Discussion Papers in Economics

VICTIMISATION AND BIRTH OUTCOMES

By

Lívia Menezes
(University of Birmingham)

&

Martin Foureaux Koppensteiner
(University of Surrey).

DP 07/23

School of Economics
University of Surrey
Guildford
Surrey GU2 7XH, UK
Telephone +44 (0)1483 689380
Facsimile +44 (0)1483 689548
Web https://www.surrey.ac.uk/school-economics
ISSN: 1749-5075
Victimisation and Birth Outcomes*

Lívia Menezes† Martin Foureaux Koppensteiner‡

June 27, 2023

Abstract

We estimate the causal effect of individual criminal victimisation in robbery and theft on birth outcomes using a unique dataset from Brazil combining information on the universe of victims of crime with vital statistics data. We find that victimisation during pregnancy reduces birthweight by about 16 grams – 3 percent of a standard deviation in birthweight – and increases the likelihood of low and extremely low birthweight by about 8.5 and 30 percent, respectively, compared to the baseline. The results are robust to the inclusion of place of residence, maternal and time fixed effects and to the inclusion of a very large array of mother and pregnancy characteristics. We also show that victimisation leads to behavioural adjustments of mothers as we observe a reduction in the number of prenatal visits. Effects are stronger for individuals of lower socio-economic background, indicating that victimisation might contribute to the intergenerational transmission of poverty.

JEL Classification: I12, J13, K42, O12

Keywords: Victimisation, crime, birth outcomes, health investments

*We would like to thank Anna Bindler, Jennifer Doleac, Randi Hjarlmarsson, Jesse Matheson, Olivier Marie, James Rockey, and seminar participants at Birmingham, Gothenburg, Leicester, Surrey, and the annual congress of the European Economic Association in Manchester for very useful comments. The usual disclaimer applies.
†University of Birmingham, Edgbaston, Birmingham B15 2TT, UK. Email: l.menezes@bham.ac.uk
‡University of Surrey, Guildford, Surrey, GU2 7XH, UK. Email: m.koppensteiner@surrey.ac.uk
1 Introduction

Falling victim to crime is a major concern for citizens around the world, in particular when it involves violence or the threat of violence. The reality of Brazil, and indeed many other countries suffering from very high crime rates, is one of exposure to everyday violence and crime. Robberies often involve the use or threat of use of violence, including the use of firearms or knives, leading to traumatic experiences of the victims involved. This is also reflected in crime being a top concern for citizens in the region.\(^1\) In addition to a potential financial loss from items apprehended through crime or criminal damage (Cohen et al. (2004)), victimisation in crime is linked to a myriad of adverse effects on victims, ranging from the direct health consequences due to injury (Miller et al. (1993)) and reductions in life expectancy (Auger et al. (2016)) from violent crime, the economic impact from lost productivity (Cabral et al. (2016)), to the psychological costs of becoming a victim (Hanson et al. (2010)).

Most of the literature on the consequences of victimisation relies on cross-sectional data from surveys suffering from endogeneity and merely provides correlates of victimisation on a number of outcomes. The use of survey data also restricts the analysis from investigating rare events or events focused on smaller populations, such as the effect of victimisation during pregnancy on birth outcomes. In this paper, we investigate the effect of individual victimisation - in robbery and theft - during pregnancy on health outcomes at birth, including birthweight (BW), gestational length, and infant mortality making use of a unique dataset from Brazil linking the universe of crime reports—including information on all victims—with the universe of birth records for the period between 2011 to 2017.

There are two potential underlying channels that may lead maternal victimisation during pregnancy to affect birth outcomes. First, given the violent nature of many crimes in the Brazilian context, being victimised may provide for a traumatic experience for the mother and may in turn affect the development of the fetus in utero. Second, the material loss from crime, either through the direct loss of valuables or criminal damage, may pose an economic shock to households, which - in particular for poor households - may detrimentally impact nutrition during pregnancy and hence affect birth outcomes. These two competing channels have different implications, for example, on when during pregnancy victimisation has the most detrimental impact. Maternal stress has been

\(^1\)Latinobarómetro provides regular public opinion surveys for countries in Latin America (http://www.latinobarometro.org). In survey responses, crime and violence regularly score highly when participants are asked about the countries’ most important problems.
established to affect the unborn child most severely during the first trimester, while inter-uterine growth retardation, due to nutritional deficiency is expected to most severely affect BW late in pregnancy, when the fetus gains most weight in absolute terms.

