | 0.087  | 0.003          | 0.036                 | 0.036     |
|                          | (0.024)    | (0.255) | (0.038)        | (0.023)               | (0.033)   |
| % with no qualifications | -0.001     | 0.436**| 0.026          | 0.002                 | 0.035     |
|                          | (0.015)    | (0.204) | (0.027)        | (0.024)               | (0.027)   |
| Unemployment rate        | 0.010      | 0.095  | 0.017          | 0.011                 | 0.014     |
|                          | (0.007)    | (0.094) | (0.014)        | (0.009)               | (0.014)   |
| Average house price      | 0.062*     | 1.193**| 0.008          | -0.058                | 0.007     |
| (£000s)                  | (0.034)    | (0.467) | (0.057)        | (0.036)               | (0.032)   |

Proportion of crime

|                          |           |       |               |                       |           |
|--------------------------|-----------|-------|---------------|-----------------------|-----------|
| Theft                    | -0.019    | 0.360 | -0.034        | -0.049**              | -0.038    |
|                          | (0.029)   | (0.234)| (0.049)       | (0.021)               | (0.033)   |
| Criminal damage          | 0.050     | 0.855*| -0.062        | -0.132***             | -0.045    |
|                          | (0.049)   | (0.443)| (0.083)       | (0.048)               | (0.071)   |
| Domestic burglary        | 0.008     | 0.012 | -0.018        | -0.007                | -0.014    |
|                          | (0.015)   | (0.213)| (0.030)       | (0.014)               | (0.020)   |
| Drugs offences           | 0.004     | 0.138 | -0.038        | 0.015                 | 0.002     |
|                          | (0.018)   | (0.183)| (0.032)       | (0.021)               | (0.024)   |
| Non-domestic burglary    | 0.005     | 0.619***| 0.009         | 0.048***              | 0.019     |
|                          | (0.013)   | (0.207)| (0.029)       | (0.017)               | (0.022)   |
| Public order offences    | -0.005    | 0.166 | -0.022        | -0.001                | -0.009    |
|                          | (0.007)   | (0.120)| (0.015)       | (0.008)               | (0.010)   |
| Shoplifting              | 0.001     | 0.120 | -0.046        | 0.004                 | 0.009     |
|                          | (0.018)   | (0.165)| (0.029)       | (0.014)               | (0.025)   |
| Vehicle offences         | -0.008    | -0.108| -0.035        | -0.011                | -0.015    |
|                          | (0.016)   | (0.168)| (0.025)       | (0.012)               | (0.017)   |
| Violence without injury  | 0.019     | 0.368**| -0.016        | -0.015                | -0.023    |
|                          | (0.014)   | (0.151)| (0.030)       | (0.014)               | (0.021)   |
| Violence with injury     | 0.014     | 0.257 | -0.096**      | -0.135***             | -0.066*   |
|                          | (0.022)   | (0.351)| (0.041)       | (0.029)               | (0.037)   |
| Crime per head police force | 0.008    | 0.321**| 0.012         | 0.011                 | 0.014     |
|                          | (0.010)   | (0.144)| (0.023)       | (0.016)               | (0.014)   |
| Limited applicants       | 0.004     | -0.515**| -0.078***     | -0.003                | -0.006    |
|                          | (0.012)   | (0.229)| (0.028)       | (0.015)               | (0.017)   |
and more candidates with previous experience. Forces with a female chief constable had a greater proportion of candidates who were older and who were female—this could be because women are more likely to apply to a force headed by a female officer.

V. Police Outcomes and Recruit Quality

The primary focus of this paper has been to use a very precise dataset to investigate how local area monetary incentives (i.e. relative wages) and area characteristics (local disamenities of working in the police service) affect the quality of applicants wishing to become police officers. This research in itself has policy implications, in the light of proposed reforms to the recruitment process described in the concluding section.

