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No. 2020/4 ISSN 1478-9396

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AUGUST 2020

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Crime Heterogeneity and Welfare Spending: Theory and Empirical Evidence based on the Universal Credit System

King Yoong Lim* and Reagan Pickering**

This Version: August 2, 2020

Abstract

We examine the effects of welfare spending on crime, using the universal credit (UC) system in England and Wales as a case study. Motivated by a seemingly positive crime-UC nexus, we develop a novel theoretical model of crime and cash transfer that distinguishes between *introductory* and *level* effect, as well as a crime-specific human capital-induced heterogeneity between criminal activities. Based on county-level data for 10 crime types, we use both standard fixed-effect estimator and different instrumental variable-estimation strategies (to account for endogeneity of the UC rate) to evaluate the theoretical propositions. Criminal damage and arson are found to exhibit the characteristics of being criminal human capital-dependent. In contrast, as a policy tool to combat crime, welfare spending appears to be most effective in reducing public disorder and weapon possessions. Overall, we find the claim that UC policy has led to an increase in crime rate to be overstated.

JEL Classification Numbers: C26, H53, H75, K42.
Keywords: Crime Heterogeneity, England and Wales, Universal Credit, Welfare Spending.

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1 Introduction

Since the studies of Becker (1968) and Ehrlich (1973), the economics of crime literature, which examine criminal activities as behavioural choices made by individuals driven by economic incentives, has blossomed into a distinct field on its own. Recent contributions, including the many studies of Machin and coauthors on crime (see, for instance, Machin and Marie, 2006; Draca and Machin, 2015) highlight the significance of policies and institutions in explaining variations in crime. Specifically, if policy changes or streamlining of institutions created unintended economic incentives for agents to engage in illegal activities, then there can be disproportionate effects on crime incidence. Motivated by an expansion in the aggregate number of crime following the phased rollout of the Universal Credit (UC) system across England and Wales, where the total number of recorded crime cases rose from approximately 4.2 million in 2014 to 6 million in 2018, this study contributes to the literature by examining—both theoretically and empirically—the effect of welfare spending on crime, using the UC rollout as a measure for the former.

Initially announced back in 2010, the UC programme is a 'phased roll-out' welfare system that aims to replace the prior roles of six 'legacy' welfare system (Child Tax Credit, Employment and Support Allowance, Housing Benefit, Income Support, Jobseeker's Allowance, and Working Tax Credit) by a single, more efficient centralized payment system. Despite this purpose, the UC can be considered as an entirely new system due to the significant differences it impacts on the incentive mechanism of individuals. First, despite some existing claimants being transferred directly to the new system through 'managed migration', the UC programme is treated as an entirely new 'start-up' system, where the bulk of the registered claimants are through 'natural migration', in that, these are newly enrolled individuals with new circumstances. Second, the UC system also comes with a new set of much more stringent requirements to claimant eligibility, which includes a 'benefit cap' for maximum claimable amount, so as to increase the incentive for claimants to not perpetually stay on the system. Third, by virtue of the British government adopting a 'phased roll-out' mechanism, the different counties across England and Wales have seen vastly different dates for the actual implementation of the system, with some counties seeing its launch in early 2013 and others late into 2015. Further, due to its unique design, significant lags have been widely reported between announcement, application/enrolment, and payment, which are argued by some, such as the sociology-based study of Tiratelli *et al.* (2020), to bring about an adverse policy effect to the low-income households and subsequently, an incentive to commit crime. Given these uniqueness, it is reasonable to treat the UC programme as a new welfare system that is distinct from the other social welfare system in the UK. Although by comparison, the estimated 2.5 million individuals that utilize the system dwarfs that of the total social welfare system in the UK (estimated to cover about 20 million individuals, of which 13 million is on state pension, as reported in Department for Work and Pensions, 2020), its coverage is still wide and is the most representative welfare system that is recently launched. Indeed, as seen later, given that a key instrumental variable used in our empirical estimation is the non-UC real benefit expenditure, the results are appropriate for a general interpretation of the effects of welfare spending on crime.

In terms of the existing literature, our study is closest to Machin and Marie (2006) and Tiratelli *et al.* (2020). The former found the toughening of the Jobseekers Allowance (basically, the unemployment benefit regime) led to an increase in crime rates in the UK, whereas the latter shares the same research focus as ours, i.e. the crime-UC nexus at a local level across England and Wales. There are nonetheless many fundamental differences of our study from the latter, which documented an empirical paradox of a positive crime-UC relationship at the aggregate level. Of note, there are three novel contributions that distinguish our study: (i) by utilizing a reverse geocoding technique, we are able to account for the heterogeneity across different crime types by building our crime statistics using a bottom-up approach. This turns out to be crucial as the crime-UC nexus differs markedly across different types of crime, which the aggregate analysis of Tiratelli *et al.* (2020) has failed to identify. Indeed, the significance of crime heterogeneity is easily observed in Figure 1; (ii) we develop a novel theoretical model of crime and cash transfer that distinguishes between *introductory* effect and *level* effect, which together with a crime-specific human capital-induced heterogeneity between criminal activities, provides the scientific basis to our empirical results; (iii) we uncover the endogeneity problem associated with the UC rate measure, and account for this using instrumental variable (IV) regressions. Indeed, it turns out that their study overstates the impact of the UC welfare system in elevating crime rate in the UK; (iv) we provide a more generalizable contribution and explanations of the mechanisms linking welfare payment and crime, which is supported by empirical implementation that accounts for the role of relative human capital.

Theoretically, our criminal human capital-based explanations of crime heterogeneity is similar in spirit to Mocan *et al.* (2005), Mocan and Bali (2010), Jia and Lim (2020). Empirically, our study shares similar characteristics with a number of contributions examining the crime-welfare payment nexus, which remains largely undetermined. On one end, studies such as Hannon and Defronzo (1998), Farrall (2006), Chioda *et al.* (2016), Breckin (2019) found various temporary assistance and cash transfer programmes to facilitate crime reduction. On the other end, studies such as Burek (2005), Foley (2011), Cameron and Shah (2014) find that welfare payment can lead to unintended consequences of an increase in crime, be it due to misallocation/mistargeting of the programme, or that the welfare beneficiaries simply treat welfare-related income as supplement to their main criminal income. Further, as found by Liebertz and Bunch (2018) when evaluating the impact of *Temporary Assistance for Needy Families* programme in the United States, these effects could differ across different types of crime.

Indeed, our study is also related to other similar studies on crime that found the effects of policies or shocks to differ markedly across different types of crime. For example, in examining crime rates at the local administrative level in nineteenth-century France, Bignon *et al.* (2017) find negative income shock to cause an increase in theft and property crime, but a significant decrease in violent crime. The Colombia-based study of Cortés *et al.* (2016) found violent crime and robbery to respond differently to negative economic shock. Similarly, when assessing the effect of military enlistment on crime in the United States during the Vietnam War era, Lindo and Stoecker (2014) documented that draft eligibility increases incarceration for violent crimes but decreases incarceration for non-violent crimes. Moreover, these different effects also appear to vary across different regions, with results obtained often overturn findings based on more highly aggregated data (Cook and Winfield, 2015). Indeed, studies such as Raphael and Winter-Ebmer (2001), Arnio *et al.* (2012) found significant state- or regional-specific effects in their empirical analysis. Indeed, for our study, even at an aggregate level, Figure 2 clearly illustrates that the absolute difference between crime rate in 2013 and 2018 can be markedly different across the different counties. In addition to crime heterogeneity, this therefore highlights the equal-importance of county-level empirical analysis.

