The effects of welfare receipt on crime: A regression discontinuity and instrumental variable approach

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Abstract

Popular theories state that welfare receipt reduces criminal behavior. However, estimating the causal effect of welfare receipt on crime is empirically challenging due to unobserved characteristics influencing both welfare receipt and crime. This study exploits exogenous variation in Dutch welfare policy among individuals around the age of 27, which leaves applicants below this age threshold without discernible legitimate income. Using individual-level administrative data on the entire Dutch population around the age of 27, we estimate an instrumental variable model with a first-stage regression discontinuity design. Results show that welfare receipt reduces monthly crime rates from 0.51% to 0.19% for men and from 0.14% to 0.03% for women. For men, we find a larger reduction in financially-motivated crime compared to crime in general, whereas for women the reductions are equally sized. Our findings imply that potential effects on crime should be considered in welfare policy formation.

Keywords: welfare benefits, crime, instrumental variable, regression discontinuity

JEL codes: H31, I38

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1 Introduction

The Great Recession caused a massive rise in unemployment rates in most Western countries (e.g. Carcillo and Königs, 2015). Many countries responded by reducing welfare accessibility and increasing obligations, which often reduced welfare uptake (Bolhaar et al., 2019; Dahlberg et al., 2009; Hernæs et al., 2017). Employment rates, however, did not always increase. As a result, welfare receipt (minimum income benefits) declined among unemployed individuals. This reduction in legitimate income may lead to more criminal behavior, yet such spillover effects are often ignored in research and policy. In light of this paucity, this study assesses the causal effect of welfare receipt on crime.

From a theoretical perspective, there is a large degree of consensus that welfare receipt reduces criminal behavior. Among the most-cited theories are Becker's rational choice theory (1968) and Agnew's general strain theory (1992). Rational choice theory states that an individual determines his behavior by weighing perceived costs and benefits (Becker, 1968; Ehrlich, 1973). Providing individuals with means of subsistence via welfare benefits would reduce the relative financial gains from financially-motivated crime (e.g. property crime). Furthermore, from a general strain perspective, insufficient income can be classified as a negative stimulus that may contribute to (anticipated) failure to achieve personal goals (Agnew, 1992). This results in emotional strain, which in turn can increase criminal behavior as a coping mechanism (e.g. violent crime). Through the provision of a basic level of guaranteed income, welfare receipt may reduce strain and consequently crime in general.

While these theories agree that welfare receipt probably reduces crime, few studies have examined these causal claims using individual-level data and (quasi-)experimental research designs. Most of the existing studies offer insight into the macro-level dynamics between welfare benefits and crime. Especially in the US, a sizeable body of cross-sectional research finds evidence of an inverse relationship between welfare spending and crime on a city, county, or state level. Other studies use longitudinal data and find causal inverse effects of welfare spending on crime at the state or national level (Chamlin et al., 2002; Grant and Martinez Jr, 1997; Meloni, 2014; Worrall, 2009). Moreover, an innovative study in twelve large US cities by Foley (2011), shows an increase in crime over the amount of time that has passed since welfare payments were received, and ascribes this to financial constraints.

Unobserved differences over time or between countries, states, cities and neighborhoods may, however, bias analyses across time and regions. In difference-in-differences analyses, a concern is that the development of crime across regions may vary due to region-specific changes in the costs and benefits of engaging in criminal activity unrelated to the reform in question

¹E.g. Chamlin and Cochran (1997); DeFronzo (1983, 1992, 1996a,b, 1997); DeFronzo and Hannon (1998); Hannon and DeFronzo (1998a,b); Pratt and Cullen (2005); Zhang (1997).

(Corman et al., 2014). Furthermore, the timing of welfare reforms may be endogenous. To avoid such potential biases, this study exploits an age-based discontinuity in welfare policy to estimate average treatment effects. Dutch welfare applicants below the age of 27 are subject to a so-called 'job-search period' (JSP). This means that they are required to actively search for employment or education for a period of four weeks before their application will be processed. During this period, they are not eligible for welfare benefits and therefore without discernible legitimate income. Additionally, there is evidence that the most vulnerable youths are unable to meet the JSP policy's requirements, and consequently drop off the radar of municipalities (Van Dodeweerd, 2014; Ministry of Social Affairs and Employment, 2015). They are discouraged from applying for welfare benefits by the strict conditionality of the policy, and remain without discernable legitimate income also beyond the four-week job-search period. We use the agebased exogenous variation in welfare eligibility to instrument welfare receipt and assess the causal effects of welfare receipt on crime. We estimate an instrumental variable (IV) model with a first-stage regression discontinuity (RD) design on unique individual-level administrative data for the entire Dutch population around the age of 27. Through this approach, we assess the effects of welfare receipt compared to a lack thereof due to subjection to the job-search period policy. The analyses are run for both financially-motivated crime and crime in general.

We find that welfare receipt substantially reduces general and financially-motivated crime. Moreover, for men we find that financially-motivated crime is more heavily affected than crime in general, which supports rational choice theory (Becker, 1968; Ehrlich, 1973). For women we find comparable effects on financially-motivated crime and crime in general, which is more in line with general strain theory (Agnew, 1992). Despite the higher baseline crime rates among low-educated men and women, we do not find substantial heterogeneous effects across educational levels. All of the results are robust to changes in functional form and bandwidth size.

The contribution of this study to the literature is threefold. First, complementary to most of the existing literature, we estimate the causal effect of welfare receipt on crime using variation within geographical regions (as opposed to variation between geographical regions). Consequently, we avoid potential biases caused by endogenous timing of the welfare reform in question, and of region-specific developments unrelated to the welfare reform. Second, whereas most studies are focused on welfare benefits in the US, the Netherlands offers a different context with a relatively generous welfare system. As higher benefits levels offer more income protection, the estimates in this study are likely to provide an upper bound for the potential effects in other countries. Our third contribution concerns the sample; we assess the effects of cash transfers on crime among young adults. This includes young adults without dependent children, who are not entitled to cash transfers in the US.² In addition, we analyze young women, who have

²https://www.usa.gov/benefits.

received little attention in previous crime literature. By distinguishing between female crime and male crime, we can assess potential heterogeneous effects across gender. In this way, we aim to contribute to the ongoing discussion among scholars of whether female and male crime can be accounted for by the same factors and through similar mechanisms (see Kruttschnitt, 2013; Steffensmeier and Allan, 1996).

Some related studies focus on samples with specific characteristics. There is a substantial body of (quasi-)experimental evidence on the effect of transitional financial aid on recidivism of (high-risk) newly-released prisoners (e.g. Berk et al., 1980; Mallar and Thornton, 1978; Rauma and Berk, 1987; Yang, 2017a). Yang (2017a) assesses the causal effect of welfare receipt on recidivism among newly-released drug offenders. By exploiting individual-level data on the staggered introduction of public assistance for convicted drug offenders in the US in 1996, she finds strong evidence that welfare receipt significantly reduces recidivism among this group. Another closely related study is that of Bolhaar et al. (2019), who use an experimental research design to assess the effects of a job-search period. For a relatively highly-employable group of welfare recipients between the ages of 27 and 64,³ they find a reduction in welfare dependency, increased earnings, but no adverse effects on crime.

Finally, noteworthy is the substantial body of work on the effects of labor market conditions and (welfare-related) active labor market policies (ALMPs) on crime. Several studies show that advantageous labor market conditions reduce crime (e.g. Gould et al., 2002; Schnepel, 2018; Yang, 2017b). ALMPs, on the other hand, show mixed results. A workfare program in Denmark simultaneously reduced both welfare uptake and crime (Fallesen et al., 2018), whereas another ALMP in Sweden reduced welfare uptake, while increasing crime (Persson, 2013). Fallesen et al. (2018) hypothesize that ALMPs may increase crime if they are more focused on 'threat effects', i.e. when the negative consequences of not meeting certain requirements are emphasized (see Black et al., 2003). This is relevant for our study, because there are vulnerable individuals below the age of 27 who drop out of sight of municipalities because of the job search period policy and it's related requirements (Van Dodeweerd, 2014; Ministry of Social Affairs and Employment, 2015).

Below, Section 2 will first discuss the age-based welfare policy that we exploit to identify the effects of welfare receipt on crime (i.e. the job-search period). Section 3 describes the empirical model, after which we discuss the data, samples and some graphical evidence in section 4.

³Bolhaar et al. (2019) assess the effects of a job-search period that is somewhat similar to the one exploited in this current study, on participants who (a) are older than the age group under consideration in this study, and (b) are in welfare and expected to be able to find regular employment within six months. The employability of participants is based on various individual characteristics, such as employment history, age, and education level. Our study, instead, focuses on a general sample of young individuals around the age of 27, who have to wait up to eight weeks instead of four weeks before they receive benefits, and do not receive benefits (retrospectively) as from the beginning of the job search period (in case they return to the welfare agency after the job search period).

Section 5 contains the estimation results, including a cost-effectiveness analysis, followed by robustness checks in Section 6. We conclude and discuss the implications of the results in Section 7.

2 Welfare and the job-search period

The Dutch welfare system guarantees a minimum income for every legally-registered inhabitant of the Netherlands, who has insufficient means of subsistence. Individuals are considered eligible for welfare benefits if they: (a) are at least 18 years old, (b) have an income lower than the welfare norm (including other household members), (c) cannot claim other benefits (e.g. unemployment benefits), (d) do not have assets exceeding a certain maximum threshold, and (e) are not imprisoned. There is no maximum time period during which individuals can receive welfare. In order to receive welfare benefits, recipients must fulfill job search requirements (e.g. a weekly job application target), and are obliged to accept all jobs. Municipalities support re-integration by offering job-search assistance.

Welfare benefits are relatively high in the Netherlands. During our observation period the welfare benefit level was about 660 euros per month for singles without children, 930 euros per month for single parents, and 1320 euros per month for couples. In addition, households may receive housing subsidies, child subsidies, and health insurance subsidies. The OECD shows that in 2018 the guaranteed minimum income benefit in the Netherlands was 60% of median disposable income (OECD, 2018a). This indicator is only slightly higher in Japan (65%), Ireland (64%), and Denmark (63%), and much lower in the US (6%).

Since January 2012, all welfare applicants in the Netherlands below the age of 27 are subject by law to the so-called 'job-search period' policy. This means that they are not entitled to welfare benefits in the first four weeks after notification of their intended application. It is only after this period that their right to welfare will be determined. Upon assessment, the municipality checks the actions of the applicant during the job search period. The applicants are required to have actively pursued employment during the job-search period, of which they must convey tangible evidence in their application.

In addition, youths are required to hand over documents from which could be ascertained whether they are entitled to student grants.⁴ Applicants below the age of 27 are only considered eligible for welfare benefits if opportunities for student grants are exhausted. According to the explanatory memorandum of the law, the official goal of the job-search period policy is labor activation of youths and to emphasize their personal responsibility therein. Apart from the

⁴To complete higher or continued education, Dutch citizens were entitled to student grants that partially cover tuition fees, travel costs and living expenses. The eligibility for these grants ends once a first final degree is obtained (i.e. a master's degree), or the maximum receipt period expires.

job-search period policy, recipients on either side of the 27-year-old threshold are subject to identical rules. This also applies to the welfare benefit level, which is equal across the ages of 21 to 64.

For those who apply for benefits (after the job search period), the municipality is given eight weeks to determine entitlement to the welfare benefits. Meanwhile, welfare recipients can receive an advance payment, if they provide the requested information to the municipality timely and complete. Municipalities must pay this advance payment no later than four weeks after the date of the application. This means that, for individuals younger than 27 who are subject to the job search period, it can in total take eight weeks before one receives any income.

Noncooperation on part of the youth will lead to exclusion of their right to welfare benefits. Consequently, many applicants lack a guaranteed minimum income also beyond the four-week job-search period. While national figures are unavailable, the municipality of Utrecht⁵ reports that in the first seven months after the reform, 64% of applicants refrain from applying for welfare after the job-search period (Van Dodeweerd, 2014). About half of them found employment instead, 5% enrolled in education, and 12% received other benefits. For the remaining one-third, it is unknown how they sustain themselves.

3 Empirical methodology

Estimating the effect of welfare receipt on crime is challenging due to omitted variables affecting both the probability to receive welfare benefits as well as the probability to commit crime. For example, personality traits, such as self-control, time preferences and risk aversion, influence both welfare receipt and crime. To address this endogeneity problem, we estimate a bivariate probit instrumental variable (IV) model with a first-stage regression discontinuity (RD) design. This approach is facilitated by the sharp discontinuity in welfare policy, in the form of the 27-year-old threshold of the job-search period. By comparing individuals just above the treatment assignment threshold to those just below that threshold, the first-stage RD design enables us to instrument welfare receipt with the job-search period policy. Theoretically, by taking a narrow enough bandwidth to measure the effect on the threshold itself, the RD approach isolates treatment variation that is "as good as randomized" (Lee, 2008). The availability of data on a monthly level allows for a sharp regression discontinuity design. The job-search period policy does not only affect welfare recipients, but also seems to discourage individuals from applying for welfare benefits. We therefore include the full population around the age of

⁵Utrecht is the fourth most populous municipality in the Netherlands.

⁶E.g. Bernheim et al. (2015); Borghans et al. (2008); Coelli et al. (2007); Machin et al. (2011); Pratt and Cullen (2000).

27, to also capture potential discouragement effects.⁷ Through this approach, we fully exploit the exogenous discontinuity in welfare policy to assess the causal effects of welfare receipt on crime.

As the outcome variable crime is dichotomous and has probabilities close to zero, we use a bivariate probit (BP) model instead of a linear IV model. The BP model has been used in various areas of economics, for example, to study the effect of obesity on employment (Morris, 2007), chronic diseases on labor force participation (Zhang et al., 2009), offending on the probability of being a victim of crime (Deadman and MacDonald, 2004), fertility on female labor force participation (Carrasco, 2001), and parental smoking habits on their children's smoking decision (Loureiro et al., 2004). Bhattacharya et al. (2006) and Chiburis et al. (2012) compare the bivariate probit model with the two-step or linear probability model estimators. Their simulation results argue in favor of using the bivariate probit model, especially when the average probability of the dependent variable is close to 0 or 1 (which clearly applies to crime).