An additional pertinent question is whether recruit quality matters for police performance, akin to recent work on the effect of relative pay variation on the performance of teachers, health workers and others. As mentioned in the Introduction, differences in police force efficiency may stem from the functioning of higher management rather than the quality of the workforce; indeed, the quality of the management may be inextricably linked to the types of police officers that are recruited. Existing practices may also matter: there may be positive spillovers from higher-quality new recruits onto existing officers, but equally, new recruits may be ‘corrupted’ by existing practices.

There are two practical difficulties in making the link between recruit quality and performance. The first is that there are few direct extant measures of performance by police forces. Many measures of police activity, such as recorded crime rates and clearance rates, are endogenous in that they are manipulable by force reporting activity. Since 2014, HM Inspectorate of Constabulary has published the so-called PEEL assessments of performance of individual police forces (Performance, Effectiveness, Efficiency and Legitimacy). However, these are fairly ‘broad brush’ qualitative measures and post-date the period of our sample. More rigorous statistical attempts to measure police efficiency (such as Drake and Simper 2003, 2005) are interesting but tend to give varying rankings according to different methodologies and have no panel aspect to the measures. The second issue is the ‘stock–flow’ problem: we observe the flow of new entrants into police forces with a female chief constable had a greater proportion of candidates who were older and who were female—this could be because women are more likely to apply to a force headed by a female officer.

### Table 9

|                         | Pr(Female) | Age | Pr(Experience) | Pr(A levels or above) | Pr(White) |
|-------------------------|------------|-----|----------------|-----------------------|-----------|
| Shortlisted             | –0.003     | –0.339 | 0.056          | –0.004                | 0.052*    |
|                         | (0.021)    | (0.276) | (0.036)       | (0.025)              | (0.026)   |
| Proportion of high ranks that are female | 0.001 | 0.018 | 0.002 | 0.000 | –0.009 |
|                         | (0.005)    | (0.063) | (0.009) | (0.004) | (0.006) |
| Female chief constable  | 0.011***   | 0.205*** | 0.004 | 0.004 | 0.000 |
|                         | (0.004)    | (0.071) | (0.012) | (0.008) | (0.008) |
| R-squared               | 0.004      | 0.009 | 0.015 | 0.010 | 0.055 |

### Notes

Sample size is 38,924. Scores and non-binary explanatory variables are standardized as z-scores. Standard errors (in parentheses) are clustered at the police force level. ***, ***, * indicate statistical significance at the 1%, 5%, 10% level, respectively, calculated using scaled residuals and critical t-values to account for the relatively small number of clusters.
forces over a number of years but these are still a relatively small fraction of the stock of officers in the force. These difficulties in linking efficiency to quality of the workforce (and the economic drivers thereof) are not confined to this paper.

Nevertheless, we can provide some measures of police outcomes from published and survey data. The first is the clear-up rate of recorded crime. Although potentially manipulable by police forces, it is not as clearly so as recorded crime itself. The second is to use average household responses to the Crime Survey for England and Wales (CSEW) (previously the British Crime Survey) by police force area. We utilize responses to three questions in the year 2011 (which we assume is the first year in which our last cohort of entrants had passed through probation procedures):

QLC The mean response to the question ‘How much is your own quality of life affected by crime on a scale from 1 to 10 (where 1 is no effect, 10 is total effect)’

QLFC The mean response to the question ‘How much is your own quality of life affected by fear of crime on a scale from 1 to 10 (where 1 is no effect, 10 is total effect)’

EorGJOB The proportion of the population who answers excellent or good to ‘Taking everything into account, how good a job do you think the police in this area are doing?’

We regress these outcome indicators for each police force area on the average test scores of all applicants to each police force over the period 2007–10. We include a limited range of controls (given the limited degrees of freedom). These are officers and staff per head of population (as a proxy for workload) and some area characteristics: population density, average income per head, density of bars (taken as an indicator of basic social disorder), the proportion of households that pay rent, and the proportion of black ethnic minority residents.20 A variety of specifications is possible, but in Table 10 we give the results for the four outcome variables where we use the 25th, 50th and 75th percentiles of overall test scores and the mean scores for the three components for which we have data as our measures of average area recruit quality.