There is a growing literature in economics estimating the effects of stressful events linked to violent events on birth outcomes of children exposed in-utero. These events include terrorist attacks, war, secular crime waves and everyday violence. Papers on the effect of terrorist attacks have covered a variety of events. For example, Camacho (2008) estimates the effect of exposure to landmine explosions in Colombia during the time in-utero on BW. The author finds that exposure to landmine explosion during the first trimester leads to a 9 gram reduction in birth weight. Quintana-Domeque and Ródenas-Serrano (2017) also focus on terrorist attacks, but in the context of ETA terrorism in Spanish provinces and find that in-utero exposure early in gestation increases the prevalence of low birth weight deliveries and reduces gestational length. There is also a number of papers which study the effect of maternal stress associated with the 9/11 attacks in the US on birth outcomes (Ecclestone (2012), Eskenazi et al. (2007)), although they struggle to isolate the effect of stress from possible confounders linked to exposure to pollutants for mothers resident in New York City (Currie and Schwandt (2015)). In the context of violent conflict, Mansour and Rees (2012) focus on pregnant women resident in Palestine exposed to non-combatant fatalities from the Second Intifada finding a modest fall in BW for unborn babies of mothers exposed to higher fatalities. Foureaux Koppensteiner and Manacorda (2016) estimate the effect of exposure to homicides in rural Brazil on BW. They find that exposure early in gestation leads to a reduction in gestational length, a reduction in BW and an increase in the number of babies categorised as low BW. In contrast, Brown (2018) focusing on the secular increase in homicides linked to the war on drugs in Mexico, finds a positive effect of the escalation of homicides over the period between 2008 and 2010 on BW arguing that this effect is due to increased pre-natal care utilisation. These papers have in common that they use indirect exposure to violence and stressful events with often relatively small coefficients; the indirect exposure making it difficult to interpret the magnitude of the estimated effects as the degree of exposure is often uncertain.

In this paper, we estimate the effect of victimisation on birth outcomes, by exploiting that after controlling for place of residence, hospital of birth and time fixed effects becoming a victim of crime is conditionally random. We depart from previous studies in a number of important ways. Firstly, by linking the universe of police reports that include information on all victims of crime to the universe of birth records, we are able to study the effect of individual victimisation at the
individual level addressing concerns about the uncertainty of the degree of exposure and hence the interpretation of the magnitude of the estimated effects. Secondly, different from previous work on the effect of victimisation in assaults on birth outcomes (Currie et al. (2022), we focus on victimisation in prevalent day-to-day crimes of theft and robbery, enabling us to study heterogeneous effects and the underlying mechanisms, while excluding that any effects are driven by the physical impact on the unborn child from assaults. We make use of the crime categorisation from police records and focus on the two largest crime categories involving a victim, robbery and theft. Because these two distinct types of crime have different implications for the channels underlying the estimated effect, this allows us to investigate a number of competing hypothesis on the mechanisms. In particular, we aim at disentangling the effect on birth outcomes due to the economic impact from victimisation from the effect due to the stress associated with being a victim in these crimes, making use of the extremely detailed information we have from the crime reports, only possible due to the individual level information on victimisation we have available.

We find that victimisation, either robbery or theft, during pregnancy significantly reduces BW by about 16 grams on average. These modest average effects disguise large relative effects at lower parts of the BW distribution. We find that victimisation during pregnancy increases the incidence of low BW by 0.8 percentage points, a 9.5 percent increase compared to the baseline incidence. The effects are even more pronounced for extremely low BW; we document a 38 percent increase. The effects are driven by exposure in the last trimester, with on average 3 times more pronounced effects for BW; and even more accentuated effects for very and extremely low BW. The effect of victimisation are not limited to health at birth, but have longer-lasting effects on childrens’ health. We find a significant increase in hospitalisations of 0.7 percentage points, a 6 percent increase over the baseline. Most of the effect arises from hospitalisation shortly after birth, but we cannot rule out effects many months after birth. We also find that victimisation increases neonatal ICU utilization and ICU admittance, and results in a substantial increase in the financial cost due to hospitalisation. While we also find that victimisation leads to an increase in the length of the hospital stay, the effects are not statistically significant.

We also document important heterogeneous effects along a number of maternal characteristics. We find that effects for BW and BW classifications are more pronounced for mothers with lower socioeconomic status. We also find slightly stronger effects for low and very low birthweight for mothers with lower levels of education and stronger effects for BW and low BW for mothers not in a relationship at the point of birth.
The remainder of the paper is organised as follows. Section 2 describes the datasets used in the analysis. Section 3 details the identification strategy applied to estimate the causal effect of crime victimisation on birth outcomes. Section 4 analyses the results and section 5 presents the final remarks.

2 Data

To enable the estimation of the causal effect of criminal victimisation on birth outcomes, we construct a novel data set by combining four administrative datasets from Brazil, the universe of birth records, the universe of hospital episodes, the universe of death records and the universe of crimes.

2.1 Birth data

We use data from the Brazilian Ministry of Health collected through the Live Birth Information System (SINASC)\(^2\), over the period between 2011 and 2017. These data come from birth certificates, containing the universe of births in the state, and include detailed information on the characteristics of the mother, pregnancy, delivery and indicators of newborn’s health.\(^3\)

We determine the precise gestational length by using date of the mother’s last menstrual period reported in the birth records and the date of delivery. To investigate the effect of victimisation along the distribution of gestation, we created indicator variables for preterm and very preterm delivery, defined as gestational periods which last less than 259 days (37 weeks) and less than 224 days (32 weeks), respectively.

In addition to information on health outcomes of live births, the SINASC data also contains information on pregnancy and delivery. Prenatal visits are free in the public health system and antenatal care is generally of high quality in Brazil (Victora et al. (2011)). On average, women have around just above 8 prenatal care visits.\(^4\) Over the period from 2011 to 2017, 1,373,656 births occurred in the state, which we can use for the analysis. The large number of births we have available allow us to detect effects even if victimisation during the nine month of pregnancy is relatively rare and to investigate heterogeneous effects along a number of critical margins.

\(^2\)Sistema de Informações sobre Nascidos Vivos, in Portuguese.

\(^3\)Where the births occur in the hospital—the vast majority of cases (99%)—birth records are sent directly to the state secretariat of health; where the birth occurs in the residence, the attending midwife reports the information to the secretariat providing us with near universal coverage of births occurring in the state.