The model is specified as follows:

$$y_{it}^* = \beta_0 + \beta_1 w_{it} + \beta_2 A_{it} + \beta_3 1 (A_{it} < 27) A_{it} + \beta_4 X_i + \beta_5 T_t + v_{it}$$

$$w_{it}^* = \gamma_0 + \gamma_1 R D_{it} + \gamma_2 A_{it} + \gamma_3 1 (A_{it} < 27) A_{it} + \gamma_4 X_i + \gamma_5 T_t + \varepsilon_{it}$$

$$y_{it} = \begin{cases} 1 & \text{if } y_{it}^* > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$w_{it} = \begin{cases} 1 & \text{if } w_{it}^* > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$\begin{bmatrix} v_{it} \\ \varepsilon_{it} \end{bmatrix} \sim N \begin{pmatrix} \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \end{pmatrix}$$
For $i = 1...n$ and $t = 1...T$

Where y_{it}^* in equation (1) is a latent variable that indicates whether individual i is suspected of (financially motivated) crime in month t, w_{it} is a dummy variable indicating the welfare receipt status of individual i in month t, A_{it} is age (in months), $1(A_{it} < 27)A_{it}$ is an interaction term that allows for different slopes on both sides of the discontinuity, X_i indicates whether individual i is a native-born Dutch citizen, T_t represents a linear time trend (months) and v_{it}

⁷Other papers also argue that welfare policies may affect both recipients and non-recipients (e.g. DeLeire et al., 2006).

the error term.⁸ As we expect welfare receipt status to be endogenous, we instrument welfare receipt with the job-search period, as shown in equation (2). In this equation, w_{it}^* is the latent variable indicating welfare receipt, RD_{it} is the treatment dummy that captures the job-search period policy below the age of 27 (a value of one indicates an age below the policy threshold for individual i at time t), and ε_{it} is the error term. The error terms v_{it} and ε_{it} are assumed to follow a bivariate normal distribution with mean zero, variance one and covariance ρ . We are interested in the coefficient β_1 , which indicates the effect of welfare receipt on crime.

Although the BP model is identified by functional form (relying on the assumption of normality), we follow common practice by imposing an exclusion restriction to improve identification. Han and Vytlacil (2017) show that in a broad class of models (including the BP model) exclusion restrictions are sufficient to identify the parameters of the model. Using simulations, Li et al. (2019) show that the inclusion of valid instruments can significantly improve the precision of the estimation, and that biases decrease with sample size. They conclude that the BP model is a readily implementable and reasonably resilient empirical tool for estimating the effect of an endogenous binary regressor on a binary outcome variable.

As suggested by Chiburis et al. (2012), we recover standard errors through bootstrapping. Furthermore, following the work of Lee and Card (2008), we cluster the standard errors on the assignment variable age (in months). As our assignment variable is discrete, this clustering approach accounts for the group structure induced by potential specification errors and prevents overstatement of the significance of the estimated effects. In light of the findings by Gelman and Imbens (2018), we limit the analyses to local linear and local quadratic polynomials. For the baseline estimates, we specify a local linear model with a bandwidth of 14 months on each side of the 27th-birthday-month cut-off. 10

As robustness checks, we compare the estimates across functional forms and multiple bandwidths. Finally, to increase the interpretability of the estimates, we compute the average treatment effects (ATEs) of welfare receipt on crime as follows,

$$ATE = \frac{1}{N} \sum_{i} \sum_{t} \Phi(\beta_0 + \beta_1 + \beta_2 A_{it} + \beta_3 1 (A_{it} < 27) A_{it} + \beta_4 X_i + \beta_5 T_t)$$

$$-\Phi(\beta_0 + \beta_2 A_{it} + \beta_3 1 (A_{it} < 27) A_{it} + \beta_4 X_i + \beta_5 T_t)$$
(3)

While the combination of an instrumental variable approach with a regression discontinuity

⁸Additional analyses were performed with quadratic and cubic time trends, which do not change the conclusions.

⁹Gelman and Imbens (2018) find that using global high-order polynomials in regression discontinuity designs result in noisy estimates, poor coverage of confidence intervals, and sensitivity to the degree of the polynomial. For the quadratic model specification, we include quadratic terms for the assignment variable (A_{it}^2 and $1(A_{it} < 27)A_{it}^2$).

¹⁰The low crime probabilities make the estimates susceptible to noise when using smaller bandwidths.

design allows us to exploit the full potential of the available data and to adequately account for endogeneity, it also brings along a fair amount of model assumptions. For the first-stage RD approach, the main underlying assumption is the 'continuity assumption'. The characteristics of the participants are required to evolve smoothly over the assignment variable. The distribution of characteristics just above the threshold should not differ from the distribution just below the threshold. This assumption realistically holds, as we use age (in months) as the assignment variable, which is centrally registered and cannot be manipulated.

For the IV approach, there are two main model assumptions: instrument relevance and instrument exogeneity. We will check for instrument relevance, i.e. whether the instrument causes a sufficient amount of variation in the first-stage outcome variable. The assumption of instrument exogeneity, also known as the exclusion restriction, states that the instrument may not be correlated to the second-stage error terms and must only affect the second-stage outcome through the instrumented variable (welfare receipt). Since the instrument consists of a nationwide age-based discontinuity in welfare policy, there are no conceivable mechanisms through which this welfare policy might affect criminal behavior in other ways than through its effect on welfare receipt.¹¹

4 Data and graphical evidence

To estimate the models, we use longitudinal individual-level data from Statistics Netherlands on all registered Dutch inhabitants around the 27-year-old policy threshold. ¹² As the job-search period was introduced in January 2012 and the data are available until December 2014, we have a three-year observation window.

Administrative data on welfare are derived from municipal monthly payment registrations. The crime data are derived from crime reports of the Dutch law enforcement agencies, which have been submitted to the public prosecutor. These reports contain information concerning crimes of which individuals are officially suspected and are strong indicators of committed offenses. When brought to trial, approximately 90 percent of cases result in a conviction (Statistics Netherlands et al., 2013). Although we only observe registered crime, there is no reason to expect the unmeasured crime distribution to be correlated with the policy discontinuity at the 27-year-old threshold. The available daily crime measures are aggregated to dichotomous monthly values.

¹¹As will be discussed in Section 4, we do not find the job-search period policy to affect employment rates.

¹²Under certain conditions, these microdata are accessible to all researchers for statistical and scientific research. For further information, contact microdata@cbs.nl. Included datasets are bijstanduitkeringtab, gbaadresobjectbus, gbapersoontab, hdiplomaregtab, integraal huishoudens inkomen, integraal persoonlijk inkomen, polisbus, spolisbus, verdtab and vslgwbtab.

4.1 Sample and descriptive statistics

In line with our research design, we select all registered inhabitants of the Netherlands who reached the age of 27 in the years 2012 to 2014. This results in a full sample of 635,179 individuals, aged 24 to 29 years, and a total of 21,433,664 monthly observations between January 2012 and December 2014. The large sample size facilitates our exploitation of the welfare policy discontinuity at this age cut-off.¹³

To investigate potential heterogeneous effects, we run the analyses over four subsamples: men, women, low-educated men, and low-educated women. Men and women are considered separately, as men are more likely to commit offenses compared to women (e.g. Steffensmeier and Allan, 1996). Previous literature emphasizes the importance of analyzing the effects of welfare on crime among women, due to their higher poverty and welfare dependency rates (see Corman et al., 2014; Holtfreter et al., 2004). With regard to education, Lochner and Moretti (2004) and Machin et al. (2011) find that education reduces criminal activity. This may be caused by higher opportunity costs of crime and/or by differences in cognitive and personality traits, such as self-control and patience¹⁴. We classify individuals as being low educated if their educational attainment is below the Dutch classification of higher education (i.e. a higher vocational or university degree).¹⁵

Table 1 gives an overview of the most relevant characteristics in the selected samples. In the full sample, 3.75% of the individuals receive welfare benefits in any given month within the observation window. The employment rate is 73.42% and the monthly general and financially-motivated crime rates are 0.25% and 0.09%, respectively. Within our observation window (2012-2014), 5.30% of the full sample committed crime in general and 2.16% committed financially-motivated crime.

A comparison of the subsamples shows that men have the lowest welfare dependency rate (3.35%). This rate is higher among women (4.16%), low-educated men (4.23%), and low-educated women (6.02%). Conversely, the employment rate is highest among men (73.49%), and lowest among low-educated women (66.47%). Low-educated women show the lowest annual incomes, with an average personal primary income of $\{0.02\%\}$ and a standardized household income of $\{0.02\%\}$. These are the highest among men $(\{0.02\%\}\}$ and $\{0.02\%\}$ respectively).

¹³We take into account that all welfare applicants residing in the city of Rotterdam are subject to the job-search period, irrespective of age.

¹⁴Patient people are more likely to finish education, but education may also increase one's patience (Becker and Mulligan, 1997). Borghans et al. (2008) discuss the relation between education and personality traits. Hjalmarsson (2008) note that individuals with a low ability to make considered decisions may be more likely to commit crimes and be arrested, as well as to drop out of school. In studying the relationship between education and crime, Lochner (2004) distinguishes between unskilled crimes and white collar crimes. More educated adults should commit fewer unskilled crimes, but white collar crimes decline less (or increase) with education.

¹⁵The educational attainment data have limited coverage among first-generation immigrants, which may have resulted in unmeasured highly-educated individuals among the low-educated subsamples. Due to their limited population size, we consider any potential influence on the estimates to be negligible.

Low-educated men score the highest on all crime measures, with a monthly crime rate of 0.52%, a financially-motivated crime rate of 0.19% and on average 1.98 offenses per offender over the three-year observation window. We find the lowest crime rates among women (monthly general and financially-motivated crime rates of 0.08% and 0.04%, and on average 1.49 offenses per offender).

Table 1: Descriptive statistics, 2012-2014

	Full			Low-	Low-
	sample	Men	Women	educated	educated
	sample			men	women
Native	68.96%	69.50%	68.41%	65.15%	61.31%
Crime (monthly)	0.25%	0.41%	0.08%	0.52%	0.12%
Crime (total)	5.30%	8.34%	2.19%	10.39%	3.05%
Financially-motivated crime (monthly)	0.09%	0.15%	0.04%	0.19%	0.06%
Financially-motivated crime (total)	2.16%	3.18%	1.11%	4.05%	1.58%
Offenses per offender	1.85	1.94	1.49	1.98	1.51
Welfare dependency rate (monthly)	3.75%	3.35%	4.16%	4.23%	6.02%
Employment rate (monthly)	73.42%	73.49%	73.34%	70.44%	66.47%
Annual personal primary income	$26,\!450$	$29,\!252$	23,596	26,415	17,988
Annual standardized HH income	$22,\!641$	22,829	$22,\!450$	21,604	20,109
Number of individuals	$635,\!179$	321,466	313,713	245,223	208,632
Number of observations	21,433,664	10,815,461	10,618,203	8,172,030	6,956,063

4.2 Graphical evidence

Before turning to the estimation results, we present some exploratory graphs on the evolution of various outcomes around the 27-year-old threshold. Figures 1 to 3 present local polynomial smooth plots, along with 95% confidence intervals. As the identification in the first-stage regression discontinuity design comes from the welfare policy discontinuity at the age of 27, these graphs offer insight into the feasibility of this approach.

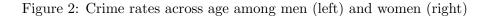
Figure 1 shows the evolution of the welfare dependency rates across age among men and women. In line with the descriptives shown in Table 1, the monthly welfare dependency rates are about 3-4%. The jumps upward at the cut-off value indicate reductions in welfare receipt due to the job-search period, which only applies to those on the left-hand side of the cut-off. The discontinuity is larger for men than for women.

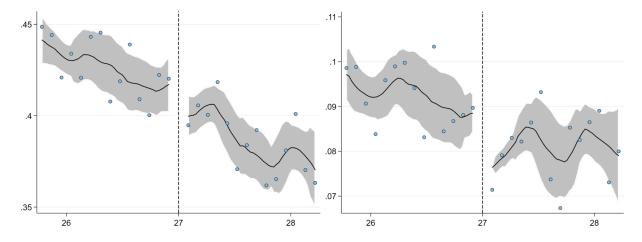
Figure 2 presents crime rates for men and women. Monthly crime rates are about 0.40% for men and 0.08% for women, in line with the descriptives shown in Table 1. Compared to men, women show a larger drop at the cut-off, relative to their average crime rate (note the different scales of the vertical axes). This may indicate heterogeneous effects of welfare receipt on crime between the sexes. As the frequency of crime is comparatively low, we also see that the confidence intervals are larger for crime than for welfare dependency rates.

This study investigates the effect of welfare receipt on crime. The main goal of the job-search period policy, however, is to increase employment. If successful, crime would likely be reduced among the activated individuals (see Lageson and Uggen, 2013). In that case, our estimates of the effect of welfare receipt on crime would be biased towards zero (and thus be a lower bound of the true effect). Figure 3 does not show discontinuities in the employment rate around the age of 27 (note the scales of the vertical axes). This is further supported by the estimates in Table A.1 of the appendix, which show statistically significant, but insubstantial discontinuities in the employment rate at the 27-year-old threshold.

4.5 3.5 2.5

Figure 1: Welfare dependency rates across age among men (left) and women (right)





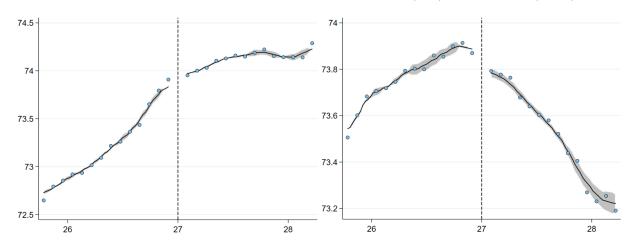


Figure 3: Employment rates across age among men (left) and women (right)

5 Results

5.1 Estimation results

Tables 2 to 5 present the baseline estimation results for crime and financially-motivated crime, for men, women and the low-educated subgroups. The standard probit models show substantial positive correlations between welfare receipt and (financially-motivated) crime. Controlling for endogeneity, however, the IV estimates reveal that welfare receipt reduces crime. The first-stage coefficients show that the instrument ('RD') is statistically highly significant across all subsamples in the baseline analyses (p<.001), which suggests a sufficiently strong instrument. We find the job-search period policy to reduce welfare receipt by approximately 6% for men and 2.5% for women.

