WP 16-07

Fraser Summerfield
University of Aberdeen, UK
The Rimini Centre for Economic Analysis, Italy

LOCAL LABOR MARKETS AND THEFT: NEW EVIDENCE FROM CANADA

The Rimini Centre for Economic Analysis
Legal address: Via Angherà, 22 – Head office: Via Patara, 3 – 47921 Rimini (RN) – Italy
www.rcfea.org – secretary@rcfea.org

Local Labor Markets and Theft: New Evidence from Canada*

Fraser Summerfield
University of Aberdeen

February 2016

Abstract

This paper provides the first causal evidence of the effect of labor market opportunities on theft crimes in Canada. Synthetic panel data are constructed by combining the Labour Force Survey with the complete Uniform Crime Reports microdata from 2007-2011. Low-skill unemployment rates and corresponding theft rates are measured for age and city-specific groups of young males. Impacts are identified using an instrumental variables approach that captures the exposure of low-skill employment to exogenous demand for exports to the US. Estimates of the elasticity of theft with respect to low-skill unemployment rates are between 0.35-0.39, slightly lower than estimates for the US aggregate data.

Keywords: Property Crime, Theft, Unemployment, Instrumental Variables
JEL Codes: J23; K42

*I would like to thank Michael Baker, Louise Grogan, Tina Hotton, Miana Plesca, Chris Robinson, Anindya Sen and participants at the CLEA and CEA meetings for helpful comments. All errors are my own. I gratefully acknowledge financial support from the Social Sciences and Humanities Research Council and data access provided through the Statistics Canada Research Data Network (CRDCN)

1 Introduction

Individuals from particular demographic groups commit crimes at higher rates than others. Stylized facts indicate that these groups include low-skill or less educated individuals (Gould et al., 2002; Lochner and Moretti, 2004; Machin and Meghir, 2004). Offense rates are also higher among the youth and, in particular, young males (Fougère et al., 2009; Phillips et al., 1972; Trussler, 2012). One reason for crime rates to differ across groups is that more individuals in certain groups are at the margin of offending. Economic theory predicts that the decision to offend depends on the opportunity cost. The availability of legitimate employment opportunities may affect crime by changing these costs. Employed individuals forgo current and future wages if captured and convicted. Even among those who are not employed, more favorable labor markets may present opportunities for higher expected earnings in the future.

Perceptions about labor market opportunities might be based heavily on experiences within an individual's community or peer group. For example, a worker that has recently been laid-off may perceive the shortage of legitimate options to be more acute if their neighbors are also unemployed. Reports of high unemployment among others with similar levels of seniority and experience, or with particular skills, might have an even stronger effect on a worker's expectations about their future employment. This intuition suggests that the unemployment-crime relationship is best observed at the individual level or within narrowly defined demographic groups.

Data on individuals who commit crimes and the labor markets they face is relatively scarce. For this reason, much of the evidence in the literature is derived from aggregated crime and unemployment rates. However, others have argued that estimates of the unemployment-crime relationship could be biased if aggregate unemployment rates reflect the labor market prospects for workers who are not at the margin of offending (Mustard, 2010). This may be a concern for modern studies of North America because many major layoffs since the 1990s have likely affected high-skilled workers.[1] Glaeser et al. (2003) has also shown that aggregate crime regressions may overstate individual responses because

[1] Since 1993, mass layoffs affecting groups of workers numbering between 19,000 and 60,000 have been handed down by companies that employ a significant number of higher skilled workers, including IBM, Citigroup, AT&T, Boeing, Bank of America, Hewlett-Packard, the Alameda School District, Merrill Lynch, Lucent Technologies, Pfizer, and Research In Motion (McGregor, 2015).

of the existence of a social multiplier in criminal activity.

This paper identifies the relationship between theft crimes and unemployment rates using recently available Canadian microdata. One contribution of the paper is to provide the first causal evidence for Canada. A second contribution is to provide nationally representative evidence from less-aggregated data than prior studies. Evidence from US microdata is available for particular cohorts from the NLSY 79 (Gould et al., 2002; Grogger, 1998) and former convicts in North Carolina (Trumbull, 1989). This paper uses a synthetic panel for the period 2007-2011. The panel is created by merging confidential versions of Canada's Uniform Crime Reports (UCR) and the Labour Force Survey (LFS) at the minimum level of aggregation possible. Each observation in the resulting data is a cell defined at the level of age, gender, and Census Metropolitan Area (CMA). This approach to the data relates the low-skill unemployment rate among 18 year old males in Toronto directly to the theft crime rate among 18 year old males in Toronto, for example. There are other advantages to this data, including its scope and time period. The UCR provides virtually 100% coverage of the reported crime incidents because it is a mandatory survey administered to police forces nationwide. The advantage of the time period in this paper is its overlap with the Great Recession, which was one of the deepest shocks to North American labor markets since the Second World War. Updated evidence may be relevant for policymakers because both Canada and the US have experienced significant reductions in overall crime since the 1980s,