The rest of the paper are structured as follows. Section 2 presents a theoretical model of crime and cash transfer, which includes the derivation of three theoretical propositions explaining the mechanism linking cash transfer and crime. Section 3 discusses the empirical strategy and data in details. Section 4 present the results and interpret these results in according to the theory. To preview, we find the property crime type of criminal damage and arson to most exhibit the characteristics of criminal human capital-driven in England and Wales, whereas public disorder and weapon possessions appears to be most responsive (negatively) to the positive income effect bought about by welfare spending. Finally, Section 5 concludes the paper.

2 A Theoretical Model of Crime and Cash Transfer

We attempt to provide a theoretical basis by developing a simple model of crime heterogeneity (two broadly-defined types of criminal activities with different nature) and cash transfer. Although in reality the British UC programme is a more sophisticated scheme than a cash transfer, we believe this set-up adequately captures the salient feature of the welfare payment being an additional exogenous income earned by the individuals effortlessly, compared to both market works and illegal/criminal activities.

There is a continuum of identical infinitely-lived individuals, $i \in [0, 1]$, in the economy, with a typical individual i deriving utility from consumption, $C_{i,t}$, and leisure, $l_{i,t}$. Each individual has a unit endowment of time, and in addition to leisure allocates time to legal employment, $n_{i,t}$ (earning real market wage rate, w_t), basic criminal activities, $\theta^B_{i,t}$, and criminal human capital-dependent crime, $\theta^C_{i,t}$. Hence, $l_{i,t} + n_{i,t} + \theta^B_{i,t} + \theta^C_{i,t} = 1$. The illegal 'earnings' from criminal human capital-dependent crime, is determined in effective terms, $h^C_{i,t}\theta^C_{i,t}$, where $h^C_{i,t}$ is akin to a crime-specific human capital level which represents the accumulated stock of 'investment' made by individual i into building up criminal human capital , with an initial endowment, $h^C_0 = 1$.[1] In contrast, basic crime, $\theta^B_{i,t}$, does not depend on it. Given that it is peripheral to our main focus, for convenience, we assume that the human capital level of legal employment is normalized

[1] We could have easily introduced a capital accumulation function to legal human capital as well, in a differentiated human capital (one for legal, another for crime-specific) framework similar to Mocan et al. (2005), Jia and Lim (2020). This is peripheral and non-essential to the understanding of the differences in crime-UC nexus, and hence abbreviated in the model.

to unity. In each period t, a typical individual i solves an intertemporal optimization problem by choosing sequences of $\{C_{i,t}\}_0^\infty, \{n_{i,t}\}_0^\infty, \{\theta_{i,t}^B\}_0^\infty, \{\theta_{i,t}^C\}_0^\infty, \{h_{i,t+1}^C\}_0^\infty$, to maximize the lifetime expected utility function:

$$U_t^i = \mathbb{E}_t \sum_{t=0}^{\infty} (1+\Lambda)^{-t} \left[\eta^C \ln(C_{i,t}) + \eta^L \ln(1 - n_{i,t} - \theta_{i,t}^B - \theta_{i,t}^C) \right], \tag{1}$$

where $\mathbb{E}_t$ is the expectation operator, $C_{i,t}$ is consumption, $\Lambda \in (0,1)$ is the discount factor, η^C and η^L are the preference parameters for consumption and leisure respectively.

In standard fashion, the budget constraint is state-dependent. Specifically, assuming a two-state Markov process, in each period at a constant probability $\pi \in (0,1)$, the individual receives net income from formal market work [similar to studies such as Imrohoroğlu et al. (2004), an assumption in which a fraction $\varrho \in (0,1)$ of this income is lost to crime is specified, which means individuals do become victims of crime too], a cash transfer/welfare payment, $Z_{i,t}$, and the illicit income from crime, $X_{i,t}$. Further, in line with Neanidis and Papadopoulou (2013), Jia et al. (2020), we assume that the amount of resources that are lost to crime, $X_{i,t}$, corresponds only to the fraction of the victim's legal income. The illegal income, $X_{i,t}$, is therefore not at risk to crime. In contrast, at a probability $1-\pi$, the individual is caught when committing crime, resulting in zero income for the period.[2] The period-specific income of the individual is therefore:

$$Income_{i,t} = \begin{cases} (1-\varrho) n_{i,t} w_t + X_{i,t} + (1-\varrho) Z_{i,t} & \text{with prob. } \pi \\ 0 & \text{with prob. } 1-\pi \end{cases}, \tag{2}$$

[2] In real-life context, this can be interpreted in a number of alternative ways yet remains analytically equivalent. We can interpret the zero income received as the individual having all the income confiscated by authorities, or simply being punished and put in jail for the specific period, hence resulting in zero income-earning opportunity. Nevertheless, we do assume that no stigma is attached to a jailed individual in the subsequent periods.

which is spent on consumption, $C_{i,t}$, and a contribution/investment made to crime-specific human capital, $J_{i,t}$. As such, $\mathbb{E}_t(Income_{i,t}) = C_{i,t} + J_{i,t}$, where for analytical convenience, the latter is assumed to be a small fraction diverted from the net cash transfer received, $J_{i,t} = \varkappa(1-\varrho)Z_{i,t}$, $\varkappa \in (0,1)$, as in those mistargeting instances described in Cameron and Shah (2014). To ensure that the cash transfer positively affects consumption, $\partial C_t/\partial Z_t > 0$, $\varkappa < \pi$ must also hold. Further, following Locher (2004), Neanidis and Papadopoulou (2013), the illegal income from crime, $X_{i,t}$, is increasing in the time individuals spent in these activities, and therefore given by:

$$X_{i,t} = (\theta^B_{i,t} + h^C_{i,t}\theta^C_{i,t})\varrho(n_{j,t}w_t + Z_{j,t}), \tag{3}$$

which linearly depends on the total resources lost to crime by another individual j, $\varrho(n_{j,t}w_t + Z_{j,t})$, $j \neq i$. Finally, the growth of the crime-specific human capital over time depends positively on the resources diverted to building up the criminal human capital, as well as the raw time spent in the activities:

$$\frac{h^C_{i,t+1}}{h^C_{i,t}} = [\varkappa(1-\varrho)Z_{i,t}]^\beta(\theta^C_{i,t})^\psi, \text{ where } \beta \geq 0, \psi \geq 0. \tag{4}$$

Assumption: $\psi = 1$. For analytical tractability, we assume that the growth of crime-specific human capital linearly depends on raw time spent on these criminal activities. Then, by imposing the terminal conditions, $\lim_{T->\infty}(1+\Lambda)^{-T}\mathbb{E}_t(\lambda_{t+T}h^C_{i,t+T+1}) = 0$, and let $\sum_{k=1}^{\infty}(1+\Lambda)^{-k}\mathbb{E}_t(Z_{i,t+k}) = Z_{i,t}/\Lambda$, solving the individuals' intertemporal optimization problem yields the first-order conditions of individual i (see Appendix A). In a symmetric equilibrium, given that the identical individuals are indexed in $i \in [0,1]$, we know that on aggregate, the individuals' optimal choices are the same, hence $n_{i,t} = n_{j,t} = n_t$, $\theta^B_{i,t} = \theta^B_t$, $\theta^C_{i,t} = \theta^C_t$, $h^C_{i,t} = h^C_t$, $C_{i,t} = C_t$, $Z_{i,t} = Z_{j,t} = Z_t$. The optimal time allocation to criminal human capital-dependent and basic criminal activities in the economy are therefore given by:

$$\theta_t^C = \frac{C_t}{C_{t-1}}\left[(1+\Lambda)^{-1}\varrho\pi n_t w_t + (1-\varrho)^{\beta}(\varkappa Z_t)^{\beta}\right]^{-1}, \text{ and} \tag{5}$$

$$\theta_t^B = \frac{1}{2}\left[1 - \frac{C_t}{\eta^C}\frac{(h_t^C - 1)\eta^L}{h_t^C[\varkappa(1-\varrho)Z_t]^{\beta}} - \frac{(1-\varrho)w_t}{\varrho} - \theta_t^C\right]. \tag{6}$$