Table 2 shows the estimation results for crime in general. The IV estimates show statistically significant negative coefficients of welfare receipt on crime for men (-0.3314) and women (-0.4235). To enhance the interpretability of the estimation results, we compute the average treatment effects (ATEs). The ATEs indicate how much the conditional probability of committing crime changes due to welfare receipt. The ATEs show that welfare receipt significantly reduces the average probability of committing crime (per month) by 0.39 percentage points among men (from 0.63% to 0.24%). For women, we find a statistically significant reduction of 0.13 percentage points (from 0.17% to 0.04%). The lack of a basic level of guaranteed income thus appears to be a major risk factor for crime. In absolute terms, we find that this effect is substantially larger for men than for women, which may partially explain the gender gap in crime. In relative terms, however, the reduction is larger for women (-77% 16) than for

^{16-0.11/0.14}

men (-64%¹⁷).¹⁸ This points to other criminogenic factors being relatively more important determinants of criminal behavior among men, compared to women.¹⁹

With regard to financially motivated crime, Table 3 presents statistically significant negative coefficients of welfare receipt on financially-motivated crime for men (-0.5072) and women (-0.3563). The ATEs show that welfare receipt reduces financially-motivated crime by 0.32 percentage points among men (from 0.51% to 0.19%), and 0.11 percentage points among women (from 0.14% to 0.03%). In line with Becker's rational choice theory, for men we find a larger relative reduction in financially-motivated crime (-82%) compared to crime in general (-64%). For women however, the relative reduction in financially-motivated crime (-73%) is rather similar to the relative reduction in crime in general (-77%). This is more in line with Agnew's general strain theory, which argues that, by alleviating financial stress, welfare receipt reduces emotional strain and consequently criminal behavior in general.

Low-educated individuals may have lower opportunity costs than highly-educated individuals, and may be less well equipped to cope with strain, due to (on average) lower self-control, patience and risk aversion (Becker and Mulligan, 1997; Borghans et al., 2008; Pratt and Cullen, 2000). Tables 4 and 5 show the estimation results for low-educated men and women, with regard to crime and financially-motivated crime, respectively. For low-educated individuals we find larger ATEs than for the general population, but the relative effects are quite similar: -64% versus -60% for men and low-educated men, and -77% versus -76% for women and low-educated women, respectively. Also, when we compare ATEs and relative reductions in financially-motivated crime they are very similar for low-educated individuals and the general population (-82% for both men and low-educated men, and -72% versus -71% for women and low-educated women, respectively). We thus do not find evidence that the absence of a basic minimum income causes a higher crime growth among low-educated individuals, compared to individuals with a higher education level.

To summarize, the estimation results show that welfare receipt reduces crime. For men we find a comparatively large reduction in financially motivated crime, while for women the effects are similar for financially motivated crime and crime in general. The relative reduction in crime as a result of a guaranteed minimum income is similar for low and highly-educated individuals.

 $^{^{17}}$ -0.32/0.51

¹⁸ATE's are roughly the same when we weigh the observations by the treatment compliance propensity (i.e. the predicted individual-level first-stage marginal effect).

¹⁹For example, men are found to be less risk averse (e.g., see Barsky et al., 1997; Borghans et al., 2009; Jianakoplos and Bernasek, 1998).

Table 2: Probit and bivariate probit (IV) estimates for crime among men and women

	PROBIT	BIPROBIT	PROBIT	BIPROBIT
	MEN	MEN	WOMEN	WOMEN
Crime				
Welfare receipt	0.5954***	-0.3314**	0.5835***	-0.4235***
	(0.0079)	(0.1108)	(0.0119)	(0.0125)
Age	-0.0024***	$-0.0012\dagger$	-0.0012	0.0005
	(0.0006)	(0.0006)	(0.0013)	(0.0012)
Age x $1(<27)$	0.0007	0.0004	-0.0024	-0.0028
	(0.0009)	(0.0009)	(0.0021)	(0.0019)
Native	-0.2329***	-0.3319***	-0.1273***	-0.2553***
	(0.0043)	(0.0177)	(0.0079)	(0.0072)
Time (month)	-0.0022***	-0.0017***	-0.0013***	-0.0010**
	(0.0002)	(0.0002)	(0.0003)	(0.0003)
Welfare receipt				
RD		-0.0279***		-0.0115***
		(0.0037)		(0.0023)
Age		0.0037***		0.0052***
		(0.0004)		(0.0002)
Age x $1(<27)$		-0.0010*		-0.0019***
		(0.0004)		(0.0003)
Native		-0.5923***		-0.5155***
		(0.0029)		(0.0046)
Time (month)		0.0025***		0.0011***
		(0.0001)		(0.0001)
$\overline{ ho}$		0.4705***		0.5361***
		(0.0642)		(0.0043)
Probabilities (per month)				
If welfare receipt = $1 (\%)$		0.19		0.03
If welfare receipt = $0 (\%)$		0.51		0.14
ATE (%point)		-0.32***		-0.11***
		(0.09)		(0.00)
Observations	6,663,749	6,663,749	6,546,177	6,546,177
Individuals	315,773	315,773	$308,\!298$	$308,\!298$

Notes. Linear model specification, 14-month bandwidth (28 months total), standard errors clustered by age (in months), *** indicates p<.001, ** p<.01, * p<.05 and † p<.10.

Table 3: Probit and bivariate probit (IV) estimates for financially-motivated crime among men and women

	PROBIT	BIPROBIT	PROBIT	BIPROBIT
	MEN	MEN	WOMEN	WOMEN
Financially-motivated crime				
Welfare receipt	0.6131***	-0.5072***	0.5967***	-0.3563***
	(0.0084)	(0.0220)	(0.0174)	(0.0170)
Age	-0.0028*	-0.0009	-0.0010	0.0007
	(0.0011)	(0.0010)	(0.0014)	(0.0013)
Age x $1(<27)$	0.0014	0.0008	$-0.0034\dagger$	-0.0037*
	(0.0018)	(0.0016)	(0.0020)	(0.0018)
Native	-0.2430***	-0.3874***	-0.1414***	-0.2638***
	(0.0086)	(0.0086)	(0.0096)	(0.0090)
Time (month)	-0.0011**	-0.0003	$-0.0012\dagger$	-0.0008
	(0.0003)	(0.0003)	(0.0007)	(0.0006)
Welfare receipt				
RD		-0.0278***		-0.0111***
		(0.0037)		(0.0023)
Age		0.0037***		0.0052***
		(0.0004)		(0.0002)
Age x $1(<27)$		-0.0009*		-0.0019***
		(0.0004)		(0.0003)
Native		-0.5924***		-0.5154***
		(0.0029)		(0.0046)
Time (month)		0.0025***		0.0011***
		(0.0001)		(0.0001)
$\overline{ ho}$		0.5912***		0.5080***
		(0.0129)		(0.0051)
Probabilities (per month)				
If welfare receipt = $1 (\%)$		0.05		0.02
If welfare receipt = $0 (\%)$		0.25		0.07
ATE (%point)		-0.20***		-0.05***
		(0.01)		(0.00)
Observations	6,663,749	6,663,749	6,546,177	6,546,177
Individuals	$315{,}773$	315,773	308,298	$308,\!298$

Notes. Linear model specification, 14-month bandwidth (28 months total), standard errors clustered by age (in months), *** indicates p<.001, ** p<.05 and † p<.10.

Table 4: Probit and bivariate probit (IV) estimates for crime among low-educated men and low-educated women

	PROBIT	BIPROBIT	PROBIT	BIPROBIT
	LE MEN	LE MEN	LE WOMEN	LE WOMEN
\overline{Crime}				
Welfare receipt	0.5453***	-0.3048**	0.5102***	-0.4171***
-	(0.0078)	(0.1174)	(0.0119)	(0.0144)
Age	-0.0020**	-0.0007	-0.0011	0.0009
	(0.0006)	(0.0007)	(0.0014)	(0.0013)
Age x $1(<27)$	0.0010	0.0006	-0.0021	-0.0027
	(0.0010)	(0.0010)	(0.0022)	(0.0020)
Native	-0.1900***	-0.2804***	-0.0601***	-0.1690***
	(0.0047)	(0.0178)	(0.0085)	(0.0081)
Time (month)	-0.0028***	-0.0024***	-0.0017***	-0.0015***
	(0.0002)	(0.0003)	(0.0004)	(0.0003)
Welfare receipt				
RD		-0.0307***		-0.0127***
		(0.0035)		(0.0023)
Age		0.0046***		0.0063***
		(0.0004)		(0.0002)
Age x $1(<27)$		-0.0011**		-0.0021***
		(0.0004)		(0.0003)
Native		-0.5562***		-0.4298***
		(0.0022)		(0.0036)
Time (month)		0.0019***		0.0004***
		(0.0001)		(0.0001)
$\overline{ ho}$		0.4379***		0.5071***
		(0.0683)		(0.0057)
Probabilities (per month)				
If welfare receipt = $1 (\%)$		0.26		0.05
If welfare receipt = $0 \ (\%)$		0.64		0.20
ATE (%point)		-0.38**		-0.15***
		(0.12)		(0.01)
Observations	5,032,325	5,032,325	4,283,703	4,283,703
Individuals	240,308	240,308	$204,\!278$	204,278

Notes. Linear model specification, 14-month bandwidth (28 months total), standard errors clustered by age (in months), *** indicates p<.001, ** p<.01, * p<.05 and † p<.10.

Table 5: Probit and bivariate probit (IV) estimates for financially-motivated crime among low-educated men and low-educated women

	PROBIT	BIPROBIT	PROBIT	BIPROBIT
	LE MEN	LE MEN	LE WOMEN	LE WOMEN
Financially-motivated crime				
Welfare receipt	0.5639***	-0.5167***	0.5252***	-0.3483***
	(0.0085)	(0.0283)	(0.0176)	(0.0189)
Age	-0.0023†	-0.0002	-0.0009	0.0010
	(0.0012)	(0.0011)	(0.0015)	(0.0014)
Age x $1(<27)$	0.0012	0.0006	-0.0031	-0.0036†
	(0.0019)	(0.0017)	(0.0021)	(0.0020)
Native	-0.2023***	-0.3416***	-0.0811***	-0.1836***
	(0.0088)	(0.0096)	(0.0098)	(0.0094)
Time (month)	-0.0017***	-0.0010**	-0.0015*	-0.0013*
	(0.0003)	(0.0003)	(0.0007)	(0.0006)
Welfare receipt				
RD		-0.0306***		-0.0123***
		(0.0035)		(0.0023)
Age		0.0046***		0.0064***
		(0.0004)		(0.0002)
Age x $1(<27)$		-0.0011*		-0.0021***
		(0.0004)		(0.0003)
Native		-0.5564***		-0.4298***
		(0.0022)		(0.0036)
Time (month)		0.0019***		0.0004***
		(0.0001)		(0.0001)
$\overline{ ho}$		0.5799***		0.4781***
		(0.0168)		(0.0064)
Probabilities (per month)				
If welfare receipt = $1 (\%)$		0.06		0.03
If welfare receipt = $0 \ (\%)$		0.32		0.10
ATE (%point)		-0.26***		-0.07***
		(0.02)		(0.00)
Observations	5,032,325	5,032,325	4,283,703	4,283,703
Individuals	240,308	240,308	$204,\!278$	$204,\!278$

Notes. Linear model specification, 14-month bandwidth (28 months total), standard errors clustered by age (in months), *** indicates p<.001, ** p<.01, * p<.05 and † p<.10.

5.2 Cost-effectiveness

Crime is high on the public policy agenda, due to the vast social and economic costs. As we find welfare receipt to substantially reduce crime, the question arises how cost-effective the provision of a basic level of guaranteed income is as a crime prevention strategy. To answer this question, we make a back of the envelope calculation. First, we compute the number of individual-month observations that switch to nonreceipt due to the job-search period policy. By multiplying this number with the average contemporary single-person monthly benefit level (€667), we approximate the total decline in welfare spending caused by the job-search period policy. Next, to determine the total absolute change in crime, we also multiply the number of switchers with the ATEs and the average number of offenses. Finally, the costs per prevented offense are approximated by dividing the change in welfare spending by the total absolute change in crime.

Table 6 presents the average amount of welfare spending in euros required per prevented (financially-motivated) offense for all subgroups. In line with the estimation results, we find the cost effectiveness to differ substantially across subgroups and crime outcomes. Welfare spending is approximately three times as cost effective in preventing crime among men compared to women, with €144,974 and €466,871 per offense respectively. For low-educated men and women, with higher absolute treatment effects, we find that the amount of welfare spending needed to prevent an offense is lower (€130,128 for men and €360,688 for women). Since financially-motivated crime is only part of all crime prevented by welfare receipt, the amount of welfare spend per prevented financially-motivated offense are higher than for crime in general.

Table 6: Welfare spending per prevented offense

€/offense	MEN	WOMEN	LE MEN	LE WOMEN
Crime	144,974	466,871	130,128	360,688
Financially-motivated crime	$204,\!596$	$948,\!367$	$165,\!895$	730,881

Note: The shown values are derived from the baseline IV estimates shown in Tables 2 to 5

To assess the cost-effectiveness of welfare spending as a crime prevention strategy, we need to compare welfare spending (shown in Table 6) with a comprehensive approximation of the costs of crime. The direct costs of crime are easily measureable (e.g. criminal justice costs and financial damages). However, it is notoriously difficult to quantify the indirect costs of crime, such as reduced labor market opportunities for the perpetrators, reduced productivity of victims and nonfinancial damages. Consequently, only few studies have attempted to comprehensively estimate all costs per offense. Among these studies there is substantial variation in estimates, due to differences in methodologies and included costs.²⁰ A seminal study in the US by Cohen et al. (2004) uses a contingent valuation method to estimate all costs per offense for several

²⁰E.g. Cohen (1988); Rajkumar and French (1997); McCollister et al. (2010).

types of crime. Compared to more traditional methods, this approach aims to generate a more comprehensive cost approximation. Converted to 2013 euros,²¹ they find costs per offense of €25,448 for household burglary, €71,253 for serious assault, €236,154 for armed robbery, €241,244 for rape/sexual assault and €9,873,682 for murder. While the costs per murder greatly exceed the amount of welfare spending required to prevent an offense, this is generally not the case for the more common crime categories. Therefore, based on our estimates we conclude that although welfare spending can significantly reduce crime, it does not seem to be a cost-effective crime prevention strategy.