\(^4\)These include extensive screening for risk factors including diabetes, pre-eclampsia, underlying infections and ultrasound scans of the fetus.
2.2 Hospital episodes data

We link birth records with hospital episodes data from the Brazilian Hospital Information System (SIH). SIH contains information on the universe of admissions to hospitals in the public health system (SUS). SIH provides information on the timing and duration of hospital episodes, direct costs from the hospitalisation to SUS, information on the hospital department used, for example whether the patient was admitted to intensive care units (ICU) or neonatal ICU, and the detailed cause of death from the WHO ICD-10 classifications of diseases.

2.3 Infant mortality data

In addition to hospital episodes, we complement measures of health at birth with mortality records for the first year of life. For this purpose, we link birth records with the universe of death records from the Brazilian Mortality Information System (SIM). This data set contains information on all natural and non-natural deaths in Brazil, including detailed cause of death and characteristics of the deceased. In case of any death occurring up to the age of one, these data also register the characteristics of mothers and birth outcomes, hence allowing us to link information on child mortality with the birth records using the unique birth identifier. We create standard measures of child mortality, including early neonatal (within 1 week of birth), neonatal (4 weeks) and infant death (1 year).

2.4 Crime data

Lastly, we have access to all crime reports involving a victim reported to police over the period between 2011 and 2017 from the Register of Occurrence (SRO). Whenever police are called to an incidence or when a crime is reported to police by the victim or a third party, a new entry into the SRO is produced. For the analysis, we focus on robberies and theft, two categories that make up the vast majority of crimes involving an individual victim, but for which we can exclude that physical violence drives any estimated effect on the health of children at birth. We link cases of

---

5 Sistema de Informações Hospitalares, in Portuguese
6 This differs from birth records, which are available for the universe of all births, including in private hospitals and home births. Any effects of victimisation on hospital episodes may hence possibly be an underestimate, given that SIH does not capture all hospitalisations.
7 We link hospitalisation records to the birth records based on place of residence (postcode) and date of birth of patients, in contrast to the other data sets in this paper, which we link using individual identifiers, limiting the number of successful links due to duplicate observations of address and date of birth observations.
8 Sistema de Informações sobre Mortalidade, in Portuguese.
9 Sistema de Registro de Ocorrência, in Portuguese.
victims of robbery and theft with the birth records data using unique individual identifiers.

3 Identification Strategy

The estimation of the causal effect of victimisation on birth outcomes is complicated by the presence of confounding factors when the propensity to being victimised is correlated with other unobserved neighbourhood characteristics. For instance, neighbourhoods with higher crime rates—putting pregnant women at higher risk of being victimised—may also be poorer and provide worse public services. It may hence be worse health services or worse parental characteristics leading to worse birth outcomes, rather than a causal effect of victimisation when not accounting for those neighbourhood characteristics.\(^\text{10}\) Lower levels of the provision of public services, for example from policing, may also affect the propensity to report or record crime, potentially leading to only the most severe crimes being reported to police.\(^\text{11}\) Therefore any evidence based on cross-sectional data might lead to erroneous inference on the relationship between criminal victimisation and measures of health at birth.

In order to address the endogeneity problem, we use a large dataset comprising all births in a large state of Brazil linked to crime records and estimate fixed effect models holding the characteristics of neighbourhoods and place of residence constant. In all specifications, we include month of conception fixed effects to capture time trends. We also make use of a large set of controls which contains a range of observed characteristics of the mother and of the pregnancy, such as age, race, marital status, educational background, dummies for the number of children born alive and stillbirths from previous pregnancies, gestation order, and birth interval (time between conceptions).

Because gestational length may mechanically affect the propensity of victimisation towards the end of pregnancy, i.e. that mothers with longer gestational length have more chances to be victimised, we make use of the very rich information on the pregnancy in our data set. First, we construct date of conception from information on the date of the last menstruation.\(^\text{12}\) Second, we

---

\(^{10}\) There is a substantial literature showing how poverty and poor nutrition during gestation leads to adverse effects on later life outcomes, and impacts health beyond birth outcomes (Chen and Zhou (2007), Lindeboom et al. (2010)) or an adverse disease environment, including poorer sanitation (Rocha and Soares (2015), Maccini and Yang (2009), Almond et al. (2011), Almond et al. (2012), Amarante et al. (2016), Bozzoli and Quintana-Domeque (2016)). Furthermore, a number of papers have documented how low socioeconomic status is related to stress, poor health and short-sighted and risk-averse decision making, which in turn may negatively affect newborn’s health beyond poor nutrition (Dohrenwend (1973), Case et al. (2002), Deaton (2002), Haushofer and Ernest (2014)).

\(^{11}\) A related issue with reporting arises from the use of crime surveys with self-reported victimisation.

\(^{12}\) This has the advantage of minimising the risk of mis-attributing victimisation to the wrong trimester or to periods before conception, when constructing trimesters by working backwards from date of birth using information of gestational length (Quintana-Domeque and Ródenas-Serrano (2017)).
assign equivalent gestational lengths to all mothers in an intention-to-treat framework: starting from conception date (defined by the medical literature as the date of the last menstrual period) we consider a full term gestation of 280 days. We then split the gestational period into three trimesters; the first and second trimesters last 93 days and the and the third 94 days. We then identify the number of times a mother was victimised in each of the above defined trimesters.