Proposition 1: *The cash transfer, Z_t, reduces the rate of criminal human capital-dependent crime, θ_t^C, if the direct marginal consumption gained from the transfer is larger than the marginal gains from diverting some welfare payment into criminal human-capital investment. In contrast, the crime-cash transfer relationship is positive if the latter outweighs the marginal consumption gain.*

$$\begin{aligned} \frac{\partial\theta_t^C}{\partial Z_t} &> 0, \text{ if } (\pi-\varkappa)^{-1}C_{t-1} < [(1-\varrho)^{\beta-1}\varkappa^{\beta}\beta(Z_t)^{\beta-1}\theta_t^C]^{-1}; \\ \frac{\partial\theta_t^C}{\partial Z_t} &< 0, \text{ if } (\pi-\varkappa)^{-1}C_{t-1} > [(1-\varrho)^{\beta-1}\varkappa^{\beta}\beta(Z_t)^{\beta-1}\theta_t^C]^{-1}. \end{aligned} \tag{7}$$

Proposition 2: *Assuming $\partial\theta_t^C/\partial Z_t \neq 0$, the relationship between the level of welfare payment and basic criminal activities is positive if the cash transfer reduces criminal human capital-dependent crime and that, the consumption level in the previous period is higher than the probability-adjusted cash transfer received in the current period, vise versa.*

$$\begin{aligned} \frac{\partial\theta_t^B}{\partial Z_t} &> 0, \text{ if } C_{t-1} \geq (\pi-\varkappa)(1-\varrho)Z_t \text{ and } \frac{\partial\theta_t^C}{\partial Z_t} < 0; \\ \frac{\partial\theta_t^B}{\partial Z_t} &< 0, \text{ if } C_{t-1} \leq (\pi-\varkappa)(1-\varrho)Z_t \text{ and } \frac{\partial\theta_t^C}{\partial Z_t} > 0. \end{aligned} \tag{8}$$

The proof for Propositions 1-2 are straightforward differentiation (see Appendix A).

In addition to the 'level' relationship between crime and cash transfer, we also examine the *introductory effect* of the UC policy to crime, based on the asymmetric characteristics of θ_t^B and θ_t^C. Specifically, by supposing that time $t = 0$ corresponds to the first disbursement of the UC payments, we can expect the policy *introductory effect* to have a comparatively short-term context. Indeed, based on (7), we would expect the sign of the *introductory effect* to depend largely on the strength of the term associated with the marginal consumption gained from cash transfer, vis-à-vis the strength of the second term, which is associated with the marginal gains from diverting the welfare payments into criminal human capital-investment. In practice, we can expect the relative strength and trade-off of these two effects to differ across criminal activities of different nature, beyond the crime-specific human capital-induced assymetry discussed. Indeed, in $t = 0$ and before the dynamic effect associated with the accumulation of crime-specific human capital can fully set in, it is likely that the direct marginal consumption gain would dominate the latter, hence $(\pi - \varkappa)(C_{t-1})^{-1} > (1 - \varrho)^{\beta-1}\varkappa^{\beta}\beta(Z_t)^{\beta-1}\theta_t^C$. This then suggests:

Proposition 3: *The introductory effect of the UC scheme is positive for criminal activities that are criminal human capital-dependent in nature, whereas the introduction of the UC scheme reduces basic crime.*

The proof is Appendix A. In short, given that $(\pi-\varkappa)(C_{t-1})^{-1} > (1-\varrho)^{\beta-1}\varkappa^{\beta}\beta(Z_t)^{\beta-1}\theta_t^C$, $\frac{\partial\theta_t^C}{\partial Z_t}|_{t=0} > 0$, which with $\frac{\partial\theta_t^B}{\partial Z_t}|_{t=0} = -\left(1 + h_0^C\right)\frac{\partial\theta_t^C}{\partial Z_t}|_{t=0}$, also implies $\frac{\partial\theta_t^B}{\partial Z_t}|_{t=0} < 0$. Hence,

$$\frac{\partial\theta_t^C}{\partial Z_t}|_{t=0} > 0, \text{ and } \frac{\partial\theta_t^B}{\partial Z_t}|_{t=0} < 0. \tag{9}$$

Finally, it is worth noting that, the two types of crime in the theory are broadly defined. In practice, based on a penal code-based classification, a number of different types of crime may fit the characteristics of θ_t^C, some other θ_t^B, and the remainders not explainable by this crime-specific human capital framework. It is part of our research objectives to let the empirical results informing these. In other words, we do not make prior assumption on which type of crime belongs to θ_t^B or θ_t^C, but instead let the empirical results speak. Specifically, we would expect a crime type that empirically exhibits both positive level and introductory effects to be crime human capital-dependent. In contrast, for a crime type that empirically exhibits both negative level and introductory effects, it is likely to be basic in nature and therefore most likely to benefit/reduce from targeted use of welfare spending.

3 Empirical Strategy and Data

As mentioned, to empirically examine the effects of welfare spending on crime rates, we focus on the case of the universal credit (UC) system in England and Wales. As the premise of the UC system rests on it being claimed as efficient due to the merging of six 'legacy' welfare system into one centralized payment system, its relatively recent implementation and wide coverage allow it to be an ideal case study in the examination of the theoretical propositions. Specifically, the benchmark form of the empirical model is given by:

$$\theta_{jt}^k = \alpha_0 + \alpha_1 Z_{jt} + \alpha_2 U_{jt} + \alpha_3 \tau_{jt} + \sum_{l=1}^{L} \psi_l X_{l,jt} + \epsilon_j + \epsilon_t + u_{jt}, \tag{10}$$

where $j(t)$ is the county/unitary authority (time) index, θ_{jt}^k refers to the logarithm of the crime rate of type k in county j and time t, Z_{jt} is the logarithm of UC rate, U_{jt} and τ_{jt} measure the *Introductory* effect of the UC policy and the associated time trend post-occurence of the first payments respectively, $\{X_{l,jt}\}_{l=1}^{L}$ denote the set of L county-specific control variables that are well-recognized determinants of crime, ϵ_j (ϵ_t)

is the time(county)-invariant county(time)-specific effects, and u_{jt} is the random error terms uncorrelated with the regressors.[3,4]

Based on the theoretical propositions, the coefficients of primary interest are α_1 and α_2. Although interpretation based solely on the sign of α_1 could indicate a crime type being either basic or criminal human capital-specific, a joint-positive estimates with α_2 would affirm its nature as being driven by criminal human capital, hence most-likely 'beneficiary' of a mistargeting of welfare payment. In contrast, a joint-negative would affirm a crime type being not influencable by criminal human capital, therefore most-effectively reduceable by welfare payment. In addition, standalone interpretation of the sign of α_2 would also enable us to provide a more accurate picture on the role of the UC policy in affecting a certain crime type (compared to Tiratelli *et al.*, 2020), despite this—if without corresponding statistical significance for α_1—not allowing us to reconcile the empirical evidence with the theory.

