

DISCUSSION PAPER SERIES

IZA DP No. 17989

Why Higher Pay Leads to More Crime

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Why Higher Pay Leads to More Crime

The effects on criminal behaviour of raising the minimum wage for those aged 25 and over in the United Kingdom are analysed, using data on police stop and search activities. A 1% increase in the minimum wage raises the fraction of people stopped by the police by 2.96%, the fraction of people caught with an incriminating item by 1.43%, and the fraction of people arrested as a consequence by 1.27%. This effect is almost entirely driven by drug searches made outside business hours, suggesting that the minimum wage raises crime principally by raising disposable income – and drug consumption – among workers.

JEL Classification: K42, J22, J31

Keywords: minimum wage, crime, stop and search

Corresponding author:

Kerry L. Papps
School of Management
University of Bradford
Bradford, BD7 1DP
United Kingdom
E-mail: k.l.papps@bradford.ac.uk

1. Introduction

This paper examines whether an increase in wage rates changes the likelihood of a person engaging in crime. According to the economic model of crime, people commit crimes when legal income opportunities are less than illegal opportunities minus the expected punishment. Therefore, one might expect higher wages to reduce crime. However, many crimes can be considered consumption activities – or spillovers from consumption activities – such as drug use or violence resulting from alcohol consumption. Higher wages may therefore lead to more crimes of this type. Previous studies have been unable to test these competing predictions because they typically lack data on a person's inclination to commit a crime and their motivations for doing so, only on crimes that were reported or for which someone was arrested.

In April 2016, the minimum wage in the U.K. was raised by 50 pence (or 70 U.S. cent), but only for those aged 25 and over. Previous research has established that this change had no effect on employment rates but did raise income levels significantly among low-wage workers. This paper compares the number of actual and potential crimes in a particular area among those aged 25-34, who experienced a minimum wage increase because of the policy change, with the equivalent number among those aged 18-24, who did not receive a minimum wage increase. Data on individual events where the police stopped and searched people are examined. By law, the police are not allowed to stop people unless they suspect them of having committed a crime and they must record which crime this is. As a result, the data give a range of measures of criminality, from suspicious behaviour (whether a person is stopped), through clear intent to commit a crime (whether a criminal item was found on a person), to evidence of a crime having been committed (whether a person is arrested). The data also include information on the exact time a person was stopped, meaning that events can be divided into those that take place during normal business hours (09:00-17:00, Monday to Friday) – when most employed people are at work – and those that take place at other times. Further, there is information on the reason a person was stopped, meaning that total stops can be divided into stops related to theft, drugs, anti-social crimes and other crimes.

The results indicate that the minimum wage increases street-level criminal activity, measured in various degrees of seriousness. A 1% increase in the minimum wage is found to raise the fraction of people who are stopped by 2.96%, the fraction of people found with illegal items on their person by 1.43% and the arrest rate by 1.27%. The pattern of stops across crime categories and times of day suggests that the crime increase was driven largely by people who benefited from the increase in the minimum wage, since stops (and arrests) rose by less during normal business hours, when this group is likely to be working, than outside these hours. In

particular, there was a significant increase in stops related to drugs outside of business hours. There was also a significant increase in stops for theft during business hours in response to the minimum wage increase, which is likely to have been driven by people who are unemployed. However, the increase in drug stops outside business hours was much larger in magnitude. Hence, the evidence is consistent with drug crimes being a normal good.

The few previous studies on this topic have found wildly different results. Studies in the U.S. by Hashimoto (1987), Beauchamp and Chan (2014) and Fone et al. (2023) all reported statistically significant positive effects of the minimum wage on crime, while Braun (2019) found a U-shaped relationship between minimum wages and crime. The only previous U.K. study, by Hansen and Machin (2002), found a significant negative relationship between the change in crime rates and the proportion of workers in an area who earned less than the minimum wage prior to its introduction in 1999. The only study to attempt to identify the mechanisms by which the minimum wage affects crime was Fone et al., who examined labour market survey data (which does not have information on crime) to identify patterns that might explain the positive relationship they found between the minimum wage and crime.

This paper makes three main contributions to knowledge of the mechanisms by which an increase in wage rates affects crime. First, by examining differences in crime rates across age groups in the same area, it has a tighter identification strategy than previous studies. Second, by using a broader range of measures of criminal behaviour and by focusing on street crime, it can measure how many people are tempted to commit crimes, not just how many crimes are actually committed and reported. Finally, by exploiting variation across types of crime and time of day, it is able to identify the motives behind a specific crime.

2. Background on minimum wages in the U.K.

A national minimum wage was introduced in the U.K. in 1999, with separate rates applying to different age groups. These rates initially applied to workers aged 18-21 and 22 and older. In 2003 coverage was extended to those aged 16-17, with a separate rate for these workers, and in 2010 the age of eligibility for the highest rate was lowered from 22 to 21.¹ Until 2016, all these rates were raised each year in October, maintaining a similar ratio between the age groups. However, on 1 April 2016, the government introduced a new “National Living Wage” (NLW), which was effectively a new rate of the minimum wage that applied only to those aged

¹ People aged under 16 are not legally allowed to work full-time. A lower minimum wage rate for apprentices was also introduced in 2010. However, this is relatively uncommon and only applies to workers during their first year on an apprentice or until they turn 19 (whichever comes soonest).