Table 10 shows that the clear-up rate is unaffected by the quality of recruits in the preceding four years: the main drivers are the number of officers per head of population and population density (both positively). Opinions on whether the local police are doing a good job also seem unaffected. Overall test scores do not seem to be strongly associated with the CSEW responses on whether crime affects quality of life, but there are significant negative associations with oral communication and written communication specifically. This could suggest that higher-quality police, at least in terms of their communication skills, may be associated with a lower reported impact of crime on quality of life. However, given these results, we would not wish to draw any clear inferences on the relationship between the effectiveness of policing and the quality of recruits.21

VI. CONCLUSIONS

In this paper we have used a novel dataset to analyse the impact of centrally regulated pay on the quality of applicants to the police in England and Wales. These data—individual test scores from the national assessment required of all applicants—provide a direct measure of ‘quality’ pertinent to the occupation in question, and therefore represent an improvement over much of the existing literature that has relied on inference from prior schooling or institutional performance.
We provide empirical evidence of two distinct channels through which national wage setting affects workforce quality. First, national wage setting implies that relative wages between the police and other occupations vary spatially and over time, and we demonstrate that a lower relative police wage is associated with lower quality applicants (as measured by their test scores). The size of the impact is relatively small, however: a one standard deviation increase in log relative wages is associated with a 0.2 standard deviation increase in overall scores. This is around two-thirds of the impact that having A levels (as opposed to GCSEs) is found to have on the pass rate. Second, national police wages cannot adjust to reflect spatial variation in the disamenity of policing, and we demonstrate that a greater disamenity of policing (as measured by crime rates and the proportion of crime that is violence) is also associated with lower-quality police applicants. Quantitatively, this channel is found to be at least as important as the impact.
of variations in relative wages and is invariant to a battery of sensitivity tests. Quantile regression suggests that the two channels act across the distribution of applicant quality, but the wage effect is concentrated in the top three-quarters of the distribution (i.e. higher relative wages encourage more good applicants in particular), while the effect of disamenities is more strongly associated with quality at the bottom end of the distribution.

It is also interesting to note that while observable characteristics of applicants can ‘explain’ a significant component of the variation in performance in police applicant assessment tests, there are unobservable differences in aptitude in assessment tests that are not accounted for by observables. One reason for this is that there may also be selection mechanisms by police forces that are unobservable to the researcher in their initial ‘screen’ of applicants. We control for observable differences in police screening mechanisms and in police force characteristics (such as the composition of senior police officers), but there are probably residual unobservables in police screening as well as applicant characteristics that may play a part in determining the quality of applicants. In the absence of a controlled experiment, there is little that can be done to tease out further results. The apparently arbitrary nature of some of these pre-screening procedures by individual police forces was criticized in HMSO (2012) and this contention enhances the likelihood that our observed results stem from self-selection of applicants rather than systematic pre-selection by police forces. Nevertheless, our results rule out the proposition that unobservables such as ‘preference for money over vocation’ induce a reverse selection by which higher relative pay lowers the quality of applicants.

In early 2016, the College of Policing, which is responsible for police training standards inter alia, put out a proposal for public consultation for wide-ranging changes to police recruitment. In particular, it proposed that police recruitment would in future comprise three entry routes: a professional three-year degree in policing, a six-month graduate conversion programme for existing graduates in other subjects, and a ‘higher-level apprenticeship’ by which an apprentice police constable could jointly work and study for a degree-level qualification for a period of 3–5 years. At the same time, there have been a series of ad hoc proposals to increase the proportion of applicants among women and ethnic minorities.