As an in-built means for robustness check, we consider three specifications: (i) $L = 0$ for Specification 1; (ii) $L = 4$ for Specification 2, where population density, logarithm of real gross weekly wage (to reflect income differences across counties), unemployment rate, and logarithm of police per capita are included. The inclusion of the first two is standard in the crime literature. The exogenous effect of unemployment on crime is well-established in studies such as Mauro and Carmeci (2007), Fougére *et*

[3] Of note, the UC rate is calculated by dividing total universal credit claimants with total population (per 1000 inhabitants), as in Tiratelli et al. (2020). As argued by them, this is pretty much the only available measure of UC payment due to the general non-availability of monetary data for UC at county level, but can be justified due to the 'Benefit Cap' limiting the maximum amount one could claim. This effectively compresses the distribution of the payment received per person. Nevertheless, as shown in our empirical estimation later, the fact that UC rate is based on a headcount measure leads to some endogeneity issues with crime rates, which is neglected in Tiratelli *et al.* (2020) but mitigated by us using instrumental variable (IV) approach.

[4] The inclusion of a time trend post-UC in accompanying the *Introductory* effect is a popular approach in the regression discontinuity design (RDD) literature. Although we are not interested in measuring any threshold effect associated with the role of such a rolling variable (as in most RDD studies), the inclusion of this time trend is consistent with the graphical evidence observed of a positive trend for both aggregate crime and UC rate in recent years.

al. (2009), and this is on top of it being a common indicator used as a proxy for business cycle (Detotto and Otranto, 2012). The significant role of law enforcers and police personnels is documented in studies such as Corman and Mocan (2000), Draca *et al.* (2011). Lastly, for Specification 3, we attempt to capture the significant lags documented in Tiratelli *et al.* (2020) between enrolment and disbursement of UC payments by modifying U_{jt} to not just equal one on the time when UC payment is first recorded for a county, but also the preceding 11 months (year) in the monthly(annual)-based regression. Furthermore, two additional controls that are of slightly longer-term nature—national-level CPI growth rate and county-level conviction rate—are included in this specification to account for the lengthier consideration of the *Introductory* effect. The former is attributed to the recent study of Draca *et al.* (2019) who documented that changing in prices leads to crime variations, whereas the latter reflects the different quality of the judiciary system across counties (Mocan *et al.*, 2020).

In terms of the data, for crime measures we employ a reverse geocoding technique similar to Bernasco and Block (2011) to build both our monthly and annually crime rates from bottom-up.[5] Specifically, from the open data source of data.police.uk, all the individual street-level crime incidence reported are tagged to the different counties based on coordinates (latitude and longitude), and then aggregated according to the nature of the crime type reported. Specifically, we examine 10 different classifications (anti-social behaviour, burglary, criminal damage and arson, drugs, other crime, public disorder and weapon possessions, robbery, theft, vehicle crime, and violent crime). These cover the months from 2010-12 to 2019-12 (for annual-based estimation, the years of 2011-19), and a total of 173 counties. For the UC data, as well as the real benefit expenditure data we used as an instrument, we obtain the county-level information from

[5] As discussed in studies such as Kwan *et al.* (2004), Tompson *et al.* (2015), Quinn *et al.* (2019), due to data protection and statistical disclosure considerations, anonymized case-level data are subject to procedures such as obsfucation and geomasking. Nevertheless, this will only have material effect on the accuracy of street-level analysis, which is not the focus of our analysis.

Department for Works and Pensions. The policing figures are sourced from the open data site of the Home Office, while the other data are primarily drawn from the Office for National Statistics. The summary statistics of the full sample are presented in Table 1, with further information on data treatments and frequency conversion documented in Appendix B. Nevertheless, it is worth noting that for econometric estimation the effective sample size is much smaller, as this is capped by the available observations for the logarithm of UC rate, at $9,975$ for the monthly data and 923 for the annual data.

In terms of econometric strategy, we first begin with a monthly-based fixed-effect estimation of the benchmark model, with the three different specifications applied to the 10 different crime types. Formal Hausman tests are implemented, but save for a negligible few of the skeletal Specification 1 estimation, test statistics are predominantly in favour of fixed-effect estimators. Endogeneity tests are then implemented, which is based on the chi-squared test documented in Baum *et al.* (2003, 2007). To preview, in at least half of the benchmark estimation the UC rate is found to be endogenous, which necessitates the adoption of an instrumental variable (IV) approach. The same set of monthly estimation is then repeated using a panel-IV estimator, where the much more exogenous monetary measure of non-UC benefit expenditure (in real terms) per claimant is used as an instrument for UC rate.

After that, we estimate the benchmark model using annual data. This serves two purposes: (i) additional robustness; (ii) the availability of county-level educational attainment data enables us to construct a proxy measure based on relative human capital level, which then allows us to use additional instruments in the subsequent IV estimation to provide better reconciliation of any *Introductory* effect observed empirically to the criminal human capital-based theoretical explanations. Specifically, this is calculated as:

$$RHC_{jt} = N_{jt}^{NQ} / N_{jt}^{Q4}, \tag{11}$$

where N_{jt}^{NQ} and N_{jt}^{Q4} are the proportion of residents without any educational qualification and with tertiary education respectively.[6]

Indeed, the same issue with endogeneity is observed again for 5/10 types of the annual crime rates examined. For the annual data-based, IV estimation, we estimate the model using different instrumenting strategies. Specifically, in addition to the strategy employed in monthly estimation, we also consider the strategies of: (i) using real benefit expenditure per head and the change of the relative human capital proxy in jointly instrumenting for UC rate and *Introductory* effect; and (ii) in addition to the two, using also the level measure of the relative human capital to serve as joint-instruments for UC rate, *Introductory* effect, and the post-UC trend measure. As we have exercised a rule-of-thumb, 'n instruments for n regressors' strategy, underidentification is more of a concern than overidentification. To test this, we implement the underidentification test of Kleibergen and Paap (2006).

4 Results and Interpretation

To begin with, the first set of results estimated using monthly data is presented in Tables 2 and 3. Disregarding the endogeneity issue identified, on the surface we observe that most crime rates do share a positive association with the UC rate, which is consistent with the empirical estimates of Tiratelli *et al.* (2020) using aggregate crime data. Unlike what they claimed, with the post-UC time trend properly accounted for, and the exogeneity of UC rate as a regressor being in doubt, we find this positive UC-crime association is largely independent of the UC policy. Indeed, a quick examination of the

[6] Strictly speaking, one could argue that the proportion of residents without any educational attainment does not necessarily reflect crime-specific human capital. However, given the well-documented inverse relationship between schooling and crime (Lochner and Moretti 2004; Machin et al. 2011), a more intuitive interpretation of RHC_{jt} is that of an inverse of the formal human capital ratio. For a given level of formal human capital, an increase in RHC_{jt} would likely imply the 'human capital' at the other end of the spectrum (crime-specific) has increased.

statistically significant estimates of the other control variables commonly documented as determinants of crime in the literature shows indicates the importance of crime heterogeneity. As an example, the estimated coefficients for police personnels are negative for burglary, vehicle crime, criminal damage and arson, but are positive for violence, public disorder and weapon possessions. In evaluating the effect of welfare spending on crime, it is therefore necessary to account for the different characteristics of crime.