25 and over. These workers received an especially large increase in minimum wage, with the new rate set at £7.20, compared to the existing rate of £6.70. As illustrated in Figure 1, the rates for younger workers did not change in April 2016 and only increased the following October, according to the usual schedule. Therefore, between October 2015 and September 2016, the only change in the minimum wage rates was the 50 pence increase (roughly equivalent to 70 U.S. cents) for those aged 25 and over in April.

There is little evidence that the minimum wage has reduced employment in the U.K. in general and all studies of the introduction of the National Living Wage specifically have found insignificant employment effects (Aitken et al. 2019, Dickens and Lind 2018, Dube 2019). Reviewing the empirical evidence, Dube (2019) concluded that “the overall number of low-wage jobs (e.g. number of jobs paying below NLW+£3) was virtually unchanged between 2012 and 2017, including after the announcement of the NLW in 2015”.

Figure 2 depicts the distribution of hourly wages in October 2015-March 2016 and April 2016-September 2016, collectively covering the period studied in this paper. The data are taken from the Labour Force Survey, restricted to those reporting an hourly wage rate. This shows that the introduction of the National Living Wage in April 2016 had a clear effect on wage rates, as seen by the large spike at £7.20 after April 2016 among those aged 25 and over. Meanwhile, the income distribution among those aged under 25 was largely unchanged before and after April 2016.

3. Background on police stops in England and Wales

This study focuses on the prevalence and outcomes of stops made by police in England and Wales. Scotland and Northern Ireland have different legal systems and are therefore excluded. There are 43 territorial police forces in England and Wales, each with authority over a distinct geographic area (see Figure 3), as well as a separate force that is responsible for policing the railway network. Each force is headed by a chief constable (or a commissioner in the case of the Metropolitan Police and City of London Police), who is responsible for day-to-day operational decisions, including the use of stop and search. The chief constable is appointed by an elected Police and Crime Commissioner (P.C.C.) in 40 of the territorial police forces (all except the Metropolitan Police, City of London Police and Greater Manchester Police, which have different arrangements). Nationwide elections for the P.C.C.s were held on 5 May 2016, which led to a change in P.C.C. in 21 police areas. This may have contributed to an increase in

turnover among chief constables in mid-2016. Therefore, data on the dates each chief constable was appointed were collected and are used in a robustness test in Section 5.²

Almost all police stops and searches in England and Wales take place according to either section 1 of the Police and Criminal Evidence Act 1984 or section 23 of the Misuse of Drugs Act 1971. These acts allow police officers to search people for objects like drugs, weapons and stolen property, provided the officer has a reasonable cause to suspect he/she will find something. Before an officer searches a person, the officer must tell the person what he/she expects to find, the reason he/she wants to search the person (for example because the person appears to be hiding something) and why they are legally allowed to search the person. The officer must offer the person a record of the search. A police officer can ask the person to take off their coat, jacket or gloves. They can also ask the person to take off other clothes, as long as they take the person somewhere out of public view and as long as they are of the same sex as the person.

Tiratelli et al. (2018) examined the relationship between stop and search and subsequent crime rates over a 10-year period, using data for each London borough covered by the Metropolitan Police. They found that stop and search had a very limited deterrence effect. Similarly, using street-level data Braakmann (2022) found that an exogenous expansion in the use of stop and search in response to a high-profile crime had little effect on property crime, weapons offences and violent crime or drug offences.

Stop and search is a common tactic among British police forces. Uniquely among police activities, it involves proactively investigating potential crimes, rather than simply reacting to reports of crime from the public. Since a stop can only take place if an officer suspects a crime has been committed or might be committed, it provides a good indication of how much risky behaviour takes place on the street and allows a much broader measure of criminal activity than the reported crime data used by previous studies. Further, since stop and search focuses on preventing street crime, it is almost exclusively used on young people, who are the group that was primarily affected by the introduction of the National Living Wage.

4. Data

Since 2014, police forces in England and Wales have been required to record information about each stop and search event. This is mostly derived from information reported by the

² Only the dates of permanent appointments as chief constable were collected, not cases where an acting chief constable was in place.

officer. However, the person being stopped should always be asked for their name and address, date of birth, and self-defined ethnicity. The stop-level information made available by the police at data.police.uk contains the date and time of the stop; whether it was a vehicle or person search (or both); the latitude and longitude of the stop (with slight geographical error to ensure anonymity); the age and gender of the person; the self-defined and officer-defined ethnicity of the person; the legislation under which the person was stopped; the object of search (controlled drugs, stolen goods etc.); the outcome of the search (nothing found, suspect arrested etc.); whether the outcome was linked to the object of search; whether the search involved the removal of more than just outer clothing. For this study, data on all stops between 1 October 2015 and 30 September 2016 were collected, that is, six months on either side of the introduction of the National Living Wage. Stops made by the British Transport Police are excluded from the analysis because they do not correspond to a particular geographical area but instead are made throughout the national railway network.

The most common aim of a search is to look for controlled drugs. Most other stops are made to look for articles for use in criminal damage, stolen goods, offensive weapons, articles for use in theft, firearms, or anything to threaten or harm anyone. A stop is considered to result in something being found if the outcome is recorded as anything other than “Nothing found – no further action”. A stop is considered to have resulted in an arrest if the suspect was arrested or summonsed to court. The most common outcome is a “no further action disposal”. Other outcomes include a community resolution (in which the offender may have to apologise to a victim or clean up any damage they have done), the offender being given a warning, or the offender being given a penalty notice (which requires them to pay an on-the-spot fine).