Equation 1 summarises the model we estimate:

\[ y_{int} = \beta_0 + \beta_1 \text{victim}_i + X_i \beta_2 + d_n + d_t + u_{int} \]  

\( y_{int} \) is the outcome of interest related to mother \( i \) in neighbourhood \( n \), \( \text{victim}_i \) is a measure for whether a mother \( i \) was a victim of robbery or theft during pregnancy; \( X_i \) is a vector of mother and pregnancy observed characteristics; \( d_n \), \( d_h \) and \( d_t \) are neighbourhood of residence, and month of conception (both linear and calendar) fixed effects; \( u_{int} \) is the error term. Standard errors are clustered at the neighbourhood level. Conditional on neighbourhood and month of conception fixed effects, mother’s exposure to victimisation in crime is as good as random and the coefficients in the above model will provide causal estimates of victimisation in crime on birth outcomes. We test the robustness of the estimates with the inclusion of additional fixed effects. First, we include neighbourhood specific time trends allowing for differential trends for each neighbourhood. Second, we include postcode fixed effects as a more granular measure of the place of residence. A concern using the above identification strategy arises from the fact that the propensity to report crime may differ by unobserved mother characteristics and reporting may be correlated with birth outcomes, for example through a correlation of public service uptake, affecting both reporting of crime to police as well as for example prenatal services. To address this concern and to make mothers in the treated and control group even more comparable, we also propose the use of an alternative control group, i.e. mothers who have been victimised any time after pregnancy. Lastly, we also estimate maternal fixed-effects, an alternative way of dealing with any differences in the propensity to report being a victim of crime. For this exercise, we focus on mothers with two or more births, reducing the sample substantially.

4 Results

In this section, we present the results of the effect of criminal victimisation during pregnancy on a number of outcomes. We start with BW in Subsection 4.1 and heterogeneous effects in Section 4.2.
We provide and discuss results for hospitalisation in 4.3. In Subsection 4.4 we look at additional birth outcomes including gestational length, type of delivery, APGAR scores, prenatal care and measures of child mortality.

4.1 Effect of crime victimisation on birth outcomes

We first investigate the effect of victimisation on BW as measured in grams. We next look at the distribution of effects along the BW distribution and estimate the effect of victimisation on indicators for low, very low and extremely low BW (<2,500 grams, <2,000 grams and <1,500 grams). Table 1 presents the results.

In column (1), we estimate the effect of being a victim of crime during pregnancy on BW, when including only neighbourhood of residence and month of conception fixed effects. Standard errors are clustered at the neighbourhood level. We find that being a victim of robbery or theft during pregnancy reduces BW significantly by about 13 grams. When including individual controls in column (2), the effect size increases somewhat to about 16 grams. These are sizeble effects and many times the effects estimated elsewhere in the literature estimating the effect to indirect exposure to crime, as expected. This is in part due because most of the papers looking at the relationship between stress caused by violence and birth outcomes estimate the intent-to-exposure for the entire population of pregnant women ‘exposed’ in a geographic unit making it difficult to compare the estimates. Next we probe the results by including additional fixed effects. First, in column (3) we include neighbourhood specific time trends. The effect is roughly the same as in column (2). In column (4), rather than using neighbourhood fixed effects, we include more granular postcode fixed effects. Again, the effect is similar, demonstrating the robustness of the effects. In column (5) we provide the coefficients as in specification for column (2), but using the alternative control group. This reduces sample size quite dramatically, as we now only have women victimized either during or after pregnancy in our sample. We find a very similar effect of a reduction of BW by about 13 grams, lending extra credibility to our estimation strategy. Lastly, in column (6), we provide the estimates using mother fixed effects. The effect on BW strengthens somewhat to about 21 grams. Our preferred specification in column (2) may therefore be an underestimate of the true effect, but the estimate is only marginally significant given the much larger standard error. To Quintana-Domeque and Rodríguez-Serrano (2017) reports a reduction of 0.3 grams in BW for women exposed to bomb casualties of ETA terrorism in Spain, Foureaux Koppensteiner and Manacorda (2016) find a reduction in BW of 2 grams as response to a one-standard deviation increase in the homicide rate in Brazilian municipalities, Mansour and Rees (2012) find an statistically insignificant effect of 2.93 grams reduction in BW, but an increase in children classified as low BW as consequence of exposure to an additional non-combatant fatality in the Second Intifada.
learn about the effects on birth outcomes along the distribution of BW, we investigate the effect on low BW. Focusing on the specification with neighbourhood fixed effects and controls, we find that victimisation increases the number of children classified as low BW by approximately 0.8 percentage points. Compared to the mean prevalence of low BW of 8 percent this corresponds to a 10 percent increase in the risk of low BW delivery. This constitutes a substantial increase in low BW births, which is associated well documented long-lasting consequences for the affected individuals (Almond et al. (2005), Black et al. (2007), Figlio et al. (2014)). Considering the large associated costs of low BW births (Almond et al. (2005)) these effects are economically very important and demonstrate the societal burden of criminal victimisation undocumented before. We also look at very low and extremely low BW. We find an increase in very low BW by about 15 percent compared to the baseline incidence, a sizeable effect, but significant only at the 10 percent level of significance. Lastly, we look at extremely low BW. We find a very large effect of about 38 percent compared to the mean incidence. The results on low BW indicators show that the effects of victimisation are particularly strong at lower parts of the BW distribution, possibly indicating that more marginally pregnancies may suffer more from victimisation. The estimates using alternative specifications provide a very similar picture to the results for BW. We are also interested in how victimisation at different points of pregnancy affects BW. To investigate this, we estimate the effect for exposure during the three trimesters. In Figure 1, we provide the results. Being victimized in the first or second trimester has a negative on BW, but the estimates are not significant at conventional levels. In contrast, we find that victimisation in the third trimester very substantially reduces BW, so that the overall effect we estimated are likely driven by third trimester victimisation. We do not observe a very clear pattern for the estimates on low BW, but find a pattern consistent with the BW estimates for very low and extremely low BW. Effects for third trimester victimisation are much larger and clearly the drivers of the overall effects for victimisation during pregnancy.