To address the endogeneity between the crime and UC rates (both are effectively 'headcount' measures), Tables 4 and 5 summarize the set of results based on the fixed-effect estimation using real benefit expenditure per claimant as an instrument for UC rate. Notwithstanding the fact that this is a more appropriate measure for welfare spending, further endogeneity tests using the instrument have indeed revealed that, except for violent crime, it is a relatively more exogenous regressor. Having accounted for the endogeneity issue, we find that both the estimated $\hat{\alpha}_1$ and $\hat{\alpha}_2$ are statistically significant for robbery and the property crimes (vehicle crime and arson). These suggest that these criminal activities exhibit the charactistics of criminal human capital-dependent, and therefore most-likely 'beneficiary' of any mistargeting of welfare payment. Indeed, the observation with property crimes appears to be consistent with the American evidence of Burek (2005) and Liebertz and Bunch (2018), but contradicts the earlier British finding of Farrall (2006), who concentrates solely on the period of economic crisis in early-2000s. On the opposite side of the spectrum, the crime of public disorder and weapon possessions, which generally covers the infamous knife crime (caught before a violent crime is committed), as well as the 'catch-all' category of other miscellaneous crime, register statistically significant negative estimates for both $\hat{\alpha}_1$ and $\hat{\alpha}_2$. In relation to the three propositions, these indicate that these crime types do not contain any criminal human capital element, and can therefore be effectively reduced through the income effect brought about by welfare spending. Non-conclusive evidence are observed for the remaining crime types, though the crime-UC positive association remains robust for anti-social behaviour. Given that these are likely to be basic crime, by virtue of Proposition 2, this may suggest that on average, anti-social behaviour in England and Wales may reflect incidence of individuals who experience a shortfall in consumption that cannot be met by the expected welfare payment received.

Next, we move on to assess the annual data-based, fixed-effect estimation results. The corresponding estimation for Tables 2 and 3 are summarized in Tables 6 and 7. Similar to the monthly results, without accounting for the endogeneity of UC rate, we observe that most crime types correlate positively to the gradual rise in UC rate. Likewise, except for robbery and theft, none of these positive associations can be directly attributed to the roll-out of the UC welfare scheme. Interesting, the robbery rate appears to respond positively to the introduction of UC, whereas theft rate registered negative estimates for $\hat{\alpha}_2$. Given what is commonly known about these two types of crime, interpreting these against Proposition 3 lends some supports to the validity of our crime heterogeneity theory.

Finally, Tables 8 and 9 summarize the set of results based on IV estimation of the full specification of (10), i.e. Specification 3, using three different instrumenting strategies.[7] As mentioned, to improve the matching of the empirical evaluation with the theory, two additional instrumental variables (based on the growth and the level of RHC_{jt}) are employed in the alternative strategies presented. In these instances, the consideration is therefore not as much of an econometric one, but driven by the desire of bringing in relative human capital/educational attainment information into the estimation. In other words, any statistical significant policy effect observed is comparatively more attributable to variation in relative human capital, and therefore more

[7] We have also implemented all three strategies on model specification 1 and 2. As the estimated coefficients for $\hat{\alpha}_1$ and $\hat{\alpha}_2$ are qualitatively similar to those presented in Tables 8 and 9, these are not presented to save space.

relatable to the theory. This being said, all but one of the Kleibergen-Paap instrument identification tests did return a P-value that is less than 0.1, which means the estimation of α_1, α_2, and α_3 remain adequately identified. In both Tables 8 and 9, we see that the positive $\hat{\alpha}_1$ and $\hat{\alpha}_2$ for criminal damage and arson remain statistically significant, which reaffirm its criminal human capital-driven nature in England and Wales. Likewise, the joint-negative $\hat{\alpha}_1$ and $\hat{\alpha}_2$ for public disorder and weapon possessions remain robust, which implies that welfare spending is likely to have a direct effect in tacking such criminal activities. Although evidence remains largely inconclusive for the other crime types, the introduction of UC appears to result in a statistically significant upward shift in the crime rates of robbery and vehicle crime. These perhaps reflect a "growing opportunity" hypothesis as documented by Wright *et al.* (2017) for the United States pre-1990s, where the increase in welfare payments, if translated to a direct increase in cash and valuables being carried around by individuals, would lead to more opportunities for robbery or vehicles' break-in. This is nonetheless not covered by our theory and therefore speculative. However, overall our findings do suggest that, the "strain theory" argument made by Tiratelli *et al.* (2020), in the tradition of Agnew (1992), overstates the impact of the UC welfare payment system in elevating crime rate in the UK.

5 Concluding Remarks

The main purposes of this paper are to examine the effects of welfare spending on crime, using the universal credit (UC) system in England and Wales as a case study. Motivated by a seemingly positive crime-UC nexus observed at the aggregate level, we develop a simple yet novel theoretical model of crime heterogeneity and cash transfer to explain the mechanisms linking welfare payment to crime, showing that the effect can differ between the different types of crime due to the presence of a criminal human capital-induced asymmetry. Moreover, we distinguish between *introductory* effect and *level* effect, which turns out to be crucial in showing that the role of the UC system in elevating crime rate in the UK has been overstated. In addition, in our fixed-effect estimation at the county level using both monthly and annual data, we find that the relationship between welfare spending and crime differs significantly across the different types of crime. Informed by the theoretical propositions, the use of different instrumental variable-estimation strategies allow us to not only account for the endogeneity problem of the conventional measure of UC rate, but also reasonably ascertain the characteristics–and hence responses to welfare spending—of some types of crime in England and Wales. Specifically, the property crime type of criminal damage and arson exhibits the characteristics of criminal human capital-dependent, and therefore most-likely 'beneficiary' of any mistargeting of welfare payment. In contrast, as a policy tool to combat crime, welfare spending is likely to be the most effective in reducing public disorder and weapon possessions, which generally includes the infamous knife crime (caught before a violent crime is committed). Lastly, we also find weak evidence of the introduction of the UC system having lead to an upward shift in the robbery rate.

For future research, it is important to take note of some of the limitations of our study. First, the conventional measure of the UC rate is by definition, more of a headcount measure instead of monetary measure. Although we manage to overcome the endogeneity issue by using an imperfect instrument of the non-UC real benefit expenditure at the county level, there is likely behavioural differences had there been county-level monetary measure for the UC claims. When these disaggregated data are made available in the future, a more updated study will be required. Second, although we jointly evaluate both the *level* and *introductory* effect of the welfare system in question, the caveat is that this is not meant to be an evaluation of policy effectivness, as we did not employ a regression discontinuity framework. Third, although the reverse geocoding technique allows us to build our data in a bottom-up approach, our study do not account for any migration pattern associated with criminal activities. For example, a crime committed in Nottinghamshire can be attributed to a person who resides in another county, and this cannot be accounted for in our study. Lastly, we acknowledge that for many of the crime types, we do not find conclusive empirical evidence that allow for their behavioural patterns to be explained by our criminal human capital-based theory. A future study that assess and compare the strength of the different theories in explaining the different types of crime will be warranted.

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Appendix A: Technical Derivations

The derivations of the **Propositions** are as follows.

To solve the dynamic optimization problem of a typical individual i, we first set up the dynamic Lagrangian:

$$L = \mathbb{E}_t \sum_{t=0}^{\infty} (1+\Lambda)^{-t} \left[\eta^C \ln(C_{i,t}) + \eta^L \ln(1 - n_{i,t} - \theta^B_{i,t} - \theta^C_{i,t})\right] \tag{1}$$
$$+ \mathbb{E}_t \sum_{t=0}^{\infty} (1+\Lambda)^{-t} \lambda_t \{h^C_{i,t}[\varkappa(1-\varrho)Z_{i,t}]^\beta (\theta^C_{i,t})^\psi - h^C_{i,t+1}\},$$

which, given the expected value form of the individual's budget constraint in time t,

$$C_t = \pi(1-\varrho)n_{i,t}w_t + \pi(\theta^B_{i,t} + h^C_{i,t}\theta^C_{i,t})\varrho(n_{j,t}w_t + Z_{j,t}) + (\pi - \varkappa)(1-\varrho)Z_{i,t},$$

is equivalent to

$$L = \mathbb{E}_t \sum_{t=0}^{\infty} (1+\Lambda)^{-t} \{\eta^C \ln[\pi(1-\varrho)n_{i,t}w_t + \pi(\theta^B_{i,t} + h^C_{i,t}\theta^C_{i,t})\varrho(n_{j,t}w_t + Z_{j,t})$$
$$+ (\pi - \varkappa)(1-\varrho)Z_{i,t}] + \eta^L \ln(1 - n_{i,t} - \theta^B_{i,t} - \theta^C_{i,t})\}$$
$$+ \mathbb{E}_t \sum_{t=0}^{\infty} (1+\Lambda)^{-t} \lambda_t \{h^C_{i,t}[\varkappa(1-\varrho)Z_{i,t}]^\beta (\theta^C_{i,t})^\psi - h^C_{i,t+1}\}. \tag{2}$$