The age of the person stopped is recorded in bands: under 10, 10-17, 18-24, 25-34, and 35 and over. Very few people in the data are under 10, therefore these observations are dropped throughout the analysis. The data reported by the West Midlands Police omitted gender throughout the sample period, therefore this area is left out of the analysis. In addition, some stops have missing gender, gender coded as “other” or missing age. In total, 8.7% of stops had missing data and are excluded from the analysis.

The stop and search data are collapsed into gender-age group-police area-date cells. An arrest rate is calculated by dividing the number of arrests for each combination of gender, age group, police area and date by the population for that gender-age group-police area combination, taken from the Office for National Statistics’ midyear population estimates for 2015 using the geographical correspondence between local authorities and police areas. The “find” rate and stop rate are similarly found, by dividing the number of cases where an object

is found and the number of stops, respectively, by the population. The arrest rate, find rate and stop rate are expressed per thousand people.

The Kaitz index value is assigned to each cell by dividing the nominal minimum wage applicable to a given age group at any point in time by the median wage in that police area in April 2015, taken from the Annual Survey of Hours and Earnings. For those aged 18-24, the nominal minimum wage is set equal to the average of the minimum wage rates applicable to 18-20- and 21-24-year-olds, weighted by the national fraction of the population in each age range. For those aged 10-17, the prevailing minimum wage is set equal to the 16-17 rate.

Figure 4 shows the national arrest rate over the sample period (October 2015-September 2016), separately by age group. The arrest rates for 25-34- and over-34-year-olds were lower than for 10-17- or 18-24-year-olds. The arrest rates for all groups fell during the sample period. However, the arrest rate for those aged 25 and over fell more slowly than the arrest rate among younger people after April 2016.

Table 1 reports means for the key variables used in the analysis, by age group and whether the observation was before or after April 2016, weighted by the population in each cell. The arrest rate fell by 9% after April 2016 among those aged 25 and over, but only by 7% among those aged 10-24. Similarly, the find rate fell by 16% and 14%, respectively. However, the fall in the stop rate was very similar between the two groups. As expected, the Kaitz index increased much more for the older age group after April 2016.

5. Results

To begin, the arrest rate, find rate and stop rate for gender-age group-police area cell i on date t are regressed in turn on a dummy for whether the National Living Wage applies to the cell, that is, whether the age group is 25-34 or 35 and over, and the date is after April 2016, along with gender-age group-police area fixed effects (γ) and date fixed effects (η), as follows:

$$RATE_{it} = \alpha \mathbf{I}(AGE \geq 25)_{it} \times \mathbf{I}(t \geq 1APR2016)_{it} + \gamma_i + \eta_t + \varepsilon_{it}. \quad (1)$$

The observations are weighted by the population of the cell and the standard errors are clustered by police area, reflecting the fact that the degree to which the minimum wage binds on a group of workers varies by location. As reported in the first three columns of Table 2, positive and significant estimates of α are found using all three dependent variables. The results imply that the introduction of the National Living Wage raised the arrest rate by 0.0005 per thousand population (equivalent to 1.8% of the standard deviation in the arrest rate), the find

rate by 0.0017 per thousand population (4.0% of the find rate standard deviation) and the stop rate by 0.0091 per thousand population (9.5% of the stop rate standard deviation).

To examine whether the under-25 and 25-and-over age groups had parallel trends in arrest rates, find rates and stop rates prior to the introduction of the National Living Wage, the three dependent variables are each regressed on a full set of interactions between month dummies and a dummy for being aged 25 and over, plus the same gender-age group-police area and month dummies as in equation 1. The only instances in which the coefficient on the 25 and over-month interaction term is significant in the pre-treatment period is for the stop rate and find rate in December 2015, which is possibly due to Christmas-related revelry, and a negative value for arrest rate in February 2016. In any case, the coefficients on the 25 and over-month interaction terms are jointly insignificant across the pre-treatment period for all three dependent variables, suggesting that the common trends assumption holds. These coefficients are depicted in Figure 5.

The results in the first three columns of Table 2 suggest that the minimum wage raises crime rates. However, although the U.K. minimum wage is the same across the country in nominal terms, its real value varies widely and it is binding for many more people in some police areas than in others. In order to take account of this variation across areas in the real value of the minimum wage, the Kaitz index is used as the measure of the minimum wage in the regression equation, as follows:

$$RATE_{it} = \beta KAITZ_{it} + \gamma_i + \eta_t + \varepsilon_{it}, \quad (2)$$

where $KAITZ$ is the Kaitz index value faced by gender-age group-police area cell i on date t .

The Kaitz index is found to have a significant positive effect on each of the three outcome measures. Setting the dependent variables and the median wage at their means, the results (shown in columns 4-6 of Table 2) imply that a 1% increase in the minimum wage raises the stop rate by 2.96%, the find rate by 1.41% and the arrest rate by 1.27%.