The rationale for these proposals derives from the type of results obtained in Table 3 of the present paper, which are indeed familiar to the College of Policing from their own research. What is perhaps less well understood is the effect of pay and local disamenities on the self-selected applicant pool as described in the present paper. In addition, the role of unobservables in recruit aptitude, as evidenced by test scores, appears also to be important. Making policing a graduate-only occupation will still involve self-selection of applicants among graduates and may discourage applicants who have a particular aptitude for policing but lack immediate qualifications—the in-house ‘apprenticeship’ presumably being a vehicle for such would-be police officers. In any event, the nature of policing is likely to change over the next few years towards a ‘professional’ core of police officers supplemented by other staff in back-up roles. The research in the present paper shows some of the hurdles that may have to be overcome to achieve such a goal.

Our paper also touched briefly on performance. There is no clear evidence of an impact of recruit quality on variations in performance across police forces in the short run. This should not be particularly surprising given the time period and the weaknesses of performance measures. It is to be hoped that future research will give better measures that permit a rigorous analysis of the relationship between workforce quality and police outcomes.
### APPENDIX

**TABLE A1**  
**SENSITIVITY TO ESTIMATE OF RELATIVE WAGE USED**

| Overall score | Written communication score | Oral communication score | Respect for race and diversity score |
|---------------|-----------------------------|--------------------------|-------------------------------------|
| **Baseline (LFS)** | | | |
| $\ln\left(\frac{W^p}{W^o}\right) = -\hat{\theta}_{1,r}$ | 0.210* | 0.035 | 0.131** | -0.188*** | 0.273** |
| | (0.108) | (0.023) | (0.063) | (0.059) | (0.122) |
| Violence without injury | 0.027 | -0.001 | 0.007 | -0.112*** | -0.042 |
| | (0.051) | (0.014) | (0.032) | (0.026) | (0.054) |
| Violence with injury | -0.357*** | -0.123*** | -0.166** | -0.171** | -0.357*** |
| | (0.105) | (0.029) | (0.076) | (0.064) | (0.090) |
| Crime per head police force | 0.008 | -0.022* | -0.044 | -0.010 | -0.008 |
| | (0.043) | (0.012) | (0.038) | (0.025) | (0.046) |
| R-squared | 0.043 | 0.021 | 0.056 | 0.024 | 0.015 |

**ASHE—assuming no variation in police wage**

| Overall score | Written communication score | Oral communication score | Respect for race and diversity score |
|---------------|-----------------------------|--------------------------|-------------------------------------|
| $\ln\left(\frac{W^p}{W^o}\right) = -\hat{\theta}_{3,r}$ | 0.124 | 0.021 | 0.054 | -0.092** | 0.183* |
| | (0.092) | (0.022) | (0.061) | (0.039) | (0.107) |
| Violence without injury | 0.045 | 0.003 | 0.019 | -0.129*** | -0.018 |
| | (0.047) | (0.014) | (0.032) | (0.026) | (0.051) |
| Violence with injury | -0.313*** | -0.116*** | -0.143* | -0.207*** | -0.295*** |
| | (0.108) | (0.029) | (0.080) | (0.070) | (0.085) |
| Crime per head police force | 0.035 | -0.017 | -0.030 | -0.033 | 0.031 |
| | (0.043) | (0.012) | (0.039) | (0.026) | (0.044) |
| R-squared | 0.042 | 0.021 | 0.055 | 0.023 | 0.014 |

**ASHE—allow variation in police wage**

| Overall score | Written communication score | Oral communication score | Respect for race and diversity score |
|---------------|-----------------------------|--------------------------|-------------------------------------|
| $\ln\left(\frac{W^p}{W^o}\right) = \hat{\theta}_{3,r}$ | 0.083** | 0.022** | 0.051* | -0.023 | 0.109** |
| | (0.037) | (0.009) | (0.026) | (0.022) | (0.044) |
| Violence without injury | 0.061 | 0.007 | 0.029 | -0.135*** | 0.003 |
| | (0.046) | (0.013) | (0.032) | (0.027) | (0.048) |
| Violence with injury | -0.337*** | -0.120*** | -0.154** | -0.189** | -0.331*** |
| | (0.105) | (0.027) | (0.076) | (0.074) | (0.080) |
| Crime per head police force | 0.070 | -0.006 | -0.006 | -0.035 | 0.073 |
| | (0.047) | (0.012) | (0.038) | (0.028) | (0.047) |
| R-squared | 0.043 | 0.022 | 0.056 | 0.023 | 0.016 |