6 Robustness checks

This section presents multiple robustness checks over (a) two functional forms: a linear and a quadratic model, and (b) four bandwidth specifications, ranging from 14 to 35 months on each side of the 27th-birthday-month cut-off.²² The latter is the upper bandwidth limit due to the three-year observation window (2012-2014). Tables 7 to 10 present the coefficients for the instrument ('RD') and the variable of interest ('Welfare receipt') per subsample. Extended estimation results can be found in Appendix B.

We find highly robust estimates for both crime and financially-motivated crime, across all subsamples. Starting with men, Table 7 shows that both coefficients change only slightly when we increase the bandwidth. Furthermore, the coefficients hardly differ between a linear and a quadratic model, and all coefficients remain statistically significant across the board. Table 8 shows that the welfare receipt estimates for women are the least sensitive to changes in functional form and bandwidth. Tables 9 and 10 present the robustness checks for low-educated men and women, which show similar results. In summary, we can be confident in interpreting the estimation results, as all estimates are highly robust.

²¹Based on US Bureau of Labor Statistics data on the consumer price index (US Bureau of Labor Statistics, 2018), an inflation rate of 1.3518 was used to convert (July) 2000 dollars to (July) 2013 dollars. The resulting figures were subsequently converted to euros using a dollar/euro conversion rate of 0.753, as reported by the OECD for the year 2013 (OECD, 2018b).

²²We limit the sensitivity analyses to first and second-order polynomials, in line with Gelman and Imbens (2018).

Table 7: IV estimates with different bandwidths and functional forms, men

D		14	21	28	35
Bandwidth		MONTHS	MONTHS	MONTHS	MONTHS
Crime					
Welfare receipt (crime eqn.)	Linear	-0.3314**	-0.3364**	-0.3163**	-0.3049**
		(0.1108)	(0.1122)	(0.1010)	(0.0900)
	Quadratic	-0.3358**	-0.3648**	-0.3247**	-0.3169**
		(0.1143)	(0.1348)	(0.1071)	(0.0968)
RD (welfare eqn.)	Linear	-0.0279***	-0.0292***	-0.0298***	-0.0310***
		(0.0037)	(0.0042)	(0.0044)	(0.0042)
	Quadratic	-0.0205***	-0.0266***	-0.0263***	-0.0267***
		(0.0015)	(0.0026)	(0.0029)	(0.0038)
$\overline{Financially ext{-}motivated\ crime}$					
Welfare receipt (crime eqn.)	Linear	-0.5072***	-0.4980***	-0.5035***	-0.4942***
		(0.0220)	(0.0222)	(0.0225)	(0.0226)
	Quadratic	-0.5193***	-0.5120***	-0.5099***	-0.5059***
		(0.0181)	(0.0192)	(0.0181)	(0.0182)
RD (welfare eqn.)	Linear	-0.0278***	-0.0293***	-0.0298***	-0.0310***
		(0.0037)	(0.0041)	(0.0043)	(0.0042)
	Quadratic	-0.0213***	-0.0267***	-0.0265***	-0.0268***
		(0.0017)	(0.0026)	(0.0029)	(0.0038)
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Notes. *** indicates p<.001, ** p<.01, * p<.05 and \dagger p<.10.

Extended estimation results can be found in Appendix Tables B.1 to B.4.

Table 8: IV estimates with different bandwidths and functional forms, women

D		14	21	28	35
Bandwidth		MONTHS	MONTHS	MONTHS	MONTHS
Crime					
Welfare receipt (crime eqn.)	Linear	-0.4235***	-0.4124***	-0.4123***	-0.4126***
		(0.0125)	(0.0130)	(0.0133)	(0.0137)
	Quadratic	-0.4205***	-0.4086***	-0.4069***	-0.4079***
		(0.0124)	(0.0126)	(0.0126)	(0.0126)
RD (welfare eqn.)	Linear	-0.0115***	-0.0143***	-0.0171***	-0.0195***
		(0.0023)	(0.0027)	(0.0029)	(0.0031)
	Quadratic	-0.0090***	-0.0097***	-0.0092***	-0.0095***
		(0.0017)	(0.0016)	(0.0022)	(0.0026)
Financially-motivated crime					
Welfare receipt (crime eqn.)	Linear	-0.3563***	-0.3423***	-0.3407***	-0.3390***
		(0.0170)	(0.0152)	(0.0149)	(0.0146)
	Quadratic	-0.3581***	-0.3410***	-0.3371***	-0.3360***
		(0.0167)	(0.0149)	(0.0143)	(0.0139)
RD (welfare eqn.)	Linear	-0.0111***	-0.0140***	-0.0168***	-0.0193***
		(0.0023)	(0.0028)	(0.0029)	(0.0032)
	Quadratic	-0.0084***	-0.0091***	-0.0087***	-0.0090**
		(0.0017)	(0.0016)	(0.0022)	(0.0026)

Notes. *** indicates p<.001, ** p<.01, * p<.05 and † p<.10.

Extended estimation results can be found in Appendix Tables B.5 to B.8.

Table 9: IV estimates with different bandwidths and functional forms, low-educated men

D 1: 141-		14	21	28	35
Bandwidth		MONTHS	MONTHS	MONTHS	MONTHS
\overline{Crime}					
Welfare receipt (crime eqn.)	Linear	-0.3048**	-0.3229*	-0.3316**	-0.3210**
		(0.1174)	(0.1258)	(0.1218)	(0.1067)
	Quadratic	-0.3067*	-0.3610*	-0.3419*	-0.3388**
		(0.1189)	(0.1633)	(0.1319)	(0.1200)
RD (welfare eqn.)	Linear	-0.0307***	-0.0322***	-0.0328***	-0.0336***
		(0.0035)	(0.0040)	(0.0042)	(0.0041)
	Quadratic	-0.0235***	-0.0290***	-0.0291***	-0.0299***
		(0.0016)	(0.0026)	(0.0028)	(0.0035)
Financially-motivated crime					
Welfare receipt (crime eqn.)	Linear	-0.5167***	-0.5119***	-0.5194***	-0.5132***
		(0.0283)	(0.0276)	(0.0273)	(0.0266)
	Quadratic	-0.5278***	-0.5270***	-0.5267***	-0.5240***
		(0.0221)	(0.0239)	(0.0220)	(0.0218)
RD (welfare eqn.)	Linear	-0.0306***	-0.0323***	-0.0329***	-0.0336***
		(0.0035)	(0.0039)	(0.0042)	(0.0041)
	Quadratic	-0.0242***	-0.0290***	-0.0294***	-0.0301***
		(0.0017)	(0.0026)	(0.0028)	(0.0035)

Notes. *** indicates p<.001, ** p<.01, * p<.05 and \dagger p<.10.

Extended estimation results can be found in Appendix Tables B.9 to B.12.

Table 10: IV estimates with different bandwidths and functional forms, low-educated women

D 1:141		14	21	28	35
Bandwidth		MONTHS	MONTHS	MONTHS	MONTHS
Crime					
Welfare receipt (crime eqn.)	Linear	-0.4171***	-0.4058***	-0.4080***	-0.4053***
		(0.0144)	(0.0149)	(0.0159)	(0.0167)
	Quadratic	-0.4144***	-0.4008***	-0.4016***	-0.4012***
		(0.0136)	(0.0141)	(0.0146)	(0.0146)
RD (welfare eqn.)	Linear	-0.0127***	-0.0152***	-0.0181***	-0.0205***
		(0.0023)	(0.0029)	(0.0030)	(0.0033)
	Quadratic	-0.0103***	-0.0107***	-0.0100***	-0.0105***
		(0.0013)	(0.0014)	(0.0022)	(0.0026)
Financially-motivated crime					
Welfare receipt (crime eqn.)	Linear	-0.3483***	-0.3338***	-0.3347***	-0.3314***
		(0.0189)	(0.0170)	(0.0171)	(0.0168)
	Quadratic	-0.3519***	-0.3331***	-0.3302***	-0.3287***
		(0.0184)	(0.0165)	(0.0158)	(0.0154)
RD (welfare eqn.)	Linear	-0.0123***	-0.0149***	-0.0178***	-0.0203***
		(0.0023)	(0.0029)	(0.0031)	(0.0034)
	Quadratic	-0.0097***	-0.0102***	-0.0095***	-0.0100***
		(0.0014)	(0.0014)	(0.0022)	(0.0026)

Notes. *** indicates p<.001, ** p<.01, * p<.05 and † p<.10.

Extended estimation results can be found in Appendix Tables B.13 to B.16.

7 Conclusion

This study examines the causal effect of welfare receipt on crime among young adults. This is empirically challenging due to omitted variables affecting both welfare receipt and crime. Confounding factors, such as self-control, time preferences and risk aversion, lead to positive correlations between welfare receipt and crime. In this study, we control for endogeneity by exploiting an age-based discontinuity in welfare policy in the Netherlands. Upon application for welfare, applicants below the age of 27 are subject to a four-week 'job-search period', during which they are not eligible for welfare benefits and therefore without discernible legitimate income. Furthermore, especially the most vulnerable youth are discouraged from applying for welfare benefits by the strict conditionality of the policy, and remain without discernable legitimate income even beyond the four-week job-search period (Van Dodeweerd, 2014; Ministry of Social Affairs and Employment, 2015). The access to a unique individual-level administrative dataset on the entire Dutch population around the age of 27, allows us to exploit this exogenous variation. We estimate an instrumental variable (IV) bivariate probit model with a first-stage regression discontinuity (RD) design. The nature of the welfare-crime relation is investigated by examining both crime in general and financially-motivated crime.

We find that welfare receipt substantially reduces crime, compared to nonreceipt of welfare benefits due to the job-search period policy. Welfare receipt reduces the monthly crime rate of men by 0.32 percentage points (from 0.51% to 0.19%). For women, we find a reduction of 0.11 percentage points (from 0.14% to 0.03%). In absolute terms, financial hardship thus has a larger effect on crime among men, which may partially explain the gender gap in crime. In relative terms, however, the reduction is smaller for men (-64%) than for women (-77%). This can likely be attributed to a higher prevalence of other criminogenic factors among men (e.g. lower risk aversion). Welfare receipt reduces financially-motivated crime among men with 0.20 percentage points (from 0.25% to 0.05%), and among women with 0.05 percentage points (from 0.07% to 0.02%). Not only in absolute terms, but also in relative terms, welfare receipt has a larger effect on male financially-motivated crime (-82%) than female financially-motivated crime (-73%). Overall, a basic level of guaranteed income appears to prevent crime. All of the results are robust to changes in functional form and bandwidth size.

Compared to previous literature our absolute effects (percentage points) are low, but the relative effects are high. Note that compared to previous literature which studied, for example, released offenders, we study the effect of a guaranteed basic income on crime for individuals around the age of 27. Since welfare is relatively generous in the Netherlands, our estimates are likely to present an upper bound, as the difference between receiving and not receiving benefits is relatively large.

The estimation results support both Becker's rational choice theory (1968) as well as Agnew's

general strain theory (1992). From a rational choice perspective, we expect welfare receipt to mainly reduce financially-motivated crime by reducing the relative financial gains from such crimes through the provision of legitimate income, whereas other types of crime would be less affected. This holds true for men, for whom we find larger relative effects on financially-motivated crime compared to crime in general. For women, however, we do not find a discernible difference in relative effect sizes between financially-motivated crime and crime in general, which is more in line with Agnew's general strain theory. This theory argues that, by alleviating financial stress, welfare receipt reduces emotional strain and consequently criminal behavior in general (Agnew, 1992). Reconciling our empirical evidence, we find that the pathway through which welfare receipt reduces crime is different for men and women. For men, welfare receipt appears to mainly reduce crime by addressing financial needs, while for women, a basic level of guaranteed income appears to reduce both financial needs and emotional strain that could otherwise lead to crime.

Women have received little attention in academic research on crime. By distinguishing between men and women in the analysis, the results of this study contribute to the ongoing discussion of whether female and male crime can be accounted for by the same factors and through similar mechanisms. Our findings add to the existing evidence that although most causes of crime are gender invariant, the effect sizes and mechanisms are heterogeneous across gender (see Kruttschnitt, 2013; Steffensmeier and Allan, 1996).

Finally, our findings suggest that the effect of financial hardship on crime is not heterogeneous across educational levels. The relative effect sizes that we find for low-educated samples are highly comparable to those for the general population. An explanation for the higher crime rates among the low-educated samples may therefore not lie in a lower ability to cope with financial strain, but in lower opportunity costs (Lochner, 2004; Lochner and Moretti, 2004), and a higher prevalence of financial hardship and other criminogenic factors (e.g. lower self-control, patience and risk aversion, see Becker and Mulligan, 1997; Borghans et al., 2008; Pratt and Cullen, 2000).

Our identification strategy enables us to assess the causal effects of welfare receipt on crime among a general population of young adults around the age threshold of 27. An inherent limitation of the RD approach is that it produces estimates that only pertain to observations around the age threshold. A key notion in developmental and life-course criminology is that determinants of criminal behavior vary by age and across developmental stages (e.g. Blokland and Nieuwbeerta, 2010; Elder, 1998). In order to examine the generalizability of our results to other age groups, further research into the welfare-crime relationship is therefore warranted.

Although a sizeable body of research has assessed the effects of welfare receipt on economic outcomes (such as poverty and unemployment), potential spillover effects on crime are often

ignored. Even though political discourse surrounding welfare is often rife with mentions of crime (e.g. Beckett and Sasson, 2003), we find micro-level research on the welfare-crime relationship to be comparatively scarce. We do not find the provision of a basic level of guaranteed income to be a cost-effective crime prevention strategy. In addition to the provision of welfare benefits being costly, this can be attributed to the limited reduction in the number of committed offenses. Nevertheless, this study shows that potential effects on crime should be considered in welfare policy formation, as the effects on crime are substantial. Offenses involve not only direct costs, but also long-term effects should be taken into account, such as reduced labor market opportunities for the perpetrators and reduced productivity of the victims. In several Western countries the current trend is to reduce welfare accessibility (e.g. Dahlberg et al., 2009; Hernæs et al., 2017). This study is relevant to increase our understanding of the consequences of this trend on crime. In order to gain a comprehensive overview of the societal costs and benefits of welfare, spillover effects on crime should be taken into account.