These elasticities are reasonable, given the results found by previous studies of the effect of the minimum wage on overall arrests. For example, Hashimoto found arrest rate elasticities in the range 0.1-0.5 and Fone et al. (2023) found elasticities of 0.2-0.3 for property crime arrests. The elasticities in Table 6 should be much larger than these for a number of reasons. First, the stop and search data provide a broader measure of criminality than reported crime rates because they include potential crimes and do not rely on incidents being reported to the police. Further, street crime is dominated by young people, who are also disproportionately affected by the minimum wage, whereas previous studies have relied on aggregate crime data.

Finally, the identification strategy here is tighter than in previous studies, by comparing crime between different age groups within a local area, rather than comparing aggregate crime rates across states. Given that areas with higher minimum wages may have less crime for exogenous reasons, it is likely that studies relying on geographic variation in minimum wages may suffer from downwards bias in their elasticities.

Robustness tests

In Table 3 a series of robustness tests are reported. In column 1, the date fixed effects are allowed to vary by police area. This controls for the possibility that underlying arrest rates in each area might have varied over the sample period, for reasons unrelated to the minimum wage increase, for example due to changes in each force's policy regarding the use of stop and search. The coefficient on the Kaitz index is still identified since it varies across age groups due to differences in median wages. Regardless of which dependent variable is used (arrest rate, find rate or stop rate), the Kaitz index coefficient falls only slightly and remains significant.

The use of stop and search as a law enforcement tactic varied across police forces and changed over time. If a police force had a policy of not using stop and search at all, the minimum wage would naturally have no effect on any of the three dependent variables in that region, regardless of the underlying level of crime in the community. By identifying calendar months where zero stops were reported by a police force, it is possible to estimate whether stop and search was used by that force. Adopting this approach, six forces appeared to introduce stop and search during the sample period. Conversely, three forces appeared to discontinue it. Four forces also had months in the middle of the sample period where they did report any stops. To control for these possible changes in policy regarding the use of stop and search, observations from months with zero stops are dropped from the sample in column 2 of Table 3. This makes little difference to the baseline results.

As an alternative way of controlling for changes in a force's approach to the use of stop and search, the gender-age group-police area fixed effects were replaced by gender-age group-chief constable fixed effects, using the data on appointment dates for chief constables. In effect, this treats each police area as a different area each time a new chief constable is appointed, thereby controlling for any changes in the prevalence of stop and search or the tactics used during stops due to a change in chief constable. As seen in column 3 of Table 3, the Kaitz rate coefficients become slightly smaller but remain significant in all cases.

In column 4 of Table 3, observations from December 2015 are excluded from the analysis, given the evidence of a significant difference between the stop rates for the two age groups in that month mentioned earlier (and visible in Figure 3). In column 5, the sample is expanded to include the 10-17 and 35-and-over age groups. The coefficients on the Kaitz index are little changed and remain significant in both cases.

Finally, for many gender-age group-police area-date combinations, zero stops were made. To address this bunching and the fact that the arrest rate can never be negative, a tobit estimator is used to estimate equation 2 in column 6 of Table 3. The coefficients on the Kaitz index are larger than that found using OLS but are more imprecisely estimated and the coefficient becomes insignificant when the arrest rate is used as the dependent variable.

Heterogeneity by nature of stop

The finding that the minimum wage increases criminal activity would seem to contradict the economic model of crime, given the evidence from previous studies that the National Living Wage had no effect on employment levels. Instead, it is consistent with a situation in which people commit more crimes when they have more income, that is, crime is a normal good. This may be because people are more able to afford illegal drugs when their income increases or because they are more able to afford alcohol, which impels them to commit anti-social acts. However, another plausible explanation is that the minimum wage reduces job turnover (Dube et al. 2016, Brochu and Green 2013, Dickson and Papps 2016), meaning that, even if the overall employment rate is unaffected, the pool of unemployed workers finds it increasingly hard to enter the workforce after a minimum wage hike and is more likely to turn to illegal income options, as predicted by the economic model of crime.

In this section, the rich nature of the stop and search data is exploited further to provide evidence on a person's motivation to commit crime. The police data do not record the income or employment status of the people who are stopped. Therefore, it is impossible to know whether they directly benefited from the minimum wage increase in April 2016. However, it is possible to draw some inference about a person's motives by making use of the information on the time of day of a stop and the object of the search. Given that most people work during business hours from Monday to Friday, stops made during this period are most likely to involve unemployed people. If the effect of the minimum wage on crime rates is no different – or is higher – during normal business hours than it is during the rest of the week, this would suggest that unemployed people are mostly responsible for the overall increase in stops or arrests.

In the first row of Table 4, equation 1 is estimated replacing the overall arrest rate first with the number of arrests made between 09:00 and 17:00 on Monday to Friday per thousand people (in column 2), and then with the number of arrests made outside these hours (in column 3). The coefficient on the Kaitz index is insignificant during business hours but is positive and significant outside business hours, indicating that the overall increase in crime resulting from the National Living Wage is mostly driven by stops made during this part of the week. The elasticity of arrests with respect to the minimum is equal to 2.021 outside business hours. Hence, it seems unlikely that the overall increase in arrests is driven solely by unemployed workers.

To examine whether arrests are connected to economic crimes or crimes committed for other motives, arrests are divided according to whether the stop was made to search for items connected to theft, to search for drugs, to search for items connected to anti-social crimes, or whether the object of the search is missing in the data. Among the reasons for stops reported in the data, the ones that most closely correspond to economic crimes are stops made to search for articles for use in theft, evidence of wildlife offences, seals or hunting equipment, game or poaching equipment, goods on which duty has not been paid etc., or stolen goods. In column 1 and row 2 of Table 4, only arrests made as the result of stops to search for these items are included in the arrest rate. A positive but insignificant coefficient on the Kaitz index is found.