The literature has established the existence of a simultaneity problem in the analysis of crime and labor market conditions (Cullen and Levitt, 1999; Gould et al., 2002; Lin, 2008; Raphael and Winter-Ebmer, 2001). Unfortunately, the direction and magnitude of the potential bias is not apparent. On one hand, a positive bias may arise because prior offenders are precisely those that struggle most to find jobs (Holzer, 2007; Western and Pettit, 2000). On the other hand, estimates may be biased downward because incarceration removes offenders from the sample. Even after their release, many individuals who have been incarcerated may choose to participate in the underground economy and thus remain outside of the unemployment pool. Studies from the US may be particularly subject to this second problem because of relatively high incarceration rates. The US incarcerated 760 persons for every 100,000 population in 2009. The comparable statistic for Canada is 116 (Wilson and Petersilia, 2011). Average incarceration lengths are also lower in Canada.

For theft crimes, the average length in 2006 was less than 60 days (Statistics Canada, 2015).[2] By contrast, US incarceration lengths for property crimes averaged 22 months (Rosenmerkel et al., 2009).

This paper addresses the potential endogeneity of unemployment using Instrumental Variable (IV) estimation. The instrument for labor market conditions exploits exogenous variation in the US demand for Canadian goods from four industries that employ a high proportion of low-skill young males. Incidentally, these industries are also among the most exposed to demand from the US. These industries are automobile manufacturing, forestry products, crude oil and fishing. Corresponding changes in demand are captured by US car sales, US housing starts, West-Texas Intermediate (WTI) oil prices and the New-England seafood catch. Demand from the US can be considered exogenous to employment in Canada because of the relatively small size of the Canadian economy and because changes in Canadian supply are unlikely to affect the particular measures of demand used in this paper. This paper finds that the elasticity of theft crimes with respect to low-skill unemployment rates ranges from 0.35-0.39. Evaluated at the 2006 unemployment rate of 6.6%, a 1 percentage point increase in the low-skill unemployment rate causes a 4.2-4.6% increase in theft rates.

Many studies in the literature use IV estimation. Empirical findings from the US (Lin, 2008; Raphael and Winter-Ebmer, 2001; Gould et al., 2002) and Europe (Altindag, 2012; Buonanno, 2006) show that unemployment rates have positive effects on property crimes. Using different identification strategies, panel data estimates from the UK (Reilly and Witt, 1996; Carmichael and Ward, 2001) and Sweden (Edmark, 2005; Oester and Agell, 2007) also suggest that crimes are higher where unemployment rates are higher. The analysis of crime in Canada in the economics literature is limited to the impact of justice system deterrence factors on crime (Avio and Clark, 1978; Curry et al., 2013; Furlong and Mehay, 1981). The unemployment-crime relationship in Canada has been estimated by criminologists but these studies have sidestepped the potential endogeneity of labor market conditions (Hartnagel and Lee, 1990; Andresen, 2012).

Canadian evidence may interest Canadian and US policymakers alike. Labor markets

[2] Canada also offers more rehabilitation for past offenders. The US Department of Justice states that inmates may earn good time credits against their sentences by participation in prison programs. In Canada, personalized rehabilitation plans are typically used (Bernhardt et al., 2012).

in Canada are likely the most suitable comparison for those in the US and property crime rates in the two countries have remained fairly similar for the past several decades. The large disparity between Canadian and US crime rates can be attributed to violent crime (Gannon, 2001). Estimates in this paper suggest that positive but small potential biases may exist among existing studies. Therefore this paper provides an important confirmation that labor market opportunities have important effects on property crimes. Yet, the findings also suggest that US estimates may somewhat overstate the magnitude of this relationship.

The remainder of the paper proceeds as follows. Section 2 relates the analysis to the economic model of crime. Section 3 discusses the two data sources, the LFS and the UCR, used to construct the synthetic panel. Section 4 outlines the identification strategy and discusses the instrument. Results using IV models with fixed-effects are presented in Section 5. Section 6 concludes.

2 Incentives and Offenses

The economic model of crime is attributed to the seminal work of Becker (1968), with later additions from Ehrlich (1973) and others. In Becker's model an individual i supplies offenses, O, according to the function:

$$O_i = O_i(p_i, f_i, u_i). \tag{1}$$

Arguments in this function represent the probability of conviction, p_i, the penalty if charged and convicted, f_i, and a portmanteau variable u_i. The first two affect the expected punishment and might be manipulated through the justice system. The third factor captures individual characteristics and externalities from other aspects of the economy that might affect decisions about crime.