4.2 Heterogeneous Effects on BW

In this section, we briefly discuss heterogeneous effects for our main outcomes along a number of mother characteristics. For this purpose, we split the sample by socio-economic status, mother’s education and marital status, for which we have information from the official birth register data. We present the results in Figure 2. We find that the results for BW and the low BW classifications are more pronounced for females with lower socio-economic status, although the differences are not statistically significant. We find a largely similar picture across outcomes for maternal education
and marital status, with a few exceptions. Particularly the effects for non-married females are accentuated for BW and low BW. Overall, the heterogeneous effects indicate that the effects of victimisation are more pronounced for females who are already disadvantaged.

4.3 Effect of crime victimisation on hospitalisation outcomes

The effects of victimisation are not limited to measures of health at birth. For this purpose, we investigate the effect victimisation during pregnancy has on measures of health for up to three years after pregnancy by linking birth records to hospitalisation records. In Table 2 we present the results using our preferred specification. We find that victimisation during pregnancy increases the propensity for hospitalisation over a three year period following birth significantly. We find an increase of 0.7 percentage points, a 6 percent increase compared to the mean. Most of this effect arises from hospitalisation shortly after birth, as indicated by the effects in columns (2)-(4), but the estimate are under-powered. Unsurprisingly, given the effects on hospitalisation, we also find that the related costs (in logs) are positively affected. In addition we make use of information in the hospitalisation records on the type of hospitalisation. We find that victimisation during pregnancy leads to a substantial increase in neonatal and regular ICU, indicating more serious (and costly) cases of hospitalisation. Victimisation, hence, may not only affect the propensity for hospitalisation, but seems to also affect the seriousness of the hospitalisation.

4.4 Effect of crime victimisation on additional outcomes

In this section we briefly discuss the effects on additional outcomes, including gestational length, Apgar scores, emergency c-section, prenatal visits, sex ration at birth and measures of child mortality. We present the results for our preferred specification in Table 3. victimisation has a negative effect on days of gestation, but the coefficient is small and not statistically significant. In line, we find positive, but insignificant, effects for measures of short gestation. This may indicate that the effects on BW are not driven by short gestation, but possibly may be caused by intra-uterine growth retardation. This is in line with the findings that the results are driven by third trimester exposure. In line with findings elsewhere in the literature, we do not find significant effects on 1 and 5 minute Apgar scores. We also do not find significant effects on emergency c-section and the sex composition. In contrast to the insignificant effects on these outcomes, we find a significant effect on the number of prenatal visits, although the effect size is relatively modest compared to the mean. This is still a significant finding, and possibly indicates that victimisation during pregnancy may lead
to behavioural changes by pregnant women, including on prenatal care utilization. Lastly, to be able to investigate infant mortality, we make use of the extraordinarily rich information in SINASC and SIM. We can link birth records with death records, in cases where the infant dies within the first year of life. We then investigate whether victimisation has an effect on different measures of infant mortality. We present results for measures of child mortality. None of the outcomes (early neonatal, neonatal, and infant mortality) are significant.

5 Final Remarks

In this paper, we provide—to our best knowledge—the first evidence on the effect of victimisation in crime—robbery and theft—on birth outcomes using a unique dataset from Brazil, that allows us to link the universe of crime incidents from police reports to the universe of birth records for the period between 2011 and 2017.

We find that victimisation significantly reduces BW and other indicators for poor health at birth, such as low BW. Controlling for neighbourhood of residence, and time fixed effects, and a large array of predetermined maternal characteristics, we find that victimisation during gestation reduces BW by about 16 grams, equivalent to a reduction of about 3 percent of a standard deviation of BW. We find important variation along the BW distribution and document a substantial increase in the likelihood of being classified as low BW of 10 percent, leading to a substantial increase in the risk for complications and adverse later life outcomes of the children affected in-utero. The effects are driven by exposure in the third trimester, suggesting a mechanism based on intra-uterine growth retardation and a nutritional channel. In line with this, we also find more accentuated effects for mothers of lower socio-economic standing.

The results are not limited to measures of health at birth. We document sizable and significant effects on downstream measures of health by investigating the effect on hospitalization. We find that victimization increases hospitalization over a three period from birth substantially. We also find effects on the intensive margin, with an increased chance of hospitalization to ICU and neonatal ICU.