Differentiating (2) with respect to $n_{i,t}$, $\theta^B_{i,t}$, $\theta^C_{i,t}$, $h^C_{i,t+1}$, we yield the first-oder conditions:

$$\frac{\partial L}{\partial n_{i,t}} = 0 \implies \frac{\eta^C \pi (1-\varrho) w_t}{C_{i,t}} = \frac{\eta^L}{1 - n_{i,t} - \theta^B_{i,t} - \theta^C_{i,t}}, \tag{3}$$

$$\frac{\partial L}{\partial \theta^B_{i,t}} = 0 \implies \frac{\eta^C \pi \varrho n_{j,t} w_t}{C_{i,t}} = \frac{\eta^L}{1 - n_{i,t} - \theta^B_{i,t} - \theta^C_{i,t}}, \tag{4}$$

$$\frac{\partial L}{\partial \theta^C_{i,t}} = 0 \implies \frac{\eta^C \pi \varrho h^C_{i,t} n_{j,t} w_t}{C_{i,t}} - \frac{\eta^L}{1 - n_{i,t} - \theta^B_{i,t} - \theta^C_{i,t}} + \lambda_t \psi \frac{h^C_{i,t+1}}{\theta^C_{i,t}} = 0, \tag{5}$$

$$\frac{\partial L}{\partial h^C_{i,t+1}} = 0 \implies -\lambda_t + (1+\Lambda)^{-1} \frac{\eta^C \pi \varrho \theta^C_{i,t+1} n_{j,t+1} w_{t+1}}{C_{i,t+1}} + \lambda_{t+1}(1+\Lambda)^{-1}[\varkappa(1-\varrho)Z_{i,t+1}]^\beta (\theta^C_{i,t+1})^\psi = 0. \tag{6}$$

Further, from (1), we also know that the optimal consumption allocation would yield:

$$(1+\Lambda)^{-1} \frac{C_{i,t+1}}{C_{i,t}} = \frac{\lambda_t}{\lambda_{t+1}}, \tag{7}$$

which, together with (6), and after subsequent algebraic manipulation, would allow us to derive:

$$\frac{C_{i,t+1}}{C_{i,t}} = \left[(1+\Lambda)^{-1}\varrho\pi n_{j,t+1}w_{t+1} + (1-\varrho)^{\beta}(\varkappa Z_{i,t+1})^{\beta}\right]\theta^{C}_{i,t+1},$$

or equivalently, after lagging all variables by one period and with further rearrangements, yields an expression for the optimal allocation of time to criminal human capital-dependent crime in time t:

$$\theta^{C}_{i,t} = \frac{C_{i,t}}{C_{i,t-1}}\left[(1+\Lambda)^{-1}\varrho\pi n_{j,t}w_{t} + (1-\varrho)^{\beta}(\varkappa Z_{i,t})^{\beta}\right]^{-1}. \tag{8}$$

Next, combining (4) and (5), and knowing that $\lambda_t = (\eta^C/C_{i,t})$, and $h^C_{i,t+1} = h^C_{i,t}[\varkappa(1-\varrho)Z_{i,t}]^{\beta}(\theta^C_{i,t})^{\psi}$, with further rearranging of terms, we write

$$\frac{(h^C_{i,t}-1)\eta^L}{1-n_{i,t}-\theta^B_{i,t}-\theta^C_{i,t}} = \frac{\eta^C\psi h^C_{i,t}[\varkappa(1-\varrho)Z_{i,t}]^{\beta}(\theta^C_{i,t})^{\psi-1}}{C_{i,t}}. \tag{9}$$

At the same time, combining (3) and (4), and with rearrangments of terms, we derive:

$$n_{j,t} = \frac{(1-\varrho)w_t}{\varrho}. \tag{10}$$

In a symmetric equilibrium, given that the identical individuals are indexed in $i \in [0,1]$, we know that on aggregate, the individuals' optimal choices are the same, hence $n_{i,t} = n_{j,t} = n_t$, $\theta^B_{i,t} = \theta^B_t$, $\theta^C_{i,t} = \theta^C_t$, $h^C_{i,t} = h^C_t$, $C_{i,t} = C_t$, $Z_{i,t} = Z_{j,t} = Z_t$. In what follows, we can therefore subsume the subscript i when presenting the model solutions and deriving the propositions.

Assumption: $\psi = 1$. If we assumed that the growth rate, h^C_{t+1}/h^C_t, depends linarly on the raw time individuals spends in engaging with criminal human capital-dependent crime, θ^C_t, then (9) is rewritten as:

$$\frac{C_t}{\eta^C}\frac{(h^C_t-1)\eta^L}{h^C_t[\varkappa(1-\varrho)Z_t]^{\beta}} = 1-n_t-\theta^B_t-\theta^C_t.$$

Substituting in (10) for n_t, and rearranging of terms, we derive an expression for the optimal allocation of time to basic criminal activities:

$$\theta^B_t = \frac{1}{2}\left[1-\frac{C_t}{\eta^C}\frac{(h^C_t-1)\eta^L}{h^C_t[\varkappa(1-\varrho)Z_t]^{\beta}} - \frac{(1-\varrho)w_t}{\varrho} - \theta^C_t\right]. \tag{11}$$

Differentiate (8) with respect to Z_t, we can write $\partial\theta_t^C/\partial Z_t$ as:

$$\begin{aligned}\frac{\partial\theta_t^C}{\partial Z_t} &= \frac{\left[(1+\Lambda)^{-1}\varrho\pi n_t w_t + (1-\varrho)^{\beta}(\varkappa Z_t)^{\beta}\right]^{-1}}{C_{t-1}}\frac{\partial C_t}{\partial Z_t} \\ &\quad - \frac{(1-\varrho)^{\beta}\varkappa^{\beta}\beta(Z_t)^{\beta-1}\theta_t^C}{\{(1+\Lambda)^{-1}\pi\varrho n_t w_t + [\varkappa(1-\varrho)Z_t]^{\beta}\}},\end{aligned} \tag{12}$$

where the first term represents the marginal consumption gained from UC, whereas the second term represents the marginal gains from diverting some UC funds into 'investing' in criminal human capital-dependent crime.