The state of the labor market is perhaps the most common component of u_i to be discussed in the empirical literature. When legitimate earnings opportunities are scarce or relatively unattractive, the opportunity cost of crime may be relatively low. For an individual on the margin of offending, a decrease in the opportunity cost may result in an offense. Likewise, a fall in the payoff from legitimate work may increase the time allocated to offending by individuals who divide their time amongst these two activities.[3]

[3]This argument assumes that the return to illegitimate activity, the price of stolen goods for example,

This relationship is visible in Canadian aggregate data. Figure 1 compares the unemployment rates for young males to the number of theft crimes for the period 2007-2011. The scatterplots are overlaid with a local moving average for both series. Both the unemployment rate and the incidence of theft crimes dipped at the end of 2007 when the economy reached a peak, increasing to high points between 2009 and 2010. Both decreased through late 2010 and 2011, although the decrease in crime outpaced the decrease in unemployment rates in the latter year.

The intuition for a tradeoff between legitimate work and theft is straightforward because both activities may provide sources of income. Grogger (1998) illustrates this tradeoff as a special case of the labor-leisure tradeoff in a standard labor supply model. Raphael and Winter-Ebmer (2001) extend this analysis and demonstrate that time allocation to criminal activities will be affected by unemployment for the subset of workers who have a low reservation wage. This result further emphasizes the potential importance of measuring labor market conditions and corresponding crime rates specific to those individuals at the margin.

3 Data

The dataset used in this paper is a unique synthetic panel of monthly observations covering the years 2007-2011. The panel is created by merging Canada's microdata record of crime incidents, the Uniform Crime Reports (UCR) survey, with Canada's Labour Force Survey (LFS) at the cell-level. Cells are unique combinations of age, gender and Census Metropolitan Area (CMA). The cell-level data relates crime rates directly to labor market conditions for specific groups of workers. Freeman (1999) and Mustard (2010) suggest that important differences in the density of individuals at the margin of offending exist across age and location. For this reason, cell-level data may be more informative than aggregate data which cannot offer the same level of detail.

Canada's UCR data is maintained by the Canadian Center for Justice Statistics (CCJS) in three files which can be matched by unique incident identifiers. The UCR data provides

remains constant. The monetary value of criminal proceeds is not observed in the Canadian data, but the empirical specification will control for time-trends and CMA-specific effects which might be expected to broadly account for differences in the market for stolen goods.

basic demographic information about the offender as well as the time, location and violation codes for each criminal incident reported to police. Surveys are administered to all police jurisdictions across the country and responses are mandatory. Further details about the UCR data are provided in the Appendix.

Several detailed violation codes are available for property crimes in the Canadian data. However, not all incidents include offender information because a suspect may not be observed. Theft crimes such as break and enter may initially go unnoticed and police may therefore not record an accused person. Several violations related to theft, including "Shoplifting $<$\$5,000," "Have Stolen Goods," "Possession of Stolen Goods $<$\$5,000," "Possession of Stolen Goods$>$\$5,000," and "Trafficking in Stolen Goods $>$\$5000", are well reported in the data with 80% or more of the reported incidents attributed to an offender. Offenders in other categories, including "Automobile Theft," "Theft$>$\$5,000", "Theft$<$\$5,000" and "Break and Enter", are often not identified. Any study of crime is likely to include the caveat that crime incident data are subject to measurement error. The decision taken in this paper is to use only well-reported crimes in an attempt to ensure the internal validity of the estimates. Theft crime rates are generated as the monthly sum of the well-reported crime incidents in each cell. Alternative estimates including these less-accurately recorded crimes are provided in the Appendix to demonstrate that the results of the paper do not hinge on this decision.

The UCR data provide information on a significant number of crimes. Frequencies of cell-level observations by monthly number of reported incidents are presented in Table 1. The majority of observations are non-zero and no single characteristic appears to be responsible for zero counts. The crime counts are distributed more evenly across age and gender than one might anticipate and no single CMA has a zero count in any given month. Figure 2 shows that the same is true for age groups. Theft crimes have a hump-shaped profile in age, peaking at age 16. Yet, even at age 40 the average number of monthly theft crimes per cell is more than 12.