References

- Agnew, R. (1992). Foundation for a general strain theory of crime and delinquency. *Criminology*, 30(1):47–88.
- Barsky, R. B., Juster, F. T., Kimball, M. S., and Shapiro, M. D. (1997). Preference parameters and behavioral heterogeneity: An experimental approach in the Health and Retirement Study. *Quarterly Journal of Economics*, 112(2):537–579.
- Becker, G. S. (1968). Crime and punishment: An economic approach. *Journal of Political Economy*, 76(2):169–217.
- Becker, G. S. and Mulligan, C. (1997). The endogenous determination of time preference. Quarterly Journal of Economics, 112(3):729–758.
- Beckett, K. and Sasson, T. (2003). The politics of injustice: Crime and punishment in America. Sage Publications, Thousand Oaks, CA.
- Berk, R. A., Lenihan, K. J., and Rossi, P. H. (1980). Crime and poverty: Some experimental evidence from ex-offenders. *American Sociological Review*, pages 766–786.
- Bernheim, B. D., Ray, D., and Yeltekin, Ş. (2015). Poverty and self-control. *Econometrica*, 83(5):1877–1911.
- Bhattacharya, J., Goldman, D., and McCaffrey, D. (2006). Estimating probit models with self-selected treatments. *Statistics in Medicine*, 25(3):389–413.

- Black, D. A., Smith, J. A., Berger, M. C., and Noel, B. J. (2003). Is the threat of reemployment services more effective than the services themselves? Evidence from random assignment in the UI system. *American Economic Review*, 93(4):1313–1327.
- Blokland, A. A. J. and Nieuwbeerta, P. (2010). Life course criminology. In Shoham, S. G., Knepper, P., and Kett, M., editors, *International handbook of criminology*, pages 51–93. CRC Press, Boca Raton, FL.
- Bolhaar, J., Ketel, N., and van der Klaauw, B. (2019). Job-search periods for welfare applicants: Evidence from a randomized experiment. *American Economic Journal: Applied economics*, 11(1):92–125.
- Borghans, L., Duckworth, A. L., Heckman, J. J., and Ter Weel, B. (2008). The economics and psychology of personality traits. *Journal of Human Resources*, 43(4):972–1059.
- Borghans, L., Golsteyn, B., Heckman, J. J., and Meijers, H. (2009). Gender differences in risk aversion and ambiguity aversion. *Journal of the European Economic Association*, 7(2/3):649–658.
- Carcillo, S. and Königs, S. (2015). NEET youth in the aftermath of the crisis: Challenges and policies. OECD Social, Employment and Migration Working Paper 164, OECD.
- Carrasco, R. (2001). Binary choice with binary endogenous regressors in panel data. *Journal of Business & Economic Statistics*, 19(4):385–394.
- Chamlin, M. B. and Cochran, J. K. (1997). Social altruism and crime. *Criminology*, 35(2):203–226.
- Chamlin, M. B., Cochran, J. K., and Lowenkamp, C. T. (2002). A longitudinal analysis of the welfare-homicide relationship: Testing two (nonreductionist) macro-level theories. *Homicide Studies*, 6(1):39–60.
- Chiburis, R. C., Das, J., and Lokshin, M. (2012). A practical comparison of the bivariate probit and linear IV estimators. *Economics Letters*, 117(3):762–766.
- Coelli, M. B., Green, D. A., and Warburton, W. P. (2007). Breaking the cycle? The effect of education on welfare receipt among children of welfare recipients. *Journal of Public Economics*, 91(7-8):1369–1398.
- Cohen, M. A. (1988). Pain, suffering, and jury awards: A study of the cost of crime to victims. Law & Society Review, 22:537.

- Cohen, M. A., Rust, R. T., Steen, S., and Tidd, S. T. (2004). Willingness-to-pay for crime control programs. *Criminology*, 42(1):89–110.
- Corman, H., Dave, D. M., and Reichman, N. E. (2014). Effects of welfare reform on women's crime. *International Review of Law and Economics*, 40:1–14.
- Dahlberg, M., Johansson, K., and Mörk, E. (2009). On mandatory activation of welfare recipients. Discussion Paper 3947, IZA Institute of Labor Economics.
- Deadman, D. and MacDonald, Z. (2004). Offenders as victims of crime?: An investigation into the relationship between criminal behaviour and victimization. *Journal of the Royal Statistical Society. Series A (Statistics in Society)*, 167:53–67.
- DeFronzo, J. (1983). Economic assistance to impoverished Americans: Relationship to incidence of crime. *Criminology*, 21:119.
- DeFronzo, J. (1992). Economic frustration and sexual assault in large American cities. *Psychological reports*, 70(3):897–898.
- DeFronzo, J. (1996a). AFDC, a city's racial and ethnic composition, and burglary. *Social Service Review*, 70(3):464–471.
- DeFronzo, J. (1996b). Welfare and burglary. Crime & Delinquency, 42:223–229.
- DeFronzo, J. (1997). Welfare and homicide. Journal of Research in Crime and Delinquency, 34(3):395–406.
- DeFronzo, J. and Hannon, L. (1998). Welfare assistance levels and homicide rates. *Homicide Studies*, 2(1):31–45.
- DeLeire, T., Levine, J. A., and Levy, H. (2006). Is welfare reform responsible for low-skilled women's declining health insurance coverage in the 1990s? *Journal of Human Resources*, 41(3):495–528.
- Ehrlich, I. (1973). Participation in illegitimate activities: A theoretical and empirical investigation. *Journal of Political Economy*, 81(3):521–565.
- Elder, G. H. (1998). The life course as developmental theory. Child development, 69(1):1–12.
- Fallesen, P., Geerdsen, L. P., Imai, S., and Tranæs, T. (2018). The effect of active labor market policies on crime: Incapacitation and program effects. *Labour Economics*, 52:263–286.
- Foley, C. F. (2011). Welfare payments and crime. The Review of Economics and Statistics, 93(1):97–112.

- Gelman, A. and Imbens, G. (2018). Why high-order polynomials should not be used in regression discontinuity designs. *Journal of Business & Economic Statistics*, pages 1–10.
- Gould, E. D., Weinberg, B. A., and Mustard, D. B. (2002). Crime rates and local labor market opportunities in the United States: 1979–1997. Review of Economics and Statistics, 84(1):45–61.
- Grant, D. S. and Martinez Jr, R. (1997). Crime and the restructuring of the US economy: A reconsideration of the class linkages. *Social Forces*, 75(3):769–798.
- Han, S. and Vytlacil, E. (2017). Identification in a generalization of bivariate probit models with dummy endogenous regressors. *Journal of Econometrics*, 199:63–73.
- Hannon, L. and DeFronzo, J. (1998a). The truly disadvantaged, public assistance, and crime. Social Problems, 45(3):383–392.
- Hannon, L. and DeFronzo, J. (1998b). Welfare and property crime. *Justice Quarterly*, 15(2):273–288.
- Hernæs, Ø., Markussen, S., and Røed, K. (2017). Can welfare conditionality combat high school dropout? *Labour Economics*, 48:144–156.
- Hjalmarsson, R. (2008). Criminal justice involvement and high school completion. *Journal of Urban Economics*, 63(2):613–630.
- Holtfreter, K., Reisig, M. D., and Morash, M. (2004). Poverty, state capital, and recidivism among women offenders. *Criminology & Public Policy*, 3(2):185–208.
- Jianakoplos, N. A. and Bernasek, A. (1998). Are women more risk averse? *Economic Inquiry*, 36(4):620–630.
- Kruttschnitt, C. (2013). Gender and crime. Annual Review of Sociology, 39:291–308.
- Lageson, S. and Uggen, C. (2013). How work affects crime -and crime affects work- over the life course. In *Handbook of life-course criminology*, pages 201–212. Springer.
- Lee, D. S. (2008). Randomized experiments from non-random selection in US House elections. Journal of Econometrics, 142(2):675–697.
- Lee, D. S. and Card, D. (2008). Regression discontinuity inference with specification error. Journal of Econometrics, 142(2):655–674.
- Li, C., Poskitt, D., and Zhao, X. (2019). The bivariate probit model, maximum likelihood estimation, pseudo true parameters and partial identification. *Journal of Econometrics*, 209:94–113.

- Lochner, L. (2004). Education, work, and crime: A human capital approach. *International Economic Review*, 45(3):811–843.
- Lochner, L. and Moretti, E. (2004). The effect of education on crime: Evidence from prison inmates, arrests, and self-reports. *American Economic Review*, 94(1):155–189.
- Loureiro, M., Sanz-de galdeano, A., and Vuri, D. (2004). Smoking habits: like father, like son, like mother, like daughter. Oxford Bulletin of Economics and Statistics, 94(1):155–189.
- Machin, S., Marie, O., and Vujić, S. (2011). The crime reducing effect of education. *The Economic Journal*, 121(552):463–484.
- Mallar, C. D. and Thornton, C. V. (1978). Transitional aid for released prisoners: Evidence from the LIFE experiment. *Journal of Human Resources*, pages 208–236.
- McCollister, K. E., French, M. T., and Fang, H. (2010). The cost of crime to society: New crime-specific estimates for policy and program evaluation. *Drug and alcohol dependence*, 108(1):98–109.
- Meloni, O. (2014). Does poverty relief spending reduce crime? Evidence from Argentina. International Review of Law and Economics, 39:28–38.
- Ministry of Social Affairs and Employment (2015). Jongeren buiten beeld.
- Morris, S. (2007). The impact of obesity on employment. Labour Economics, 14:413–433.
- OECD (2018a). Adequacy of guaranteed minimum income benefits.
- OECD (2018b). Exchange rates: Total, national currency units/US dollar, 2000–2017.
- Persson, A. (2013). Activation programs, benefit take-up, and labor market attachment. Doctoral dissertation 2013:3, IFAU Institute for Evaluation of Labour Market and Education.
- Pratt, T. C. and Cullen, F. T. (2000). The empirical status of Gottfredson and Hirschi's general theory of crime: A meta-analysis. *Criminology*, 38(3):931–964.
- Pratt, T. C. and Cullen, F. T. (2005). Assessing macro-level predictors and theories of crime: A meta-analysis. *Crime and justice*, 32:373–450.
- Rajkumar, A. S. and French, M. T. (1997). Drug abuse, crime costs, and the economic benefits of treatment. *Journal of Quantitative Criminology*, 13(3):291–323.
- Rauma, D. and Berk, R. A. (1987). Remuneration and recidivism: The long-term impact of unemployment compensation on ex-offenders. *Journal of Quantitative Criminology*, 3(1):3–27.

- Schnepel, K. T. (2018). Good jobs and recidivism. The Economic Journal, 128(608):447–469.
- Statistics Netherlands, WODC Research and Documentation Centre, and The Council for the Judiciary (2013). Criminaliteit en rechtshandhaving 2013.
- Steffensmeier, D. and Allan, E. (1996). Gender and crime: Toward a gendered theory of female offending. *Annual Review of Sociology*, 22(1):459–487.
- US Bureau of Labor Statistics (2018). Historical consumer price index for all urban consumers (CPI-U): US city average, all items, by month.
- Van Dodeweerd, M. (2014). Divosa-monitor factsheet: In- en uitstroom uit de bijstand 2013. Divosa, Utrecht.
- Worrall, J. L. (2009). Social support and homicide. *Homicide studies*, 13(2):124–143.
- Yang, C. S. (2017a). Does public assistance reduce recidivism? *American Economic Review*, 107(5):551–55.
- Yang, C. S. (2017b). Local labor markets and criminal recidivism. *Journal of Public Economics*, 147:16–29.
- Zhang, J. (1997). The effect of welfare programs on criminal behavior: A theoretical and empirical analysis. *Economic Inquiry*, 35(1):120–137.
- Zhang, X., Zhao, X., and Harris, A. (2009). Chronic diseases and labour force participation in Australia. *Journal of Health Economics*, 28:91–108.

Appendices

A Employment

Table A.1: Testing for a discontinuity in the employment rate at the age of 27

-	LINEAR	QUADRATIC	LINEAR	QUADRATIC
	MEN	MEN	WOMEN	WOMEN
Labor participation				
RD	-0.0027†	0.0042***	0.0026*	0.0010
	(0.0016)	(0.0010)	(0.0010)	(0.0012)
Age	0.0020***	0.0029***	0.0002*	0.0004
	(0.0002)	(0.0004)	(0.0001)	(0.0003)
Age squared		-0.0001*		-0.0000
		(0.0000)		(0.0000)
Age x $1(<27)$	0.0025***	0.0035***	0.0026***	0.0017***
	(0.0002)	(0.0004)	(0.0001)	(0.0004)
Age x $1(<27)$ squared	,	0.0002***	,	-0.0000†
, ,		(0.0000)		(0.0000)
Native	0.5915***	0.5915***	0.7612***	0.7612***
	(0.0013)	(0.0013)	(0.0017)	(0.0017)
Time (month)	-0.0023***	-0.0023***	-0.0031***	-0.0031***
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Observations	6,663,749	6,663,749	6,546,177	6,546,177
Individuals	$315{,}773$	315,773	308,298	308,298
Clusters	28	28	28	28

Notes. 14-month bandwidth (28 months total), standard errors clustered by age (in months), *** indicates p<.001, ** p<.01, * p<.05 and † p<.10. The RD coefficient shows a significant, but insubstantial discontinuity in the employment rate around the age of 27.

B Extended estimation results

Table B.1: Linear instrumental variable estimates of the effect of welfare receipt on crime among men

BANDWIDTH	14 MONTHS	21 MONTHS	28 MONTHS	35 MONTHS
\overline{Crime}				
Welfare receipt	-0.3314**	-0.3364**	-0.3163**	-0.3049**
	(0.1108)	(0.1122)	(0.1010)	(0.0900)
Age	-0.0012†	-0.0015***	-0.0014***	-0.0016***
	(0.0006)	(0.0004)	(0.0003)	(0.0003)
Age x $1(<27)$	0.0004	0.0006	0.0004	0.0005
	(0.0009)	(0.0005)	(0.0004)	(0.0003)
Native	-0.3319***	-0.3319***	-0.3286***	-0.3274***
	(0.0177)	(0.0177)	(0.0160)	(0.0140)
Time (month)	-0.0017***	-0.0016***	-0.0016***	-0.0016***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Welfare receipt				
RD	-0.0279***	-0.0292***	-0.0298***	-0.0310***
	(0.0037)	(0.0042)	(0.0044)	(0.0042)
Age	0.0037***	0.0030***	0.0026***	0.0024***
	(0.0004)	(0.0002)	(0.0002)	(0.0002)
Age x $1(<27)$	-0.0010*	0.0005	0.0014***	0.0015***
	(0.0004)	(0.0004)	(0.0003)	(0.0003)
Native	-0.5923***	-0.5944***	-0.5949***	-0.5949***
	(0.0029)	(0.0031)	(0.0030)	(0.0031)
Time (month)	0.0025***	0.0024***	0.0023***	0.0022***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$\overline{ ho}$	0.4705***	0.4733***	0.4621***	0.4550***
	(0.0642)	(0.0640)	(0.0574)	(0.0511)
Probabilities (per month)				
If welfare receipt = $1 (\%)$	0.19	0.19	0.20	0.21
If welfare receipt = $0 \ (\%)$	0.51	0.52	0.52	0.52
ATE (%point)	-0.32***	-0.33***	-0.32***	-0.31***
	(0.09)	(0.09)	(0.08)	(0.08)
Observations	6,663,749	8,766,366	10,053,511	10,515,037
Respondents	315,773	$319,\!595$	$321,\!335$	$321,\!457$
Clusters	28	42	56	70

Notes. Linear model specification, standard errors clustered by age (in months), *** indicates p<.001, ** p<.05 and † p<.10.