Our results contribute to a growing literature on the effects of exposure to crime and violent events on birth outcomes. Rather than focussing on secular trends or extreme events, such as terrorism or war (Brown (2018), Quintana-Domeque and Ródenas-Serrano (2017), Mansour and Rees (2012)) we make use of individual level variation while including place of residence and time
fixed effects. Individual level exposure to crime and violence, rather than indirect exposure as in Foureaux Koppensteiner and Manacorda (2016) or Camacho (2008) allows to shed additional light on the underlying mechanisms. For this purpose, we also make use of the very detailed vital statistics data and show that victimisation may also impact birth outcomes through behavioural channels, for example through avoidance strategies, affecting relevant inputs into pregnancies, for example prenatal visits.

Finally, our results contribute to the understanding of the societal cost of crime. Previous studies on the cost of victimisation in crime mostly focus on the health consequences and direct health costs of injury inflicted in violent crime. A few papers have tried to quantify the intangible costs of criminal victimisation brought on the victims through the psychological, social, educational, or occupational/professional consequences (Anderson (1999), Dolan et al. (2005), Brewster (2014)) mostly in accounting exercises. We add to this literature with the first estimates of individual victimisation in crime on birth outcomes documenting important cost of crime so far neglected in the literature.
References


Table 1: Effect of crime victimisation on birthweight

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
<th>(9)</th>
<th>(10)</th>
<th>(11)</th>
<th>(12)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>BW</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Victim (Pregnancy)</td>
<td>−12.7293</td>
<td>−15.9245</td>
<td>−16.4979</td>
<td>−14.0713</td>
<td>−12.8857</td>
<td>−21.4988</td>
<td>0.0065</td>
<td>0.0076</td>
<td>0.0078</td>
<td>0.0077</td>
<td>0.0057</td>
<td>0.0099</td>
</tr>
<tr>
<td>(Robust)</td>
<td>(4.3024)***</td>
<td>(4.3230)***</td>
<td>(4.4045)***</td>
<td>(4.7552)***</td>
<td>(4.8022)***</td>
<td>(11.1893)*</td>
<td>(0.0025)***</td>
<td>(0.0025)***</td>
<td>(0.0026)***</td>
<td>(0.0024)***</td>
<td>(0.0028)**</td>
<td>(0.0069)</td>
</tr>
<tr>
<td>Mean dep. var.</td>
<td>3,160.4314</td>
<td>3,160.4314</td>
<td>3,160.4314</td>
<td>3,154.8685</td>
<td>3,171.2192</td>
<td></td>
<td>0.0799</td>
<td>0.0799</td>
<td>0.0799</td>
<td>0.0799</td>
<td>0.0827</td>
<td>0.0748</td>
</tr>
<tr>
<td>Clusters</td>
<td>32,411</td>
<td>31,805</td>
<td>31,805</td>
<td>43,734</td>
<td>9,390</td>
<td>119,370</td>
<td>32,411</td>
<td>31,805</td>
<td>31,805</td>
<td>43,734</td>
<td>9,390</td>
<td>119,370</td>
</tr>
<tr>
<td>Observations</td>
<td>1,433,566</td>
<td>1,373,656</td>
<td>1,373,656</td>
<td>1,363,003</td>
<td>120,555</td>
<td>244,825</td>
<td>1,433,566</td>
<td>1,373,656</td>
<td>1,373,656</td>
<td>1,363,003</td>
<td>120,555</td>
<td>244,825</td>
</tr>
<tr>
<td><strong>Very low BW</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Victim (Pregnancy)</td>
<td>0.0018</td>
<td>0.0016</td>
<td>0.0018</td>
<td>0.0015</td>
<td>0.0014</td>
<td>0.0050</td>
<td>0.0016</td>
<td>0.0015</td>
<td>0.0015</td>
<td>0.0013</td>
<td>0.0016</td>
<td>0.0030</td>
</tr>
<tr>
<td>(Robust)</td>
<td>(0.0010)*</td>
<td>(0.0010)*</td>
<td>(0.0010)*</td>
<td>(0.0009)*</td>
<td>(0.0011)</td>
<td>(0.0028)*</td>
<td>(0.0006)**</td>
<td>(0.0006)**</td>
<td>(0.0007)**</td>
<td>(0.0006)**</td>
<td>(0.0007)**</td>
<td>(0.0022)</td>
</tr>
<tr>
<td>Mean dep. var.</td>
<td>0.0105</td>
<td>0.0105</td>
<td>0.0105</td>
<td>0.0105</td>
<td>0.0115</td>
<td>0.0099</td>
<td>0.0040</td>
<td>0.0040</td>
<td>0.0040</td>
<td>0.0040</td>
<td>0.0046</td>
<td>0.0041</td>
</tr>
<tr>
<td>Clusters</td>
<td>32,411</td>
<td>31,805</td>
<td>31,805</td>
<td>43,734</td>
<td>9,390</td>
<td>119,370</td>
<td>32,411</td>
<td>31,805</td>
<td>31,805</td>
<td>43,734</td>
<td>9,390</td>
<td>119,370</td>
</tr>
<tr>
<td>Observations</td>
<td>1,433,566</td>
<td>1,373,656</td>
<td>1,373,656</td>
<td>1,363,003</td>
<td>120,555</td>
<td>244,825</td>
<td>1,433,566</td>
<td>1,373,656</td>
<td>1,373,656</td>
<td>1,363,003</td>
<td>120,555</td>
<td>244,825</td>
</tr>
<tr>
<td><strong>Extremely low BW</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Controls</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Neighbourhood FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Time FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Neigh x Time FE</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Postcode FE</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Alternative Sample</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Mother FE</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>

* p < 0.1, ** p < 0.05, *** p < 0.01. Robust standard errors clustered at the neighbourhood level in parentheses.