In column 1 and row 3 of Table 4, the arrest rate includes only arrests made as the result of stops to search for controlled drugs or psychoactive substances.³ The coefficient is positive and significant and is equivalent to an elasticity of 1.751. In column 1 and row 4, only arrests made for anti-social crimes are included in the dependent variable. Specifically, this includes stops made to search for anything to threaten or harm anyone, articles for use in criminal damage, crossbows, firearms, fireworks, or offensive weapons. The coefficient on the Kaitz index is negative and significant and implies an elasticity of -1.663. In the final row of column 1 of the table, only arrests made on searches the object of which is missing are included. The coefficient on the Kaitz index is insignificant.

In Tables 5 and 6, the regressions from Table 4 are repeated using the find rate and the stop rate as dependent variables, respectively. A similar pattern is found, except that the overall increases in the find rate and stop rate for thefts are significant and the overall increase in the stop rate for anti-social crimes is insignificant. In all cases, the increase in drug crimes is much

³ Stops where no object is listed but which were made under the Misuse of Drugs Act 1971 (section 23) are also included in this group.

larger than the change in the other crime categories and is responsible for most of the overall increase in crime. Hence, while there is some evidence that the National Living Wage increased thefts, which may be motivated by economic concerns, there is much stronger evidence that it increased drug crimes, which may be connected to people having higher incomes.

To examine this further, Table 4 breaks up the arrest rate according to both when the stop was made during the week *and* what the object of the stop was. The only significant coefficients on the Kaitz index relate to arrests for thefts during business hours, anti-social crimes outside of business hours and drug crimes outside of business hours. The pattern for thefts is consistent with a scenario in which the minimum wage increases crimes committed by unemployed people for economic reasons. Similarly, the finding regarding anti-social crimes is consistent with employed people reducing criminal activity in response to higher wages, although there is no economic motive. However, both effects are very small in comparison to the overall increase in arrests resulting from the introduction of the National Living Wage. By far, the largest contributor to overall arrests is the increase in drug arrests made outside of business hours, which is roughly equal to the overall increase (since the changes in the other categories in Table 4 roughly cancel each other out).

The positive effect of the National Living Wage on drug arrests outside of business hours could be driven by unemployed people selling drugs or by employed people purchasing drugs (or a combination of the two). Unfortunately, the data do not distinguish between the two types of crime. However, penalties are higher for those suspected of supplying drugs and police guidance is that they “will probably charge you if they suspect you of supplying drugs”.⁴ Therefore, arrests are likely to reflect a combination of drug possession and drug dealing, whereas stops where drugs are found but no arrest is made are likely to reflect solely people carrying drugs for personal use. Given this distinction, the results in Table 4, which uses the arrest rate as the dependent variable, can be compared with the results in Table 5, which uses the find rate, to provide an indication of how the minimum wage affected the prevalence of each type of drug crime. When the find rate for drugs outside business hours is used as the dependent variable (in the third column and third row of Table 5), the elasticity is almost identical to when the arrest rate is used (3.068 for the find rate compared to 3.058 for the arrest rate, using the means of the dependent and independent variables). These results imply that the minimum wage raises the number of drug stops where something is found but no arrest is made by the around the same amount (in percentage terms) as it raises the number of cases where an

⁴ This guidance is provided here: <https://www.gov.uk/penalties-drug-possession-dealing>.

arrest is made. This suggests that the minimum wage does not solely affect the rate of drug dealing but has at least a similar (and possibly larger) effect on the amount of drug use.

6. Conclusion

This paper has examined whether higher wages affect levels of street crime, focusing on the effects of a 7.5% increase in the minimum wage in the U.K. in 2016, which only applied to those aged 25 and over. Overall, the results indicate that criminal activity increases sharply when the minimum wage rises, but that this effect is more pronounced among less serious measures of criminality (the number of stops and the number of instances where an incriminating object is found on a person) than arrests and is overwhelmingly driven by drug crimes, most likely drug use. Compared to those aged 18-24, who did not receive a minimum wage increase, the minimum wage increased the probability of 25-34-year-olds being stopped by police, the probability of an illegal item being found on their person and the probability of them being arrested. The minimum wage had a smaller effect on the number of stops and arrests during business hours than the equivalent number outside business hours, suggesting that the increase in crime was not solely driven by unemployed people. Stops and arrests for theft went up during business hours, consistent with an increase in economically motivated crime among those who were hurt by the minimum wage. However, stops and arrests connected with drugs went up outside business hours, consistent with an increase in crime due to higher disposable incomes among the beneficiaries of the minimum wage. The latter is far larger than the former.