Table B.2: Quadratic instrumental variable estimates of the effect of welfare receipt on crime among men

$ \begin{array}{ c c c c c c } \hline \textit{Crime} \\ \hline \textit{Welfare receipt} & -0.3358^{**} & -0.3648^{**} & -0.3247^{**} & -0.3169^{**} \\ \hline & (0.1143) & (0.1348) & (0.1071) & (0.0968) \\ \hline \textit{Age} & -0.0018 & -0.0003 & -0.0014 & -0.0009 \\ \hline & (0.0023) & (0.0014) & (0.0009) & (0.0008) \\ \hline \textit{Age squared} & 0.0000 & -0.0001 & -0.0000 & -0.0000 \\ \hline & (0.0002) & (0.0001) & (0.0000) & (0.0000) \\ \hline \textit{Age x 1}(<27) & 0.0018 & -0.0005 & 0.0006 & -0.0001 \\ \hline & (0.0038) & (0.0020) & (0.0015) & (0.0011) \\ \hline \end{array} $
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(0.0002) (0.0001) (0.0000) $(0.0000)Age x 1(<27) 0.0018 -0.0005 0.0006 -0.0001$
Age x $1(<27)$ 0.0018 -0.0005 0.0006 -0.0001
(0.0038) (0.0020) (0.0015) (0.0011)
(0.0030) (0.0020) (0.0013) (0.0011)
Age x $1(<27)$ squared 0.0000 0.0001 0.0000 0.0000
$(0.0002) \qquad (0.0001) \qquad (0.0000) \qquad (0.0000)$
Native -0.3326^{***} -0.3365^{***} -0.3300^{***} -0.3292^{***}
$(0.0184) \qquad (0.0219) \qquad (0.0170) \qquad (0.0152)$
Time (month) -0.0017^{***} -0.0015^{***} -0.0016^{***} -0.0016^{***}
$(0.0002) \qquad (0.0002) \qquad (0.0002) \qquad (0.0002)$
Welfare receipt
RD -0.0205^{***} -0.0266^{***} -0.0263^{***} -0.0267^{***}
$(0.0015) \qquad (0.0026) \qquad (0.0029) \qquad (0.0038)$
Age 0.0085^{***} 0.0062^{***} 0.0055^{***} 0.0047^{***}
$(0.0003) \qquad (0.0006) \qquad (0.0004) \qquad (0.0005)$
Age squared $-0.0003***$ $-0.0002***$ $-0.0001***$ $-0.0001***$
$(0.0000) \qquad (0.0000) \qquad (0.0000) \qquad (0.0000)$
Age x $1(<27)$ $-0.0076***$ $-0.0053***$ $-0.0037***$ $-0.0022***$
$(0.0006) \qquad (0.0007) \qquad (0.0005) \qquad (0.0006)$
Age x $1(<27)$ squared 0.0002^{***} 0.0000 0.0000 0.0000
$(0.0000) \qquad (0.0000) \qquad (0.0000) \qquad (0.0000)$
Native $-0.5923*** -0.5943*** -0.5949*** -0.5949***$
$(0.0029) \qquad (0.0031) \qquad (0.0030) \qquad (0.0031)$
Time (month) 0.0025^{***} 0.0024^{***} 0.0023^{***} 0.0022^{***}
$(0.0001) \qquad (0.0001) \qquad (0.0001) \qquad (0.0001)$
ρ 0.4729*** 0.4894*** 0.4669*** 0.4617***
$(0.0663) \qquad (0.0773) \qquad (0.0610) \qquad (0.0551)$
Probabilities (per month)
If welfare receipt = $1 (\%)$ 0.19 0.18 0.20
If welfare receipt = $0 (\%)$ 0.51 0.53 0.52
ATE (%point) -0.33^{***} -0.35^{**} -0.32^{***}
(0.09) (0.11) (0.09) (0.08)
Observations 6,663,749 8,766,366 10,053,511 10,515,037
Respondents 315,773 319,595 321,335 321,457
Clusters 28 42 56 70 Notes Oughestic model aposification standard arrows electored by aga (in months) *** indi

Notes. Quadratic model specification, standard errors clustered by age (in months), *** indicates p<.001, ** p<.01, * p<.05 and \dagger p<.10.

Table B.3: Linear instrumental variable estimates of the effect of welfare receipt on financially-motivated crime among men

BANDWIDTH	14 MONTHS	21 MONTHS	28 MONTHS	35 MONTHS
Financially-motivated crime				
Welfare receipt	-0.5072***	-0.4980***	-0.5035***	-0.4942***
	(0.0220)	(0.0222)	(0.0225)	(0.0226)
Age	-0.0009	-0.0015**	-0.0014***	-0.0017***
	(0.0010)	(0.0005)	(0.0004)	(0.0003)
Age x $1(<27)$	0.0008	$0.0016\dagger$	0.0015*	0.0018**
	(0.0016)	(0.0009)	(0.0006)	(0.0006)
Native	-0.3874***	-0.3842***	-0.3843***	-0.3821***
	(0.0086)	(0.0078)	(0.0076)	(0.0074)
Time (month)	-0.0003	-0.0001	-0.0001	-0.0002
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Welfare receipt				
RD	-0.0278***	-0.0293***	-0.0298***	-0.0310***
	(0.0037)	(0.0041)	(0.0043)	(0.0042)
Age	0.0037***	0.0030***	0.0026***	0.0024***
	(0.0004)	(0.0002)	(0.0002)	(0.0002)
Age x $1(<27)$	-0.0009*	0.0005	0.0014***	0.0015***
	(0.0004)	(0.0004)	(0.0003)	(0.0003)
Native	-0.5924***	-0.5945***	-0.5950***	-0.5950***
	(0.0029)	(0.0031)	(0.0030)	(0.0031)
Time (month)	0.0025***	0.0024***	0.0023***	0.0022***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
ho	0.5912***	0.5877***	0.5900***	0.5832***
	(0.0129)	(0.0128)	(0.0127)	(0.0130)
Probabilities (per month)				
If welfare receipt = $1 (\%)$	0.05	0.05	0.05	0.05
If welfare receipt = $0 \ (\%)$	0.25	0.25	0.25	0.24
ATE (%point)	-0.20***	-0.20***	-0.20***	-0.19***
	(0.01)	(0.01)	(0.01)	(0.01)
Observations	6,663,749	8,766,366	10,053,511	10,515,037
Respondents	315,773	$319,\!595$	$321,\!335$	$321,\!457$
Clusters	28	42	56	70

Notes. Linear model specification, standard errors clustered by age (in months), *** indicates p<.001, ** p<.01, * p<.05 and \dagger p<.10.

Table B.4: Quadratic instrumental variable estimates of the effect of welfare receipt on financially-motivated crime among men

BANDWIDTH	14 MONTHS	21 MONTHS	28 MONTHS	35 MONTHS
Financially-motivated crime				
Welfare receipt	-0.5193***	-0.5120***	-0.5099***	-0.5059***
	(0.0181)	(0.0192)	(0.0181)	(0.0182)
Age	0.0017	0.0014	-0.0002	0.0000
	(0.0042)	(0.0022)	(0.0014)	(0.0012)
Age squared	-0.0002	-0.0002	-0.0000	-0.0001
	(0.0003)	(0.0001)	(0.0001)	(0.0000)
Age x $1(<27)$	-0.0017	-0.0025	-0.0003	-0.0006
	(0.0073)	(0.0035)	(0.0023)	(0.0019)
Age x $1(<27)$ squared	0.0003	0.0001	0.0000	0.0000
	(0.0003)	(0.0001)	(0.0001)	(0.0000)
Native	0.3898***	-0.3869***	-0.3855***	-0.3844***
	(0.0079)	(0.0073)	(0.0069)	(0.0067)
Time (month)	-0.0003	-0.0001	-0.0001	-0.0001
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Welfare receipt				
RD	-0.0213***	-0.0267***	-0.0265***	-0.0268***
	(0.0017)	(0.0026)	(0.0029)	(0.0038)
Age	0.0084***	0.0062***	0.0054***	0.0047***
	(0.0003)	(0.0005)	(0.0004)	(0.0004)
Age squared	-0.0003***	-0.0002***	-0.0001***	-0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Age x $1(<27)$	-0.0076***	-0.0052***	-0.0037***	-0.0021***
	(0.0006)	(0.0007)	(0.0005)	(0.0006)
Age x $1(<27)$ squared	0.0002***	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Native	-0.5924***	-0.5945***	-0.5950***	-0.5950***
	(0.0029)	(0.0031)	(0.0030)	(0.0031)
Time (month)	0.0025***	0.0024***	0.0023***	0.0022***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$\overline{\rho}$	0.5982***	0.5959***	0.5937***	0.5901***
	(0.0095)	(0.0100)	(0.0099)	(0.0099)
Probabilities (per month)				
If welfare receipt = $1 (\%)$	0.05	0.05	0.05	0.05
If welfare receipt = $0 \ (\%)$	0.25	0.25	0.25	0.25
ATE (%point)	-0.21***	-0.20***	-0.20***	-0.20***
	(0.01)	(0.01)	(0.01)	(0.01)
Observations	6,663,749	8,766,366	10,053,511	10,515,037
Respondents	$315{,}773$	$319,\!595$	$321,\!335$	$321,\!457$
Clusters	28	42	56	70

Notes. Quadratic model specification, standard errors clustered by age (in months), *** indicates p<.001, ** p<.01, * p<.05 and \dagger p<.10.

Table B.5: Linear instrumental variable estimates of the effect of welfare receipt on crime among women

BANDWIDTH	14 MONTHS	21 MONTHS	28 MONTHS	35 MONTHS
\overline{Crime}				
Welfare receipt	-0.4235***	-0.4124***	-0.4123***	-0.4126***
	(0.0125)	(0.0130)	(0.0133)	(0.0137)
Age	0.0005	-0.0008	-0.0014**	-0.0015**
	(0.0012)	(0.0007)	(0.0005)	(0.0005)
Age x $1(<27)$	-0.0028	0.0003	0.0017*	0.0019*
	(0.0019)	(0.0011)	(0.0008)	(0.0008)
Native	-0.2553***	-0.2491***	-0.2504***	-0.2496***
	(0.0072)	(0.0066)	(0.0065)	(0.0065)
Time (month)	-0.0010**	-0.0009**	-0.0010**	-0.0010**
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Welfare receipt				
RD	-0.0115***	-0.0143***	-0.0171***	-0.0195***
	(0.0023)	(0.0027)	(0.0029)	(0.0031)
Age	0.0052***	0.0044***	0.0040***	0.0038***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Age x $1(<27)$	-0.0019***	-0.0008**	-0.0002	-0.0000
	(0.0003)	(0.0003)	(0.0002)	(0.0002)
Native	-0.5155***	-0.5181***	-0.5207***	-0.5218***
	(0.0046)	(0.0047)	(0.0048)	(0.0047)
Time (month)	0.0011***	0.0012***	0.0011***	0.0011***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$\overline{ ho}$	0.5361***	0.5317***	0.5314***	0.5301***
	(0.0043)	(0.0050)	(0.0056)	(0.0059)
Probabilities (per month)				
If welfare receipt = $1 (\%)$	0.03	0.03	0.03	0.03
If welfare receipt = $0 (\%)$	0.14	0.14	0.14	0.14
ATE (%point)	-0.11***	-0.11***	-0.11***	-0.11***
	(0.00)	(0.00)	(0.00)	(0.00)
Observations	6,546,177	8,611,854	9,871,600	10,323,410
Respondents	308,298	311,818	$313,\!550$	313,708
Clusters	28	42	56	70

Notes. Linear model specification, standard errors clustered by age (in months), *** indicates p<.001, ** p<.05 and † p<.10.

Table B.6: Quadratic instrumental variable estimates of the effect of welfare receipt on crime among women

BANDWIDTH	14 MONTHS	21 MONTHS	28 MONTHS	35 MONTHS
\overline{Crime}				
Welfare receipt	-0.4205***	-0.4086***	-0.4069***	-0.4079***
	(0.0124)	(0.0126)	(0.0126)	(0.0126)
Age	0.0033	0.0035	0.0019	0.0012
	(0.0055)	(0.0028)	(0.0018)	(0.0015)
Age squared	-0.0002	-0.0002	-0.0001†	-0.0001†
	(0.0004)	(0.0001)	(0.0001)	(0.0001)
Age x $1(<27)$	-0.0114	-0.0104*	-0.0062*	-0.0039
	(0.0096)	(0.0045)	(0.0031)	(0.0026)
Age x $1(<27)$ squared	-0.0003	-0.0001	-0.0001	-0.0000
	(0.0003)	(0.0001)	(0.0001)	(0.0001)
Native	-0.2547***	-0.2484***	-0.2494***	-0.2487***
	(0.0070)	(0.0065)	(0.0063)	(0.0062)
Time (month)	-0.0010**	-0.0009**	-0.0010**	-0.0010**
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Welfare receipt	· · · · · ·	,	,	
RD	-0.0090***	-0.0097***	-0.0092***	-0.0095***
	(0.0017)	(0.0016)	(0.0022)	(0.0026)
Age	0.0073***	0.0070***	0.0064***	0.0061***
	(0.0005)	(0.0003)	(0.0003)	(0.0004)
Age squared	-0.0001***	-0.0001***	-0.0001***	-0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Age x $1(<27)$	-0.0051***	-0.0047***	-0.0033***	-0.0027***
	(0.0006)	(0.0004)	(0.0004)	(0.0005)
Age x $1(<27)$ squared	0.0001	0.0001**	0.0001***	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Native	-0.5155***	-0.5181***	-0.5207***	-0.5218***
	(0.0046)	(0.0047)	(0.0048)	(0.0047)
Time (month)	0.0011***	0.0012***	0.0011***	0.0011***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$\overline{ ho}$	0.5343***	0.5295***	0.5282***	0.5273***
	(0.0040)	(0.0046)	(0.0049)	(0.0050)
Probabilities (per month)				
If welfare receipt = $1 (\%)$	0.03	0.03	0.03	0.03
If welfare receipt = $0 (\%)$	0.14	0.14	0.14	0.14
ATE (%point)	-0.11***	-0.11***	-0.10***	-0.10***
	(0.00)	(0.00)	(0.00)	(0.00)
Observations	6,546,177	8,611,854	9,871,600	10,323,410
Respondents	308,298	311,818	$313,\!550$	313,708
Clusters	28	42	56	70
Clusters Notes Overdratic model speed	28	42	56	70

Notes. Quadratic model specification, standard errors clustered by age (in months), *** indicates p<.001, ** p<.05 and \dagger p<.10.