**Notes**

Sample size is 41,485. Scores and non-binary explanatory variables are standardized as $z$-scores. Regressions also control for year dummies, London, educational composition of the local workforce, local unemployment rate, average house prices, and the proportion of crime accounted for by other crime types as in our main specification (all estimated coefficients available on request). Standard errors (in parentheses) are clustered at the police force level.  
***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively, calculated using scaled residuals and critical $t$-values to account for the relatively small number of clusters.
### TABLE A2
**Excluding the London Metropolitan Police**

|                         | Overall score | Written communication score | Oral communication score | Respect for race and diversity score |
|-------------------------|---------------|-----------------------------|--------------------------|--------------------------------------|
| **Baseline**            |               |                             |                          |                                      |
| ln \( \frac{WP}{WO} \) | 0.210*        | 0.035                       | 0.131**                  | -0.188***                            |
|                         | (0.108)       | (0.023)                     | (0.063)                  | (0.059)                              |
| Violence without injury | 0.027         | -0.001                      | 0.007                    | -0.112***                            |
|                         | (0.051)       | (0.014)                     | (0.032)                  | (0.026)                              |
| Violence with injury    | -0.357***     | -0.123***                   | -0.166**                 | -0.171**                             |
|                         | (0.105)       | (0.029)                     | (0.076)                  | (0.064)                              |
| Crime per head police force | 0.008         | -0.022*                     | -0.044                   | -0.010                              |
|                         | (0.043)       | (0.012)                     | (0.038)                  | (0.025)                              |
| R-squared               | 0.043         | 0.021                       | 0.056                    | 0.024                               |
| **Excluding London**    |               |                             |                          |                                      |
| ln \( \frac{WP}{WO} \) | 0.161         | 0.028                       | 0.129*                   | -0.174***                            |
|                         | (0.107)       | (0.024)                     | (0.066)                  | (0.061)                              |
| Violence without injury | 0.029         | 0.000                       | 0.007                    | -0.108***                            |
|                         | (0.046)       | (0.014)                     | (0.032)                  | (0.026)                              |
| Violence with injury    | -0.437***     | -0.134***                   | -0.175**                 | -0.133**                             |
|                         | (0.100)       | (0.030)                     | (0.082)                  | (0.062)                              |
| Crime per head police force | 0.021         | -0.019*                     | -0.044                   | -0.013                              |
|                         | (0.041)       | (0.011)                     | (0.038)                  | (0.023)                              |
| R-squared               | 0.049         | 0.023                       | 0.042                    | 0.032                               |

**Notes**

Sample size is 28,143. Scores and non-binary explanatory variables are standardized as z-scores. Regressions also control for year dummies, London, educational composition of the local workforce, local unemployment rate, average house prices, and the proportion of crime accounted for by other crime types as in our main specification (all estimated coefficients available on request). Standard errors (in parentheses) are clustered at the police force level.