**Note:** The analysis includes mothers over the period between 2011 and 2017. Birthweight is reported in grams. Low birthweight and Very low birthweight are dummies which indicate newborns up to 2,500 and 1,500 grams respectively. Explanatory variable Victim (Pregnancy) indicate whether the mother was a victim of robbery or theft during pregnancy. Controls include dummies for mother’s age, race, marital status, education and occupation and dummies for the number of children born alive and stillbirths from previous pregnancies, gestation order, and birth interval (time between conceptions). All regressions include month of conception fixed effects.
<table>
<thead>
<tr>
<th>Victim (Pregnancy)</th>
<th>Hospitalization (3 years)</th>
<th>Hospitalization (1st year)</th>
<th>Hospitalization (28 days)</th>
<th>Hospitalization (7 days)</th>
<th>Cost</th>
<th>ICU (Neonatal)</th>
<th>ICU</th>
<th>Length of Stay</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
<td>(7)</td>
<td>(8)</td>
</tr>
<tr>
<td>Mean dep. var.</td>
<td>0.1201</td>
<td>0.0982</td>
<td>0.0663</td>
<td>0.0597</td>
<td>350.8267</td>
<td>0.0185</td>
<td>0.0224</td>
<td>1.1698</td>
</tr>
<tr>
<td>Clusters</td>
<td>24,060</td>
<td>24,060</td>
<td>24,060</td>
<td>24,060</td>
<td>24,060</td>
<td>24,060</td>
<td>24,060</td>
<td>24,060</td>
</tr>
<tr>
<td>Observations</td>
<td>833,600</td>
<td>833,600</td>
<td>833,600</td>
<td>833,600</td>
<td>833,600</td>
<td>833,600</td>
<td>833,600</td>
<td>833,600</td>
</tr>
</tbody>
</table>

* * p < 0.1, ** p < 0.05, *** p < 0.01. Robust standard errors clustered at the neighbourhood level in parentheses.

Note: The analysis includes mothers over the period between 2011 and 2017. Birthweight is reported in grams. Low birthweight and Very low birthweight are dummies which indicate newborns up to 2,500 and 1,500 grams respectively. Explanatory variable Victim indicate whether the mother was a victim of robbery or theft during pregnancy. Controls include dummies for mother’s age, race, marital status, education and occupation and dummies for the number of children born alive and stillbirths from previous pregnancies, gestation order, and birth interval (time between conceptions). All regressions include month of conception fixed effects.
### Table 3: Effect of crime victimisation on additional outcomes

<table>
<thead>
<tr>
<th></th>
<th>Gestation (days) (&lt;259)</th>
<th>Gestation (days) (&lt;224)</th>
<th>Gestation (days) (&lt;196)</th>
<th>1st minute APGAR</th>
<th>5th minute APGAR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Victim (Pregnancy)</td>
<td>0.1951</td>
<td>0.0008</td>
<td>0.0017</td>
<td>0.0008</td>
<td>−0.0086</td>
</tr>
<tr>
<td></td>
<td>(0.1258)</td>
<td>(0.0026)</td>
<td>(0.0011)</td>
<td>(0.0006)</td>
<td>(0.0105)</td>
</tr>
<tr>
<td>Mean dep. var.</td>
<td>269.6314</td>
<td>0.1031</td>
<td>0.0131</td>
<td>0.0036</td>
<td>8.4107</td>
</tr>
<tr>
<td>Clusters</td>
<td>31,805</td>
<td>31,805</td>
<td>31,805</td>
<td>31,805</td>
<td>31,392</td>
</tr>
<tr>
<td>Observations</td>
<td>1,373,656</td>
<td>1,373,656</td>
<td>1,373,656</td>
<td>1,373,656</td>
<td>1,332,545</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Emergency C-section</th>
<th>Prenatal visits</th>
<th>Female</th>
<th>Early neonatal (1 week)</th>
<th>Neonatal (4 weeks)</th>
<th>Infant (1 year)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Victim (Pregnancy)</td>
<td>0.0026</td>
<td>−0.1170</td>
<td>0.0052</td>
<td>0.0002</td>
<td>0.0003</td>
<td>0.0000</td>
</tr>
<tr>
<td></td>
<td>(0.0031)</td>
<td>(0.0219)***</td>
<td>(0.0043)</td>
<td>(0.0005)</td>
<td>(0.0005)</td>
<td>(0.0006)</td>
</tr>
<tr>
<td>Mean dep. var.</td>
<td>0.2001</td>
<td>8.0569</td>
<td>0.4883</td>
<td>0.0029</td>
<td>0.0038</td>
<td>0.0052</td>
</tr>
<tr>
<td>Clusters</td>
<td>31,805</td>
<td>31,648</td>
<td>31,802</td>
<td>31,805</td>
<td>31,805</td>
<td>31,805</td>
</tr>
<tr>
<td>Observations</td>
<td>1,373,656</td>
<td>1,358,990</td>
<td>1,373,451</td>
<td>1,373,656</td>
<td>1,373,656</td>
<td>1,373,656</td>
</tr>
</tbody>
</table>

* p < 0.1, ** p < 0.05, *** p < 0.01. Robust standard errors clustered at the neighbourhood level in parentheses.