Table B.7: Linear instrumental variable estimates of the effect of welfare receipt on financially-motivated crime among women

BANDWIDTH	14 MONTHS	21 MONTHS	28 MONTHS	35 MONTHS
Financially-motivated crime				
Welfare receipt	-0.3563***	-0.3423***	-0.3407***	-0.3390***
	(0.0170)	(0.0152)	(0.0149)	(0.0146)
Age	0.0007	-0.0014	-0.0018**	-0.0018**
	(0.0013)	(0.0009)	(0.0007)	(0.0006)
Age x $1(<27)$	-0.0037*	0.0006	$0.0019\dagger$	0.0020*
	(0.0018)	(0.0014)	(0.0011)	(0.0009)
Native	-0.2638***	-0.2582***	-0.2602***	-0.2601***
	(0.0090)	(0.0081)	(0.0079)	(0.0077)
Time (month)	-0.0008	-0.0007	-0.0008	-0.0008
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Welfare receipt				
RD	-0.0111***	-0.0140***	-0.0168***	-0.0193***
	(0.0023)	(0.0028)	(0.0029)	(0.0032)
Age	0.0052***	0.0044***	0.0040***	0.0038***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Age x $1(<27)$	-0.0019***	-0.0008**	-0.0002	-0.0000
	(0.0003)	(0.0003)	(0.0002)	(0.0002)
Native	-0.5154***	-0.5180***	-0.5206***	-0.5217***
	(0.0046)	(0.0047)	(0.0048)	(0.0047)
Time (month)	0.0011***	0.0012***	0.0011***	0.0011***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$\overline{ ho}$	0.5080***	0.5033***	0.5033***	0.5014***
	(0.0051)	(0.0055)	(0.0060)	(0.0060)
Probabilities (per month)				
If welfare receipt = $1 (\%)$	0.02	0.02	0.02	0.02
If welfare receipt = $0 (\%)$	0.07	0.07	0.07	0.07
ATE (%point)	-0.05***	-0.05***	-0.05***	-0.05***
	(0.00)	(0.00)	(0.00)	(0.00)
Observations	6,546,177	8,611,854	9,871,600	10,323,410
Respondents	308,298	311,818	$313,\!550$	313,708
Clusters	28	42	56	70

Notes. Linear model specification, standard errors clustered by age (in months), *** indicates p<.001, ** p<.05 and † p<.10.

Table B.8: Quadratic instrumental variable estimates of the effect of welfare receipt on financially-motivated crime among women

	BANDWIDTH	14 MONTHS	21 MONTHS	28 MONTHS	35 MONTHS
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Financially-motivated crime				
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		-0.3581***	-0.3410***	-0.3371***	-0.3360***
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		(0.0167)	(0.0149)	(0.0143)	(0.0139)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Age	0.0109*	$0.0049\dagger$	0.0020	0.0008
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		(0.0043)	(0.0026)	(0.0018)	(0.0018)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Age squared	-0.0007*	-0.0003*	-0.0001*	-0.0001
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		(0.0003)	(0.0001)	(0.0001)	(0.0001)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Age x $1(<27)$	-0.0222*	-0.0130**	-0.0077*	-0.0043
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		(0.0090)	(0.0043)	(0.0030)	(0.0028)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Age x $1(<27)$ squared	0.0002	-0.0001	-0.0001	-0.0001
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	_	(0.0004)	(0.0002)	(0.0001)	(0.0001)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Native				
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		(0.0089)	(0.0080)	(0.0077)	(0.0076)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Time (month)	-0.0008	-0.0007	-0.0008	-0.0008
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		(0.0006)	(0.0006)	(0.0006)	(0.0006)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Welfare receipt	,	,	,	
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	RD	-0.0084***	-0.0091***	-0.0087***	-0.0090**
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		(0.0017)	(0.0016)	(0.0022)	(0.0026)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Age	0.0073***	0.0070***	0.0065***	0.0062***
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		(0.0005)	(0.0003)	(0.0003)	(0.0004)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Age squared	-0.0001***	-0.0001***	-0.0001***	-0.0001***
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Age x $1(<27)$	-0.0050***	-0.0047***	-0.0033***	-0.0027***
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		(0.0006)	(0.0004)	(0.0004)	(0.0005)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Age x $1(<27)$ squared	$0.0001\dagger$	0.0001**	0.0001***	0.0001***
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Native	-0.5154***	-0.5180***	-0.5206***	-0.5217***
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$		(0.0046)	(0.0047)	(0.0048)	(0.0047)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Time (month)	0.0011***	0.0012***	0.0011***	0.0011***
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
$ \begin{array}{ c c c c c c c c } \hline Probabilities (per month) \\ \hline If welfare receipt = 1 (\%) & 0.02 & 0.02 & 0.02 & 0.02 \\ If welfare receipt = 0 (\%) & 0.07 & 0.07 & 0.07 & 0.07 \\ ATE (\%point) & -0.05^{***} & -0.05^{***} & -0.05^{***} & -0.05^{***} \\ \hline & & & & & & & & & & & & & & & & & &$	$\overline{ ho}$	0.5090***	0.5025***	0.5012***	0.4996***
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		(0.0045)	(0.0048)	(0.0051)	(0.0050)
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	Probabilities (per month)				
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	If welfare receipt = $1 (\%)$	0.02	0.02	0.02	0.02
	If welfare receipt = $0 (\%)$	0.07	0.07	0.07	0.07
Observations 6,546,177 8,611,854 9,871,600 10,323,410 Respondents 308,298 311,818 313,550 313,708	ATE (%point)	-0.05***	-0.05***	-0.05***	-0.05***
Respondents 308,298 311,818 313,550 313,708		(0.00)	(0.00)	(0.00)	(0.00)
	Observations	6,546,177	8,611,854	9,871,600	10,323,410
Clusters 28 42 56 70	Respondents	308,298	311,818	$313,\!550$	313,708
	Clusters	28	42	56	70

Notes. Quadratic model specification, standard errors clustered by age (in months), *** indicates p<.001, ** p<.01, * p<.05 and \dagger p<.10.

Table B.9: Linear instrumental variable estimates of the effect of welfare receipt on crime among low-educated men

BANDWIDTH	14 MONTHS	21 MONTHS	28 MONTHS	35 MONTHS
\overline{Crime}				
Welfare receipt	-0.3048**	-0.3229*	-0.3316**	-0.3210**
-	(0.1174)	(0.1258)	(0.1218)	(0.1067)
Age	-0.0007	-0.0011*	-0.0009*	-0.0010**
	(0.0007)	(0.0004)	(0.0004)	(0.0003)
Age x $1(<27)$	0.0006	0.0007	0.0006	$0.0007\dagger$
	(0.0010)	(0.0005)	(0.0005)	(0.0004)
Native	-0.2804***	-0.2822***	-0.2834***	-0.2821***
	(0.0178)	(0.0192)	(0.0188)	(0.0163)
Time (month)	-0.0024***	-0.0023***	-0.0023***	-0.0023***
	(0.0003)	(0.0002)	(0.0002)	(0.0002)
Welfare receipt				
RD	-0.0307***	-0.0322***	-0.0328***	-0.0336***
	(0.0035)	(0.0040)	(0.0042)	(0.0041)
Age	0.0046***	0.0039***	0.0035***	0.0033***
	(0.0004)	(0.0002)	(0.0002)	(0.0002)
Age x $1(<27)$	-0.0011**	0.0003	0.0011***	0.0014***
	(0.0004)	(0.0003)	(0.0003)	(0.0002)
Native	-0.5562***	-0.5578***	-0.5579***	-0.5575***
	(0.0022)	(0.0022)	(0.0021)	(0.0022)
Time (month)	0.0019***	0.0018***	0.0016***	0.0016***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$\overline{ ho}$	0.4379***	0.4483***	0.4535***	0.4467***
	(0.0683)	(0.0722)	(0.0700)	(0.0612)
Probabilities (per month)				
If welfare receipt = $1 (\%)$	0.26	0.26	0.25	0.26
If welfare receipt = $0 (\%)$	0.64	0.66	0.66	0.66
ATE (%point)	-0.38**	-0.40**	-0.41**	-0.40***
	(0.12)	(0.13)	(0.13)	(0.11)
Observations	5,032,325	6,620,974	7,594,865	7,945,022
Respondents	240,308	$243,\!628$	$245,\!131$	$245,\!215$
Clusters	28	42	56	70

Notes. Linear model specification, standard errors clustered by age (in months), *** indicates p<.001, ** p<.01, * p<.05 and † p<.10.

Table B.10: Quadratic instrumental variable estimates of the effect of welfare receipt on crime among low-educated men

BANDWIDTH	14 MONTHS	21 MONTHS	28 MONTHS	35 MONTHS
\overline{Crime}				
Welfare receipt	-0.3067*	-0.3610*	-0.3419*	-0.3388**
	(0.1189)	(0.1633)	(0.1319)	(0.1200)
Age	-0.0015	0.0003	-0.0009	-0.0004
	(0.0024)	(0.0015)	(0.0011)	(0.0008)
Age squared	0.0001	-0.0001	-0.0000	-0.0000
	(0.0002)	(0.0001)	(0.0000)	(0.0000)
Age x $1(<27)$	0.0022	-0.0003	0.0007	0.0001
	(0.0042)	(0.0022)	(0.0016)	(0.0013)
Age x $1(<27)$ squared	0.0000	0.0001	0.0000	0.0000
	(0.0002)	(0.0001)	(0.0000)	(0.0000)
Native	-0.2806***	-0.2882***	-0.2850***	-0.2849***
	(0.0181)	(0.0258)	(0.0206)	(0.0185)
Time (month)	-0.0024***	-0.0023***	-0.0023***	-0.0023***
	(0.0003)	(0.0003)	(0.0002)	(0.0002)
Welfare receipt				
RD	-0.0235***	-0.0290***	-0.0291***	-0.0299***
	(0.0016)	(0.0026)	(0.0028)	(0.0035)
Age	0.0091***	0.0071***	0.0064***	0.0056***
	(0.0004)	(0.0006)	(0.0004)	(0.0004)
Age squared	-0.0003***	-0.0002***	-0.0001***	-0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Age x $1(<27)$	-0.0073***	-0.0052***	-0.0038***	-0.0025***
	(0.0006)	(0.0007)	(0.0005)	(0.0005)
Age x $1(<27)$ squared	0.0002***	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Native	-0.5562***	-0.5578***	-0.5579***	-0.5575***
	(0.0022)	(0.0022)	(0.0021)	(0.0022)
Time (month)	0.0019***	0.0018***	0.0016***	0.0016***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
ho	0.4390***	0.4701***	0.4593***	0.4568***
	(0.0693)	(0.0943)	(0.0759)	(0.0691)
Probabilities (per month)				
If welfare receipt = $1 (\%)$	0.26	0.23	0.25	0.25
If welfare receipt = $0 \ (\%)$	0.64	0.67	0.67	0.67
ATE (%point)	-0.38**	-0.44**	-0.42**	-0.42**
	(0.12)	(0.17)	(0.14)	(0.12)
Observations	$5,\!032,\!325$	6,620,974	7,594,865	7,945,022
Respondents	240,308	243,628	$245,\!131$	$245,\!215$
Clusters Notes Ovedratio model speci	faction stands	42	56	70

Notes. Quadratic model specification, standard errors clustered by age (in months), *** indicates p<.001, ** p<.01, * p<.05 and \dagger p<.10.

Table B.11: Linear instrumental variable estimates of the effect of welfare receipt on financially-motivated crime among low-educated men

BANDWIDTH	14 MONTHS	21 MONTHS	28 MONTHS	35 MONTHS
Financially-motivated crime				
Welfare receipt	-0.5167***	-0.5119***	-0.5194***	-0.5132***
	(0.0283)	(0.0276)	(0.0273)	(0.0266)
Age	-0.0002	-0.0008	-0.0008†	-0.0010**
	(0.0011)	(0.0006)	(0.0004)	(0.0004)
Age x $1(<27)$	0.0006	0.0015	0.0016*	0.0019**
	(0.0017)	(0.0009)	(0.0007)	(0.0006)
Native	-0.3416***	-0.3389***	-0.3393***	-0.3377***
	(0.0096)	(0.0088)	(0.0086)	(0.0083)
Time (month)	-0.0010**	-0.0008**	-0.0008**	-0.0009**
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Welfare receipt				
RD	-0.0306***	-0.0323***	-0.0329***	-0.0336***
	(0.0035)	(0.0039)	(0.0042)	(0.0041)
Age	0.0046***	0.0039***	0.0035***	0.0033***
	(0.0004)	(0.0002)	(0.0002)	(0.0002)
Age x $1(<27)$	-0.0011*	0.0003	0.0012***	0.0014***
	(0.0004)	(0.0003)	(0.0003)	(0.0002)
Native	-0.5564***	-0.5579***	-0.5580***	-0.5576***
	(0.0022)	(0.0022)	(0.0020)	(0.0022)
Time (month)	0.0019***	0.0018***	0.0016***	0.0016***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$\overline{ ho}$	0.5799***	0.5790***	0.5826***	0.5776***
	(0.0168)	(0.0161)	(0.0157)	(0.0154)
Probabilities (per month)				
If welfare receipt = $1 (\%)$	0.06	0.06	0.06	0.06
If welfare receipt = $0 (\%)$	0.32	0.32	0.32	0.32
ATE (%point)	-0.26***	-0.26***	-0.26***	-0.26***
	(0.02)	(0.02)	(0.02)	(0.02)
Observations	5,032,325	6,620,974	7,594,865	7,945,022
Respondents	240,308	$243,\!628$	$245,\!131$	$245,\!215$
Clusters	28	42	56	70

Notes. Linear model specification, standard errors clustered by age (in months), *** indicates p<.001, ** p<.05 and † p<.10.