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Figure 1: National Minimum Wage rates by age group, October 2014-October 2017

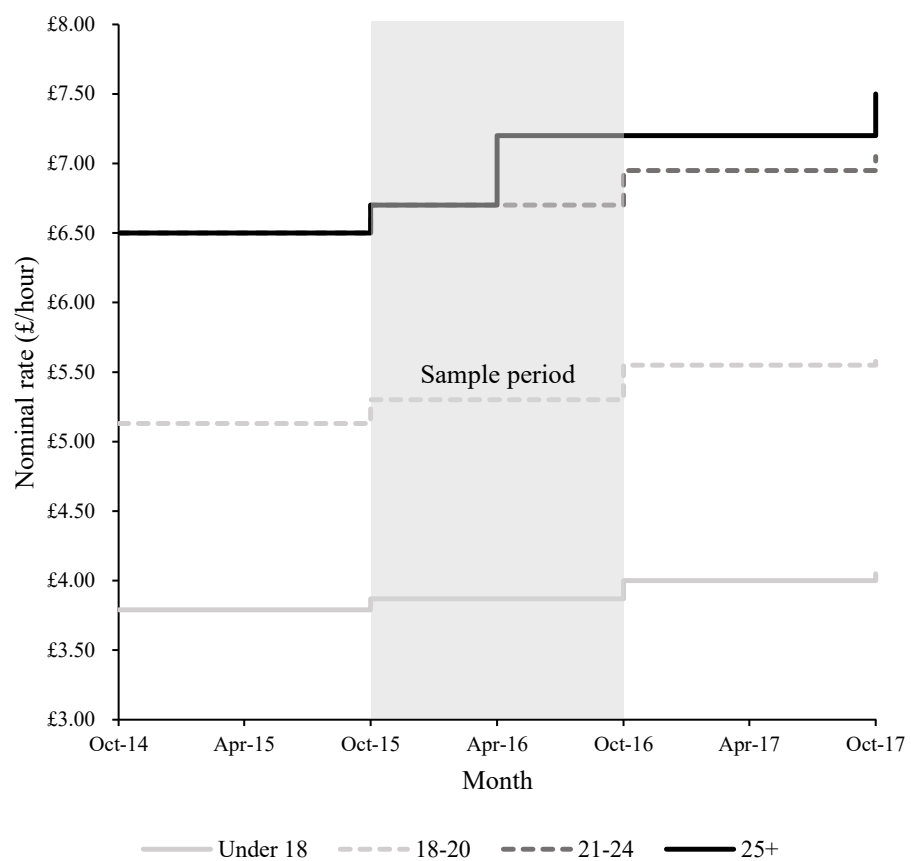
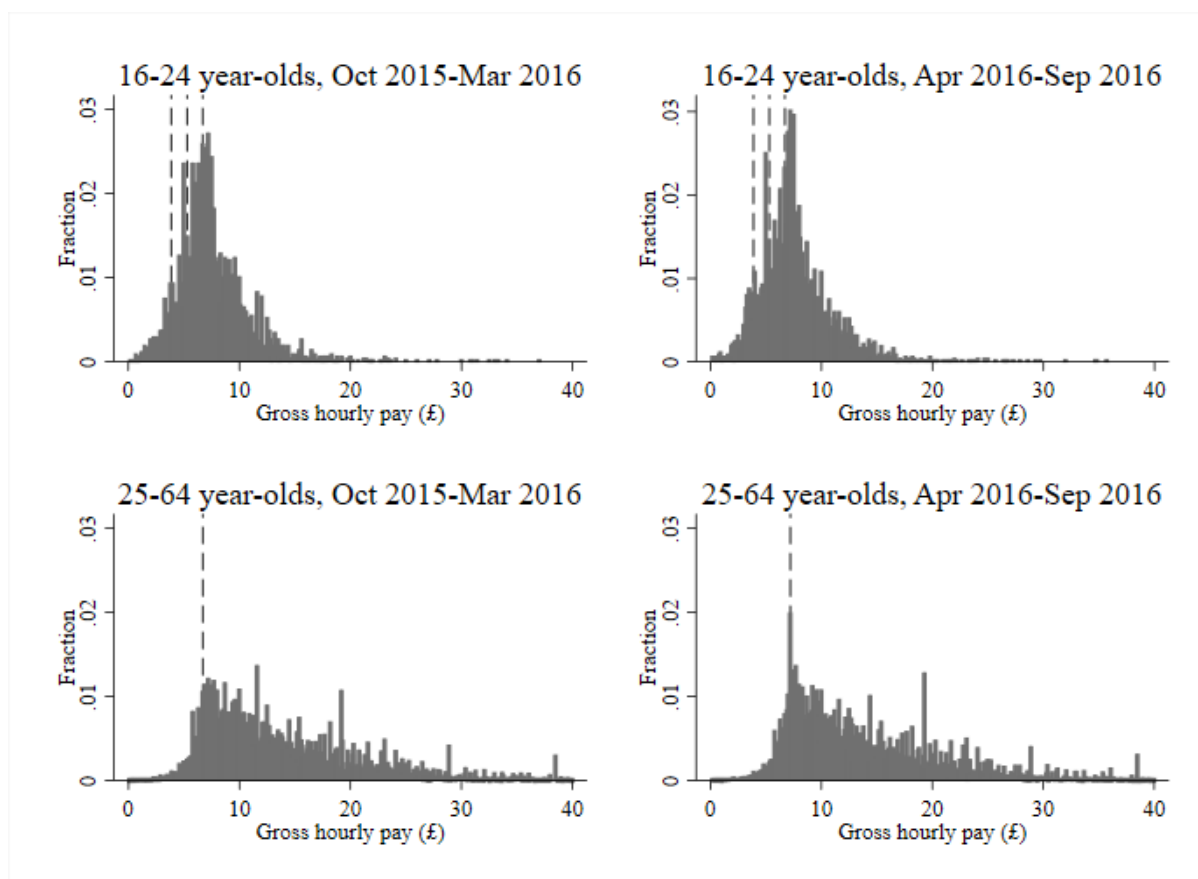