***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively, calculated using scaled residuals and critical t-values to account for the relatively small number of clusters.
## Table A3

### Association of Applicant Quality with Outside Wage, Controlling for Applicant Characteristics

|                        | Overall score | Written communication score | Oral communication score | Respect for race and diversity score |
|------------------------|---------------|-----------------------------|--------------------------|-------------------------------------|
| **Without controls for applicant characteristics** |               |                             |                          |                                     |
| $\ln (W^P/W^O)$         | 0.210*        | 0.035                       | 0.131**                  | 0.273**                             |
| (0.108)                 | (0.023)       | (0.063)                     | (0.059)                  | (0.122)                             |
| Violence without injury | 0.027         | 0.001                       | 0.007                    | 0.002                               |
| (0.051)                 | (0.014)       | (0.032)                     | (0.026)                  | (0.054)                             |
| Violence with injury    | −0.357***     | −0.123***                   | −0.166**                 | −0.357***                           |
| (0.105)                 | (0.029)       | (0.076)                     | (0.064)                  | (0.090)                             |
| Crime per head police force | 0.008       | −0.022*                     | −0.044                   | −0.008                              |
| (0.043)                 | (0.012)       | (0.038)                     | (0.025)                  | (0.046)                             |
| R-squared               | 0.043         | 0.021                       | 0.056                    | 0.015                               |

### With controls for applicant characteristics

|                      | Overall score | Written communication score | Oral communication score | Respect for race and diversity score |
|----------------------|---------------|-----------------------------|--------------------------|-------------------------------------|
| $\ln (W^P/W^O)$      | 0.152         | 0.016                       | 0.091                    | 0.227**                             |
| (0.095)              | (0.022)       | (0.058)                     | (0.065)                  | (0.111)                             |
| Violence without injury | 0.015      | 0.004                       | 0.003                    | 0.004                               |
| (0.049)              | (0.014)       | (0.029)                     | (0.027)                  | (0.051)                             |
| Violence with injury | −0.264**      | −0.095***                   | −0.106                   | −0.295***                           |
| (0.102)              | (0.030)       | (0.075)                     | (0.067)                  | (0.088)                             |
| Crime per head police force | −0.020    | −0.030**                    | −0.060*                  | −0.032                              |
| (0.043)              | (0.011)       | (0.035)                     | (0.027)                  | (0.043)                             |
| R-squared            | 0.166         | 0.081                       | 0.118                    | 0.087                               |

### Notes

Sample size is 41,485. Scores and non-binary area-level explanatory variables are standardized as z-scores. Additional controls for applicant characteristics: quadratic in age, sex, 4 levels of educational attainment, 3 levels of outside experience, 7 ethnic categories. Regressions also control for year dummies, London, educational composition of the local workforce, local unemployment rate, average house prices, and the proportion of crime accounted for by other crime types as in our main specification (all estimated coefficients available on request). Standard errors (in parentheses) are clustered at the police force level. ***, **, * indicate statistical significance at the 1%, 5%, 10% level, respectively, calculated using scaled residuals and critical t-values to account for the relatively small number of clusters.

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NOTES

1. In similar methodological vein to the present study, Bell et al. (2007) and Elliott et al. (2007) examine the impact of outside pay differentials on local vacancy rates for nurses in the UK’s National Health Service, while Combes et al. (2015) undertake a similar exercise for French hospital workforces. However, it should be noted that there is no shortage of recruits to the police service in England and Wales; it is the quality of recruits that is the primary issue here.

2. Drawing on some examples from the extensive discussion of this issue in HMSO (2011), according to ASHE data, median earnings of police officers at sergeant rank and below (SOC code 3312) are around 15% more than private sector white collar managers and professionals (SOC codes 1 and 2) in Wales and North-East England but around 20% less than in London (and slightly less than in the South-East) (HMSO 2012, Table 5a). This pattern is characteristic of police officers and staff (and, indeed, other public sector professionals relative to the private sector) in the areas of low regional pay relative to London and the South-East. However, in the period discussed here, London Metropolitan police officers did get free travel to work within 70 miles of London as a benefit in kind (see text).

3. Note that we are suggesting not that our particular indicators of the amenity value of policing, such as the local incidence of violent crime, deter police recruits per se, merely that the type of recruit may be affected: such crime may deter more highly qualified or female recruits, for example.