Given that $\partial C_t/\partial Z_t = (\pi-\varkappa)(1-\varrho) > 0$ for reasonable values of $\varkappa < \pi$ (it is perfectly reasonable to assume that the universal credit positively affects consumption), both terms in (12) are positive. We therefore have:

$$\begin{aligned}&\frac{\partial\theta_t^C}{\partial Z_t} > 0, \text{ if } (\pi-\varkappa)^{-1}C_{t-1} < [(1-\varrho)^{\beta-1}\varkappa^{\beta}\beta(Z_t)^{\beta-1}\theta_t^C]^{-1}; \\ &\frac{\partial\theta_t^C}{\partial Z_t} < 0, \text{ if } (\pi-\varkappa)^{-1}C_{t-1} > [(1-\varrho)^{\beta-1}\varkappa^{\beta}\beta(Z_t)^{\beta-1}\theta_t^C]^{-1}.\end{aligned} \tag{13}$$

Likewise, differentiate (11) with respect to Z_t, we can write $\partial\theta_t^B/\partial Z_t$ as:

$$\begin{aligned}\frac{\partial\theta_t^B}{\partial Z_t} &= -\frac{(\eta^C)^{-1}(h_t^C-1)\eta^L}{2h_t^C[\varkappa(1-\varrho)Z_t]^{\beta}}\frac{\partial C_t}{\partial Z_t} \\ &\quad + \frac{C_t(h_t^C-1)\eta^L}{2\eta^C h_t^C(1-\varrho)^{\beta}\varkappa^{\beta}(Z_t)^{\beta+1}} \\ &\quad - \left(1+h_t^C\right)\frac{\partial\theta_t^C}{\partial Z_t},\end{aligned} \tag{14}$$

where, with $h_t^C \geq 1$, the first term by virtue of the negative sign in front is negative, the second term is positive, and the third term is ambiguous as it depends on the condition in (13).

Indeed, simplifying the first two terms further (by cancellation of similar terms), we can derive the mathematical conditions:

$$\frac{\partial\theta_t^B}{\partial Z_t} > 0, \tag{15}$$

if $C_{t-1} < (\pi-\varkappa)(1-\varrho)Z_t$ and $\dfrac{\partial\theta_t^C}{\partial Z_t} = 0$, or $C_{t-1} \geq (\pi-\varkappa)(1-\varrho)Z_t$ and $\dfrac{\partial\theta_t^C}{\partial Z_t} < 0$;

$$\frac{\partial \theta_t^B}{\partial Z_t} < 0, \tag{16}$$

$$\text{if } C_{t-1} > (\pi - \varkappa)(1-\varrho)Z_t \text{ and } \frac{\partial \theta_t^C}{\partial Z_t} = 0, \text{ or } C_{t-1} \leq (\pi - \varkappa)(1-\varrho)Z_t \text{ and } \frac{\partial \theta_t^C}{\partial Z_t} > 0.$$

Conditional on (13) holds, which means $\frac{\partial \theta_t^C}{\partial Z_t} \neq 0$, (15) and (16) can be simplified to:

$$\begin{aligned} \frac{\partial \theta_t^B}{\partial Z_t} > 0, \text{ if } C_{t-1} \geq (\pi - \varkappa)(1-\varrho)Z_t \text{ and } \frac{\partial \theta_t^C}{\partial Z_t} < 0; \\ \frac{\partial \theta_t^B}{\partial Z_t} < 0, \text{ if } C_{t-1} \leq (\pi - \varkappa)(1-\varrho)Z_t \text{ and } \frac{\partial \theta_t^C}{\partial Z_t} > 0. \end{aligned} \tag{17}$$

To assess the *introductory effect* of UC to θ_t^C, the initial admission stage of the UC would take place at time $t = 0$. Given that $h_0^C = 1$, and the dynamic effect of the accumulation of h_{t+1}^C has not yet set in at $t = 0$, we can rewrite (14) as

$$\frac{\partial \theta_t^B}{\partial Z_t} = -\left(1 + h_0^C\right) \frac{\partial \theta_t^C}{\partial Z_t}, \tag{18}$$

which shows the policy effect of UC on θ_t^B is opposite that of θ_t^C.

With the *introductory effect* effect concentrates relatively on the short-term horizon, in (12), we would expect its sign to depend largely on the strength of the term associated with the marginal consumption gained from UC transfer, vis-à-vis the strength of the second term, which is associated with the marginal gains from diverting UC funds into criminal human capital-dependent crime. Empirically, we can expect the trade-off of these two to depend on the different nature of the criminal activities in question.

Indeed, when the former dominates the latter, which can simply be shown as we 'muted' out the $[\varkappa(1-\varrho)Z_t]^\beta$ term (which is from the h_{t+1}^C equation), it is then obvious that $(\pi - \varkappa)(C_{t-1})^{-1} > (1-\varrho)^{\beta-1}\varkappa^\beta \beta (Z_t)^{\beta-1}\theta_t^C$ will hold in period $t = 0$, hence giving

$$\frac{\partial \theta_t^C}{\partial Z_t}|_{t=0} > 0, \tag{19}$$

which, by virtue of (18), implies that,

$$\frac{\partial \theta_t^B}{\partial Z_t}|_{t=0} < 0. \tag{20}$$

Combining the derived conditions in (13), (17), (19), and (20), we establish the theoretical basis underlying our four-quadrant proposition underlying the Crime-UC nexus.

This Working Paper presents work in progress.
The authors would welcome comments and feedback on the current state of the research presented here.

APPENDIX B: DATA IN BRIEF - Crime Heterogeneity and Welfare Spending: Theory and Empirical Evidence based on the Universal Credit System

King Yoong Lim, Reagan Pickering

Abstract

This Data In Brief document forms part of the online supplementary appendices that accompanies the article: **Lim, K.Y., Pickering, R.**, 2020. "Crime Heterogeneity and Welfare Spending: Theory and Empirical Evidence based on the Universal Credit System". It provides descriptions of the county-level data that can be utilised to replicate estimation results contained in the article. Note that this dataset is by definition, a secondary dataset as it is the end product of the integration and linking of data from different governmental sources, all made available publicly and licensed under *Open Government Licence v3.0*.

Specification Table

Specifically, this dataset covers 173 counties/unitary authorities in England and Wales at monthly frequency, starting from December 2010 to December 2019. As there are reporting gaps and inconsistency across the different police force in England and Wales, the dataset is balanced but with data gaps. Post-processed crime rate variables contained in the dataset includes the ten categories of anti-social behaviour, burglary, criminal damage and arson, drugs, other crime, public disorder and weapon possessions, robbery, theft, vehicle crime, and violent crime. In addition, the Universal Credit (UC) rate variable, the real benefit expenditure per head variable, and all the control and instrumental variables employed in the article are also contained in this dataset.

The detailed specification of this dataset is presented in Tables B1 and B2. The former lists all 173 counties contained in the dataset, as well as the original sources and relevant definition of the variables contained in the dataset. Table 2 provides further details in terms of the data treatment and frequency conversion procedures employed in the article.

Value of Data

The determinants of crime have been a long standing research topic for both academics and policymakers in the United Kingdom. Although this dataset is by construction, an end-product that integrates and links variables from different sources, it is valuable in the sense that it contains many of the variables that are relevant in the examination of the nexus between crime and welfare spending in England and Wales, covering the 10-year period that spans both before and after the roll-out of the universal credit system. In addition, this dataset also provides the following values:

- This dataset provides a compiled dataset of crime across all 43 Police Forces, using a bottom-up approach based on reverse geocoding technique. It therefore allows for more granular information to be accessed at the county/unitary authority level.
- The inclusion of several spatial specific aspects (*County/UA, Region and Police Force*) allows various geographically focused strains of analysis.

Data

The crux of the dataset is crime recorded data, which has been accessed from *data.police.uk*. The original data source provides *monthly* data releases by the different Police Forces in England and Wales at an anonymized, individual case level. Each Police Force's monthly dataset was compiled into a single Year-Month format. From there, using QGIS, the different crime incidence are aggregated into the different counties, utilising ONS boundary data to calculate which geospatial region a specific crime has taken place (specifically, based on the latitude and longitude information attached to each individual case).

After the core crime series are constructed, these are then linked to the other relatively macro-level

variables contained in Table B1. Most of the series for these variables are originally presented at county level, which then allows us to integrate them with the aggregated recorded crime series. Some of these are originally in annual frequency, and they are convered to monthly frequency using standard slicing technique, based on the respective economic definition. These are further explained in Table B2.