Table B.12: Quadratic instrumental variable estimates of the effect of welfare receipt on financially-motivated crime among low-educated men

BANDWIDTH	14 MONTHS	21 MONTHS	28 MONTHS	35 MONTHS
Financially-motivated crime				
Welfare receipt	-0.5278***	-0.5270***	-0.5267***	-0.5240***
	(0.0221)	(0.0239)	(0.0220)	(0.0218)
Age	0.0019	0.0021	0.0008	0.0009
_	(0.0043)	(0.0023)	(0.0015)	(0.0013)
Age squared	-0.0002	-0.0002	-0.0001	-0.0001†
	(0.0003)	(0.0001)	(0.0001)	(0.0000)
Age x $1(<27)$	-0.0013	-0.0026	-0.0010	-0.0011
	(0.0077)	(0.0038)	(0.0025)	(0.0021)
Age x $1(<27)$ squared	0.0002	0.0001	0.0000	0.0000
, , <u>,</u>	(0.0003)	(0.0001)	(0.0001)	(0.0000)
Native	-0.3438***	-0.3418***	-0.3407***	-0.3398***
	(0.0086)	(0.0082)	(0.0077)	(0.0075)
Time (month)	-0.0010**	-0.0008**	-0.0008**	-0.0008**
,	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Welfare receipt	,	,	,	,
RD	-0.0242***	-0.0290***	-0.0294***	-0.0301***
	(0.0017)	(0.0026)	(0.0028)	(0.0035)
Age	0.0091***	0.0070***	0.0063***	0.0056***
	(0.0004)	(0.0005)	(0.0004)	(0.0004)
Age squared	-0.0003***	-0.0002***	-0.0001***	-0.0001***
.	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Age x $1(<27)$	-0.0074***	-0.0051***	-0.0038***	-0.0024***
5 ()	(0.0006)	(0.0006)	(0.0005)	(0.0005)
Age x $1(<27)$ squared	0.0002***	0.0000	0.0000	0.0000
J (/ 1	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Native	-0.5564***	-0.5579***	-0.5580***	-0.5576***
	(0.0022)	(0.0022)	(0.0020)	(0.0022)
Time (month)	0.0019***	0.0018***	0.0016***	0.0016***
,	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$\overline{ ho}$	0.5864***	0.5879***	0.5868***	0.5839***
,	(0.0121)	(0.0129)	(0.0122)	(0.0121)
Probabilities (per month)	/	,	, ,	,
If welfare receipt = $1 (\%)$	0.06	0.06	0.06	0.06
If welfare receipt = $0 (\%)$	0.33	0.32	0.32	0.32
ATE (%point)	-0.27***	-0.27***	-0.27***	-0.26***
(* -1 /	(0.01)	(0.01)	(0.01)	(0.01)
Observations	5,032,325	6,620,974	7,594,865	7,945,022
Respondents	240,308	243,628	245,131	245,215
Clusters	28	42	56	70
Notes Quadratic model spec				

Notes. Quadratic model specification, standard errors clustered by age (in months), *** indicates p<.001, ** p<.01, * p<.05 and \dagger p<.10.

Table B.13: Linear instrumental variable estimates of the effect of welfare receipt on crime among low-educated women

BANDWIDTH	14 MONTHS	21 MONTHS	28 MONTHS	35 MONTHS
\overline{Crime}				
Welfare receipt	-0.4171***	-0.4058***	-0.4080***	-0.4053***
-	(0.0144)	(0.0149)	(0.0159)	(0.0167)
Age	0.0009	-0.0004	-0.0010†	-0.0013*
	(0.0013)	(0.0007)	(0.0006)	(0.0005)
Age x $1(<27)$	-0.0027	0.0004	0.0018*	0.0021**
	(0.0020)	(0.0011)	(0.0009)	(0.0008)
Native	-0.1690***	-0.1631***	-0.1651***	-0.1641***
	(0.0081)	(0.0075)	(0.0073)	(0.0072)
Time (month)	-0.0015***	-0.0014***	-0.0015***	-0.0015***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Welfare receipt				
RD	-0.0127***	-0.0152***	-0.0181***	-0.0205***
	(0.0023)	(0.0029)	(0.0030)	(0.0033)
Age	0.0063***	0.0055***	0.0051***	0.0048***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Age x $1(<27)$	-0.0021***	-0.0009***	-0.0004†	-0.0001
	(0.0003)	(0.0003)	(0.0002)	(0.0002)
Native	-0.4298***	-0.4320***	-0.4344***	-0.4355***
	(0.0036)	(0.0036)	(0.0036)	(0.0036)
Time (month)	0.0004***	0.0004***	0.0004***	0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$\overline{ ho}$	0.5071***	0.5024***	0.5034***	0.5005***
	(0.0057)	(0.0065)	(0.0075)	(0.0081)
Probabilities (per month)				
If welfare receipt = $1 (\%)$	0.05	0.05	0.05	0.05
If welfare receipt = $0 (\%)$	0.20	0.20	0.20	0.20
ATE (%point)	-0.15***	-0.15***	-0.15***	-0.15***
	(0.01)	(0.01)	(0.01)	(0.01)
Observations	4,283,703	5,636,719	6,464,560	6,762,853
Respondents	$204,\!278$	$207,\!150$	$208,\!531$	$208,\!627$
Clusters	28	42	56	70

Notes. Linear model specification, standard errors clustered by age (in months), *** indicates p<.001, ** p<.01, * p<.05 and † p<.10.

 $\begin{tabular}{ll} Table B.14: Quadratic instrumental variable estimates of the effect of welfare receipt on crime among low-educated women \\ \end{tabular}$

BANDWIDTH	14 MONTHS	21 MONTHS	28 MONTHS	35 MONTHS
\overline{Crime}				
Welfare receipt	-0.4144***	-0.4008***	-0.4016***	-0.4012***
	(0.0136)	(0.0141)	(0.0146)	(0.0146)
Age	0.0052	0.0042	0.0024	0.0021
	(0.0057)	(0.0029)	(0.0020)	(0.0016)
Age squared	-0.0003	-0.0002	-0.0001†	-0.0001*
	(0.0004)	(0.0001)	(0.0001)	(0.0001)
Age x $1(<27)$	-0.0127	-0.0107*	-0.0061†	-0.0043
	(0.0097)	(0.0046)	(0.0033)	(0.0026)
Age x $1(<27)$ squared	-0.0001	-0.0001	-0.0001	0.0000
	(0.0004)	(0.0001)	(0.0001)	(0.0001)
Native	-0.1685***	-0.1623***	-0.1641***	-0.1635***
	(0.0078)	(0.0073)	(0.0070)	(0.0068)
Time (month)	-0.0015***	-0.0014***	-0.0015***	-0.0015***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Welfare receipt				
RD	-0.0103***	-0.0107***	-0.0100***	-0.0105***
	(0.0013)	(0.0014)	(0.0022)	(0.0026)
Age	0.0086***	0.0083***	0.0076***	0.0073***
	(0.0004)	(0.0002)	(0.0003)	(0.0004)
Age squared	-0.0002***	-0.0001***	-0.0001***	-0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Age x $1(<27)$	-0.0057***	-0.0052***	-0.0037***	-0.0032***
	(0.0005)	(0.0003)	(0.0004)	(0.0005)
Age x $1(<27)$ squared	$0.0001\dagger$	0.0001**	0.0001***	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Native	-0.4298***	-0.4320***	-0.4344***	-0.4356***
	(0.0036)	(0.0036)	(0.0036)	(0.0036)
Time (month)	0.0004***	0.0004***	0.0004***	0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$\overline{ ho}$	0.5056***	0.4994***	0.4996***	0.4981***
	(0.0048)	(0.0057)	(0.0063)	(0.0065)
Probabilities (per month)				
If welfare receipt = $1 (\%)$	0.05	0.05	0.05	0.05
If welfare receipt = $0 (\%)$	0.20	0.20	0.20	0.20
ATE (%point)	-0.15***	-0.15***	-0.15***	-0.14***
	(0.00)	(0.00)	(0.01)	(0.01)
Observations	4,283,703	5,636,719	6,464,560	6,762,853
Respondents	204,278	$207,\!150$	$208,\!531$	$208,\!627$
Clusters Notes Ovedratio model speci	28	42	56	70

Notes. Quadratic model specification, standard errors clustered by age (in months), *** indicates p<.001, ** p<.01, * p<.05 and \dagger p<.10.

Table B.15: Linear instrumental variable estimates of the effect of welfare receipt on financially-motivated crime among low-educated women

BANDWIDTH	14 MONTHS	21 MONTHS	28 MONTHS	35 MONTHS
Financially-motivated crime				
Welfare receipt	-0.3483***	-0.3338***	-0.3347***	-0.3314***
	(0.0189)	(0.0170)	(0.0171)	(0.0168)
Age	0.0010	-0.0009	-0.0014*	-0.0016*
	(0.0014)	(0.0009)	(0.0007)	(0.0007)
Age x $1(<27)$	-0.0036†	0.0003	$0.0020\dagger$	0.0022*
	(0.0020)	(0.0015)	(0.0011)	(0.0010)
Native	-0.1836***	-0.1777***	-0.1805***	-0.1802***
	(0.0094)	(0.0087)	(0.0082)	(0.0080)
Time (month)	-0.0013*	-0.0012*	-0.0013*	-0.0013*
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Welfare receipt				
RD	-0.0123***	-0.0149***	-0.0178***	-0.0203***
	(0.0023)	(0.0029)	(0.0031)	(0.0034)
Age	0.0064***	0.0055***	0.0051***	0.0048***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Age x $1(<27)$	-0.0021***	-0.0009**	-0.0004†	-0.0001
	(0.0003)	(0.0003)	(0.0002)	(0.0002)
Native	-0.4298***	-0.4319***	-0.4343***	-0.4355***
	(0.0036)	(0.0036)	(0.0036)	(0.0036)
Time (month)	0.0004***	0.0004***	0.0004***	0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
ho	0.4781***	0.4724***	0.4738***	0.4711***
	(0.0064)	(0.0069)	(0.0075)	(0.0076)
Probabilities (per month)				
If welfare receipt = $1 (\%)$	0.03	0.03	0.03	0.03
If welfare receipt = $0 \ (\%)$	0.10	0.10	0.10	0.10
ATE (%point)	-0.07***	-0.07***	-0.07***	-0.07***
	(0.00)	(0.00)	(0.00)	(0.00)
Observations	$4,\!283,\!703$	5,636,719	$6,\!464,\!560$	6,762,853
Respondents	$204,\!278$	$207,\!150$	$208,\!531$	$208,\!627$
Clusters	28	42	56	70

Notes. Linear model specification, standard errors clustered by age (in months), *** indicates p<.001, ** p<.01, * p<.05 and \dagger p<.10.

Table B.16: Quadratic instrumental variable estimates of the effect of welfare receipt on financially-motivated crime among low-educated women

BANDWIDTH	14 MONTHS	21 MONTHS	28 MONTHS	35 MONTHS
$\overline{Financially ext{-}motivated\ crime}$				
Welfare receipt	-0.3519***	-0.3331***	-0.3302***	-0.3287***
	(0.0184)	(0.0165)	(0.0158)	(0.0154)
Age	0.0125**	$0.0054\dagger$	0.0028	0.0017
	(0.0046)	(0.0028)	(0.0020)	(0.0019)
Age squared	-0.0008*	-0.0003*	-0.0002*	-0.0001
	(0.0003)	(0.0001)	(0.0001)	(0.0001)
Age x $1(<27)$	-0.0233*	-0.0125**	-0.0082*	-0.0049
	(0.0092)	(0.0046)	(0.0033)	(0.0030)
Age x $1(<27)$ squared	0.0003	-0.0000	-0.0001	-0.0000
	(0.0004)	(0.0002)	(0.0001)	(0.0001)
Native	-0.1842***	-0.1776***	-0.1799***	-0.1798***
	(0.0093)	(0.0085)	(0.0080)	(0.0078)
Time (month)	-0.0013*	-0.0012*	-0.0013*	-0.0013*
,	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Welfare receipt	,		,	,
RD	-0.0097***	-0.0102***	-0.0095***	-0.0100***
	(0.0014)	(0.0014)	(0.0022)	(0.0026)
Age	0.0086***	0.0083***	0.0077***	0.0074***
_	(0.0004)	(0.0002)	(0.0003)	(0.0004)
Age squared	-0.0002***	-0.0001***	-0.0001***	-0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Age x $1(<27)$	-0.0057***	-0.0052***	-0.0037***	-0.0032***
	(0.0005)	(0.0003)	(0.0004)	(0.0005)
Age x $1(<27)$ squared	0.0001*	0.0001***	0.0001***	0.0001***
, , <u>,</u>	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Native	-0.4298***	-0.4319***	-0.4343***	-0.4355***
	(0.0036)	(0.0036)	(0.0036)	(0.0036)
Time (month)	0.0004***	0.0004***	0.0004***	0.0004***
,	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$\overline{ ho}$	0.4801***	0.4719***	0.4712***	0.4695***
,	(0.0055)	(0.0059)	(0.0061)	(0.0061)
Probabilities (per month)	, ,	,	,	,
If welfare receipt $= 1 (\%)$	0.03	0.03	0.03	0.03
If welfare receipt = 0 (%)	0.10	0.10	0.10	0.10
ATE (%point)	-0.07***	-0.07***	-0.07***	-0.07***
(1 /	(0.00)	(0.00)	(0.00)	(0.00)
Observations	4,283,703	5,636,719	6,464,560	6,762,853
Respondents	204,278	207,150	208,531	208,627
Clusters	28	42	56	70
Notes Quadratic model specification standard errors clustered by age (in months) *** indi-				

Notes. Quadratic model specification, standard errors clustered by age (in months), *** indicates p<.001, ** p<.01, * p<.05 and \dagger p<.10.