4. Scotland and Northern Ireland each have a unified police force.

5. In March 2010, 76% of police officers were constables, 16% were sergeants, 5% were inspectors, 1% were chief inspectors, and 1% were higher-ranked officers.

6. The seven competency areas assessed are: community and customer focus, effective communication, personal responsibility, problem solving, resilience, respect for race and diversity, and teamworking. Effective communication is further broken down into oral communication and written communication.

7. Prior to this period, national tests were utilized by police forces to assess applicant quality. However, pass scores could, and did, vary across police forces (HMSO 2012, p. 74).

8. There is no published percentage of successful candidates who then take a job with another force, but senior officers and police officials have reported to us that it is a very small percentage. Applications to be a police officer must be made through a specific force, and costs are incurred by both the force and the individual in doing so. Over time, some officers will transfer to other forces, but even here the percentages are small: according to police returns to the Home Office (ADR581), between 2004–5 and 2014–15 voluntary transfers as a percentage of workforce averaged less than 1% per year (though transfer rates out of police forces surrounding London into the London Metropolitan Police are somewhat higher).

9. In the simple setup above, where there is no heterogeneity in wages, disutility or preferences conditional on skill type, $P_k$ will take the value 1 if $\ln(W_k^r) - D_k > \ln(W_{r,\ell}^* / P_r)$ and the value 0 otherwise.

10. Few candidates were submitted in the two years after 2010 due to cuts in spending on the police as part of the then Coalition government’s austerity programme.

11. The pass marks were set at these levels in November 2007. Prior to this, the pass marks had been 44% for written communication and 60% for oral communication, RfRD and overall.

12. Identification strategies in the context of estimating public sector wage ‘premia’ or ‘penalties’ are discussed at some length in Disney and Gosling (2003).

13. The reason why we treat this as sensitivity analysis rather than our main approach is that the ASHE data have more limited information on individual characteristics than those in the LFS—in particular, we cannot condition wages on education; see Office for National Statistics (2017). This does not preclude examining variation in police wages across the country (since police officers could be argued to be relatively homogeneous), but it does cause problems when estimating geographical variation in relative wages if the educational composition of the workforce is very different in different areas.

14. The urge to increase the number of successful applicants from ethnic minority groups led to a reduction in the pass score for written communication from 50% to 44% a year after SEARCH was introduced. A little reflection suggests that the signalling implication of this change was perverse, in terms of attracting ‘better-quality applicants’ (including those from ethnic minority communities), and that it would be better to deal with the ‘white male culture perception’ directly. In fact, HMSO (2012) is extremely critical of this decision and argues strongly for an increase in the pass score for written communication. We discuss some implications of this, and the findings of our paper, in Section VI.

15. For a survey of house prices and local amenity values in the UK, see Gibbons and Machin (2008).

16. London also has a second police force, the City of London Police, which is very small—covering only the square mile of the City of London. This force is already excluded from all our analysis as it is not possible to obtain data on the outside wage or most of the other covariates in our analysis for this area.

17. Accessed via the ‘Wayback Machine’, https://archive.org/web (accessed 16 March 2018).
18. We could also think of these as (dis)amenities for certain types of recruits as well as indicators of recruitment policy. This is why it is hard in practice to separate preferences of applicants from selection procedures of police forces, since the latter will influence the former.

19. An interesting question is whether the nature of policing is endogenous to types of crime—for example, as to whether police are armed (which is not always the case in the UK) and in the nature of patrolling; see Southwick (1998) for a discussion in the US context. However, we would not expect applicants to be aware of these differences across police forces.

20. These are typical measures of ‘relative need’ used in the Home Office computations of the police grant formula.

21. In practice it is hard to draw any conclusions as to the relationship in recent years between police performance, police numbers, recruitment and resourcing; see Disney and Simpson (2017).

22. See www.college.police.uk/News/College-news/Pages/peqf_consultation.aspx (accessed 16 March 2018).

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