Disclaimer

Any discrepancies observed between this dataset and officially reported figures at the aggregate level may be due to:

- Difference in crime classifications included;
- Different geospatial area groupings;
- Obscuration and geomasking of the recorded data at case level made by the data owner and data provider, which is required to ensure that any open data made available to the public would satisfy the safe statistical disclosure requirements that are consistent with the UK Data Protection Act.

Appendix B

Table B1: Variables, Data, and Sample

Sample Counties/Unitary Authorities (n=173) - Balanced panel, but with data gaps*

Barking&Dagenham, Barnet, Barnsley, Bath&NE Somerset, Bedford, Bexley, Birmingham, Blackburn w.Darwen, Blackpool, Blaenau Gwent, Bolton, Bracknell Forest, Bradford, Brent, Bridgend, Brighton&Hove, Bristol, B.C. & Poole, Bromley, Buckinghamshire, Bury, Caerphilly, Calderdale, Cambridgeshire, Camden, Cardiff, Carmarthenshire, Central Bedfordshire, Ceredigion, Cheshire East, Cheshire West, City of London, Conwy, Cornwall, County Durham, Coventry, Croydon, Cumbria, Darlington, Denbighshire, Derby, Derbyshire, Devon, Doncaster, Dorset, Dudley, Ealing, East Riding of Yorkshire, East Sussex, Enfield, Essex, Flintshire, Gateshead, Gloucestershire, Greenwich, Gwynedd, Hackney, Halton, Hammersmith&Fulham, Hampshire, Haringey, Harrow, Hartlepool, Havering, Herefordshire County, Hertfordshire, Hillingdon, Hounslow, Isle of Anglesey, Isle of Scilly, Isle of Wight, Islington, Kensington&Chelsea, Kent, Kingston upon Hull, Kingston upon Thames, Kirklees, Knowsley, Lambeth, Lancashire, Leeds, Leicester, Leicestershire, Lewisham, Lincolnshire, Liverpool, Luton, Manchester, Medway, Merthyr Tydfil, Merton, Middlesbrough, M.Keynes, Monmouthshire, N.P. Talbot, Newcastle upon Tyne, Newham, Newport, Norfolk, NE Lincolnshire, North Lincolnshire, North Somerset, North Tyneside, North Yorkshire, Northamptonshire, Northumberland, Nottingham, Nottinghamshire, Oldham, Oxfordshire, Pembrokeshire, Peterborough, Plymouth, Portsmouth, Powys, Reading, Redbridge, Redcar&Cleveland, Rhondda Cynon Taff, Richmond upon Thames, Rochdale, Rotherham, Rutland, Salford, Sandwell, Sefton, Sheffield, Shropshire, Slough, Solihull, Somerset, South Gloucestershire, South Tyneside, Southampton, Southend-on-Sea, Southwark, St. Helens, Staffordshire, Stockport, Stockton-on-Tees, Stoke-on-Trent, Suffolk, Sunderland, Surrey, Sutton, Swansea, Swindon, Tameside, Telford and Wrekin, Thurrock, Torbay, Torfaen, Tower Hamlets, Trafford, Vale of Glamorgan, Wakefield, Walsall, Waltham Forest, Wandsworth, Warrington, Warwickshire, West Berkshire, West Sussex, Westminster, Wigan, Wiltshire, Windsor and Maidenhead, Wirral, Wokingham, Wolverhampton, Worcestershire, Wrexham, York.

Table B1: Variables, sources, and definitions

Variables	Sources	Remarks
Crime rates:		**Total recorded crimes for the specific category per 1,000 inhabitants**
Anti-social behaviour	data.police.uk	Includes personal, environmental and nuisance anti-social behaviour.
Burglary	data.police.uk	Includes offences where a person enters a house or other building with the intention of stealing.
Criminal damage & arson	data.police.uk	Includes damage to buildings and vehicles and deliberate damage by fire
Drugs	data.police.uk	Includes offences related to possession, supply and production.
Other crime	data.police.uk	Includes forgery, perjury, & other white-collar crimes
Public disorder and weapon possessions	data.police.uk	Includes all three categories of possession of weapons, public order, and public disorder
Robbery	data.police.uk	Includes offences where a person uses force or threat of force to steal.
Theft	data.police.uk	Includes all three categories of theft from the person, bicycle theft, shoplifting and other theft.
Vehicle crime	data.police.uk	Includes theft from or of a vehicle or interference with a vehicle
Violent crime	data.police.uk	Includes offences against the person such as common assaults, Grievous Bodily Harm and sexual offences.
Welfare spending/Cash transfer measures:		
UC rate	DWP (StatXplore)	Total Universal Credit Claimants as a rate of total population.
Real benefit expenditure	DWP	Real benefit expenditure divided by total welfare claimants (per 1000 inhabitants).
Real benefit expenditure per head	DWP	Benefit expenditure by local authority, deflated using national-level CPI index.
Other variables		
Proportion of residents who are welfare claimants	NOMIS (ONS)	Proportion of residents (16-64) who are claimants.
Proportion with NVQ4 qualification & above	NOMIS (ONS)	Proportion of residents (16-64) with NVQ4+.
Propotion with no qualification	NOMIS (ONS)	Proportion of residents (16-64) with No Qualification.
Real gross weekly pay	NOMIS (ONS)	Median Earnings.
Population density	NOMIS (ONS)	Total population divided by land area in acres
Unemployment rate	NOMIS (ONS)	Total unemployed economically active individuals divided by total population
Number of policing staff	Home Office	Number of Policing Staff by Police Force and Job Role.
CPI growth rate	ONS	Monthly rate figure, with 2015=100.
County-level conviction rate	Minstry of Justice	Released according to Police Force, and appended according to what Police Force operates in that area

* For some of the counties, data for second half of 2019 are not made available at the time of the analysis.

Table B2: Data treatment and frequency conversion

Variables	Origial frequency at source	Remarks
Crime incidence data:		
Anti-social behaviour	Individual recorded cases	-Cases are aggregated based on their recorded penal code categories to both monthly and annual frequency. Although anonymized, there are geographical tags (latitude/longitude information) recorded to cases and these are assigned to the corresponding Counties/Unitary Authorites using reverse geocoding technique.
Burglary	Individual recorded cases	
Criminal damage & arson	Individual recorded cases	
Drugs	Individual recorded cases	
Other crime	Individual recorded cases	
Public disorder and weapon possessions	Individual recorded cases	
Robbery	Individual recorded cases	
Theft (includes theft from the person, bicycle theft, & other theft)	Individual recorded cases	
Vehicle crime	Individual recorded cases	
Violent crime	Individual recorded cases	
Other data:		
Universal credit enrolment data	Monthly data	-Original source data is at county/UA level and in monthly frequency.
Benefit expenditure	Annual data	-Original source data is at county/UA level and in annual frequency. For the conversion to montly frequency, we apply equal weighting by dividing
Population	Annual data	-Original source data is at county/UA level. As it is a stock measure and is mainly used as a denominator in calculating rate measures, the same population is used for all the months within a year.
Gross weekly pay	Annual data	-The same measures are used as controls in both monthly- and annual-based estimations.
Unemployment	Quarterly data	-Original source data is at county/UA level and in quarterly frequency.
Police headcount	Annual data	-Police Force figures are appended according to each corresponding Force's operating boundaries.
Education attainment data	Annual data	-Original source data is at county/UA level.
CPI	Monthly data	-Original source data is at national level, and used to construct inflator/deflator to bring variables to real terms.
Convinction data	Annual data	-Original source data is at Police Force level and annual frequency, appending was conducted according to which Police Force operates in each area using boundary data.
Education attainment data	Annual data	-Original source data is at county/UA level and annual frequency.

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