Figure 2: Histograms of hourly pay by age group, 2015-2016



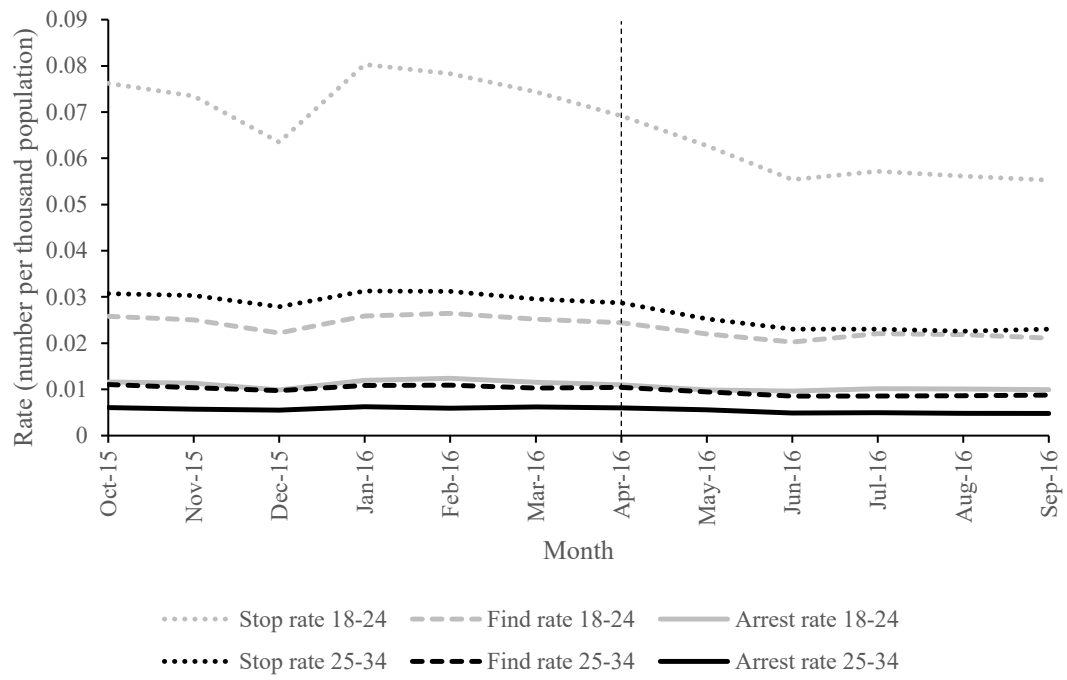
Notes: Data are on hourly pay from the Annual Population Survey, 2015-2016.
The vertical dotted lines denote the prevailing minimum wage rate(s) for the age group in the given period.

Figure 3: Police areas in England and Wales



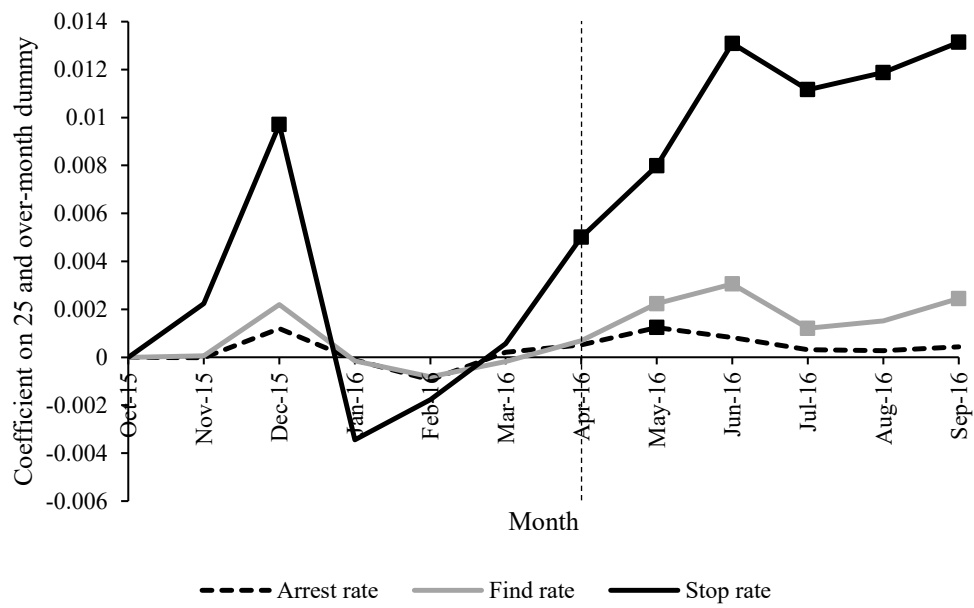
Note: In addition to the police forces shown, the British Transport Police is responsible for the railway network throughout England, Wales and Scotland.
Police force area boundaries were taken from <https://geoportal.statistics.gov.uk>.

Figure 4: Stop, find and arrest rates by month and age group



Notes: Vertical dotted line depicts the introduction of the National Living Wage.