**Note:** The analysis includes mothers over the period between 2011 and 2017. Birthweight is reported in grams. Low birthweight and Very low birthweight are dummies which indicate newborns up to 2,500 and 1,500 grams respectively. Explanatory variable Victim indicate whether the mother was a victim of robbery or theft during pregnancy. Controls include dummies for mother’s age, race, marital status, education and occupation and dummies for the number of children born alive and stillbirths from previous pregnancies, gestation order, and birth interval (time between conceptions). All regressions include month of conception fixed effects.
Figure 1: Effect of Victimization on Birth Weight by Trimester
Figure 2: Effect of Victimisation on Birth Weight by Socioeconomic Status
## Annex

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1) Control</th>
<th></th>
<th>(2) Treatment</th>
<th></th>
<th>Normalized difference (1)-(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>Mean/SE</td>
<td>N</td>
<td>Mean/SE</td>
<td></td>
</tr>
<tr>
<td><strong>Age</strong></td>
<td>1275892</td>
<td>26.922 (0.006)</td>
<td>12423</td>
<td>27.589 (0.056)</td>
<td>-0.101</td>
</tr>
<tr>
<td><strong>20 or less</strong></td>
<td>1275892</td>
<td>0.200 (0.000)</td>
<td>12423</td>
<td>0.149 (0.003)</td>
<td>0.128</td>
</tr>
<tr>
<td><strong>21 to 35</strong></td>
<td>1275892</td>
<td>0.690 (0.000)</td>
<td>12423</td>
<td>0.737 (0.004)</td>
<td>-0.102</td>
</tr>
<tr>
<td><strong>35 and beyond</strong></td>
<td>1275892</td>
<td>0.111 (0.000)</td>
<td>12423</td>
<td>0.115 (0.003)</td>
<td>-0.014</td>
</tr>
<tr>
<td><strong>White</strong></td>
<td>1275892</td>
<td>0.344 (0.000)</td>
<td>12423</td>
<td>0.360 (0.004)</td>
<td>-0.034</td>
</tr>
<tr>
<td><strong>Black</strong></td>
<td>1275892</td>
<td>0.078 (0.000)</td>
<td>12423</td>
<td>0.067 (0.002)</td>
<td>0.043</td>
</tr>
<tr>
<td><strong>Asian</strong></td>
<td>1275892</td>
<td>0.006 (0.000)</td>
<td>12423</td>
<td>0.006 (0.001)</td>
<td>0.001</td>
</tr>
<tr>
<td><strong>Mixed</strong></td>
<td>1275892</td>
<td>0.506 (0.000)</td>
<td>12423</td>
<td>0.508 (0.004)</td>
<td>-0.005</td>
</tr>
<tr>
<td><strong>Indigenous</strong></td>
<td>1275892</td>
<td>0.002 (0.000)</td>
<td>12423</td>
<td>0.001 (0.000)</td>
<td>0.020</td>
</tr>
<tr>
<td><strong>Single</strong></td>
<td>1275892</td>
<td>0.398 (0.000)</td>
<td>12423</td>
<td>0.452 (0.004)</td>
<td>-0.110</td>
</tr>
<tr>
<td><strong>Married</strong></td>
<td>1275892</td>
<td>0.442 (0.000)</td>
<td>12423</td>
<td>0.408 (0.004)</td>
<td>0.069</td>
</tr>
<tr>
<td><strong>Widowed</strong></td>
<td>1275892</td>
<td>0.002 (0.000)</td>
<td>12423</td>
<td>0.003 (0.001)</td>
<td>-0.020</td>
</tr>
<tr>
<td><strong>Separated divorced</strong></td>
<td>1275892</td>
<td>0.016 (0.000)</td>
<td>12423</td>
<td>0.024 (0.001)</td>
<td>-0.064</td>
</tr>
<tr>
<td><strong>Stable union</strong></td>
<td>1275892</td>
<td>0.132 (0.000)</td>
<td>12423</td>
<td>0.103 (0.003)</td>
<td>0.084</td>
</tr>
<tr>
<td><strong>Low education</strong></td>
<td>1249140</td>
<td>0.198 (0.000)</td>
<td>12239</td>
<td>0.116 (0.003)</td>
<td>0.205</td>
</tr>
<tr>
<td><strong>Mid education</strong></td>
<td>1249140</td>
<td>0.605 (0.000)</td>
<td>12239</td>
<td>0.603 (0.004)</td>
<td>0.003</td>
</tr>
<tr>
<td><strong>High education</strong></td>
<td>1249140</td>
<td>0.197 (0.000)</td>
<td>12239</td>
<td>0.280 (0.004)</td>
<td>-0.208</td>
</tr>
</tbody>
</table>
(a) Birth Weight

(b) Low Birth Weight

(c) Very Low Birth Weight

(d) Extremely Low Birth Weight

(e) Prenatal Visits

Figure 3: Effect of Victimisation on BW - Heterogeneity by Trimester type of crime and Socioeconomic Status

Note:
Figure 4: Effect of Victimisation on BW - Heterogeneity by Trimester type of crime and Socioeconomic Status

Note: [Details of note provided if necessary]
(a) Birth Weight

(b) Low Birth Weight

(c) Very Low Birth Weight

(d) Extremely Low Birth Weight

(e) Prenatal Visits

Figure 5: Effect of Victimization on BW, Heterogeneity by Trimester and Socioeconomic Status.