Figure 5: Test of the common trends assumption



Notes: Lines represent coefficients on 25 and over-month interactions from regressions using the dependent variables indicated. Square markers denote coefficients that are significant at the 10% level.

All models also include gender-age group-police area fixed effects and month fixed effects.

Observations are weighted by the population in each age group-police area cell.

Standard errors are clustered by police area.

Vertical dotted line depicts the introduction of the National Living Wage.

Table 1: Means for the estimation sample

Variables	October 2015-March 2016		April 2016-September 2016	
	18-24	25-34	18-24	25-34
Arrest rate	0.011	0.006	0.010	0.005
Find rate	0.025	0.008	0.022	0.009
Stop rate	0.074	0.029	0.059	0.024
Kaitz index	0.527	0.563	0.527	0.605
Number of observations	15,372	15,372	15,372	15,372

Notes: The sample is restricted to the sample used in Table 2.

Table 2: Baseline regression estimates

Variable	Dependent variable					
	(1) Arrest rate	(2) Find rate	(3) Stop rate	(4) Arrest rate	(5) Find rate	(6) Stop rate
Aged 25 plus \times post-April 2016	0.001*** (0.000)	0.002*** (0.000)	0.009*** (0.003)			
Kaitz index				0.017** (0.006)	0.038*** (0.009)	0.224*** (0.075)
Elasticity	0.071	0.110	0.215	1.274	1.431	2.958
R-squared	0.388	0.515	0.704	0.380	0.515	0.704
Number of observations	61,488	61,488	61,488	61,488	61,488	61,488

Notes: All models also include gender-age group-police area fixed effects and date fixed effects.

Observations are weighted by the population in each age group-police area cell.

Standard errors are clustered by police area and are presented in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 3: Robustness tests

Dependent variable	(1) Full sample	(2) Full sample	(3) Forces with stops	(4) Excluding Dec 2015	(5) Aged 10+	(6) Tobit
Arrest rate	0.015*** (0.005)	0.011* (0.006)	0.019*** (0.007)	0.017** (0.006)	0.018** (0.007)	0.035 (0.026)
Find rate	0.041*** (0.010)	0.029*** (0.008)	0.043*** (0.009)	0.049*** (0.009)	0.040*** (0.009)	0.058** (0.029)
Stop rate	0.215*** (0.067)	0.201*** (0.071)	0.244*** (0.076)	0.268*** (0.099)	0.223*** (0.063)	0.297*** (0.085)
Gender-age group-police area fixed effects	Yes	No	Yes	Yes	Yes	Yes
Gender-age group-chief constable fixed effects	No	Yes	No	No	No	No
Police area-date fixed effects	Yes	No	No	No	No	No
Date fixed effects	No	Yes	Yes	Yes	Yes	Yes
Number of observations	61,488	66,528	58,560	56,280	122,976	61,488

Notes: Observations are weighted by the population in each gender-age group-police area cell. Standard errors are clustered by police area (or chief constable in column 2) and are presented in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 4: Heterogeneity in Kaitz index coefficient according to time and object of stop using arrest rate

Crimes	All hours	Business hours	Non-business hours
All crimes	0.017** (0.006)	-0.001 (0.003)	0.018** (0.009)
Theft crimes	0.003 (0.002)	0.002** (0.001)	0.001 (0.001)
Drug crimes	0.014*** (0.004)	-0.002 (0.003)	0.017*** (0.006)
Anti-social crimes	-0.005** (0.003)	-0.003 (0.002)	-0.002** (0.001)
Other crimes	0.005 (0.006)	0.002 (0.002)	0.003 (0.004)

Notes: All models also include gender-age group-police area fixed effects and date fixed effects.

Observations are weighted by the population in each gender-age group-police area cell. Standard errors are clustered by police area and are presented in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 5: Heterogeneity in Kaitz index coefficient according to time and object of stop using find rate

Crimes	All hours	Business hours	Non-business hours
All crimes	0.038*** (0.009)	-0.007 (0.009)	0.046*** (0.014)
Theft crimes	0.005** (0.002)	0.003*** (0.001)	0.002 (0.002)
Drug crimes	0.034*** (0.007)	-0.008 (0.008)	0.042*** (0.010)
Anti-social crimes	-0.008** (0.004)	-0.005 (0.003)	-0.003*** (0.001)
Other crimes	0.007 (0.008)	0.003 (0.003)	0.005 (0.005)

Notes: All models also include gender-age group-police area fixed effects and date fixed effects.

Observations are weighted by the population in each gender-age group-police area cell. Standard errors are clustered by police area and are presented in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 6: Heterogeneity in Kaitz index coefficient according to time and object of stop using stop rate

Crimes	All hours	Business hours	Non-business hours
All crimes	0.224*** (0.075)	0.014** (0.006)	0.210*** (0.075)
Theft crimes	0.021*** (0.007)	0.005** (0.002)	0.016*** (0.005)
Drug crimes	0.192*** (0.062)	0.008 (0.006)	0.184*** (0.063)
Anti-social crimes	-0.015 (0.011)	-0.010 (0.008)	-0.005 (0.004)
Other crimes	0.026 (0.031)	0.011 (0.011)	0.015 (0.020)

Notes: All models also include gender-age group-police area fixed effects and date fixed effects.

Observations are weighted by the population in each gender-age group-police area cell. Standard errors are clustered by police area and are presented in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.