The probability of capture and conviction in equation (1), p, is measured using CMA-specific theft crime clearance rates. This measure is the fraction of reported thefts in a given CMA that are cleared by charge each month. Clearance rates may be preferable to other proxies for the apprehension of offenders that are based on police numbers or budgets. For example, the number of police officers in a jurisdiction could be more reflective of the mix of part-time and full-time officers, or other factors such as jurisdiction boundaries. Furthermore, police numbers and budget amounts are more difficult to attribute to particular crimes and could reflect the level of enforcement in unrelated areas such as traffic or homicide. A local measure, in this case at the CMA level, may be a particularly good measure because offenders likely respond to local police presence and conviction rates in their communities.

Low-skill employment and unemployment rates are generated from the LFS data. These measures capture labor market conditions for the share of workers with no post-secondary education in each cell. Both wages and unemployment rates have been found to cause crime. Property crimes have been shown to respond more to wages than employment measures in the US (Gould et al., 2002) and Britain (Machin and Meghir, 2004). However, it will turn out that earnings in Canada display much less variation throughout this period and therefore may not be a suitable representation of labor market options. Appendix Figure A.1 plots the average weekly earnings and unemployment rates from 1998-2012. Unlike the unemployment rate, which fluctuates as expected during the Great Recession, earnings in Canada do not display much volatility. This observation is consistent with the findings of Card (1990) that wage rigidity leads employment rather than wage changes in Canada's unionized sectors.

The synthetic panel structure facilitates the elimination of potentially important unobserved population characteristics, including local "tastes" for stolen goods, with cell-level fixed-effects. These controls may not be required for identification with IV but will provide important efficiency gains in estimation. Efficiency gains may be particularly important if the crime data are noisy. Shares of workers that are foreign-born, married, separated widowed or divorced, and have less than high school (LHS) or high school (HS) education are also used as time-varying demographic controls. These characteristics are informative regarding how offending in Canada differs across broad population characteristics that are commonly discussed in the literature. Following the literature, the data used for estimation are restricted to those most likely to commit crime: males age 15-25.

Summary statistics for the cell-level estimation sample are presented in Table 2. A comparison of the left and right columns provides a simple illustration of how population characteristics and crime counts vary with low-skill unemployment rates among young males. The unconditional relationship between the low-skill unemployment rate and theft crime matches the prediction of the model outlined in Section 2. Individuals in cells with unemployment rates below the median commit an average of 366 theft offenses per month. Those in cells above the median commit an average of 731 per month, almost twice as many.

Other descriptive statistics are also informative regarding the young male population in Canada. The share of foreign born men is slightly higher where greater unemployment rates are observed. This is consistent with the fact that immigrants may face discrimination in the labor market or struggle to find jobs if they lack language skills or other human capital specific to the Canadian economy. The share of workers with less than high school education ranges from 36-48% and the share who have completed high school but no post-secondary education is 21-24 %. Together, approximately 60% of workers are considered to be "low-skill". This high share is reasonable for a sample of the population aged 15-25. The clearance rate is slightly higher for observations where unemployment rates are lower. This may reflect an increased police presence in more affluent areas. Marital status is less informative. The share of widowed separated or divorced among the young male population is essentially zero and the share of married workers differs by less than 1%.

4 Estimation

This section details the reduced form estimation of equation (1). The empirical specification for the supply of theft offenses is given by:

$$\ln o_{jt} = \gamma \ln \bar{u}_{jt}^{LS} + \theta \ln \bar{c}_{jt} + \bar{X}'_{jt}\beta + \tau_t + \alpha_j + T'_{rt}\pi + \epsilon_{jt} \quad (2)$$

The variable $\ln o_{jt}$ is the natural log of theft crime rates per 100,000 population in cell j in month t. The variables $\ln \bar{u}_{jt}^{LS}$ and $\ln \bar{c}_{jt}$ are the natural log cell-average unemployment and clearance rates, respectively. The natural log of unemployment is used because the relationship between unemployment and crime is likely to be non-linear. Individuals are much more likely to perceive their labor market prospects as deteriorating when changes in the unemployment rate are larger. An added advantage of this specification choice is that γ has an elasticity interpretation.[4] The vector $\bar{X}$ contains cell-level average demographic

[4]Several other studies use a log-linear model and interpret γ as the elasticity of crime with respect to the level of unemployment or the semi-elasticity of crime with respect to the unemployment rate.

covariates including the shares of foreign-born workers, the share of HS and LHS educated workers, and shares of workers according to their marital status. Cell-specific intercepts α_j, which capture age and any CMA-specific heterogeneity which is bound to be important in accounting for crime rates, are also included. Because employment policies and various elements of the justice system including legal aid are administered at the provincial level, time trends specific to the province r are also included.[5] Finally, all specifications include monthly time dummies to capture any non-linear trends in crime at the national level. To address the possibility of serial correlation within panels, estimates are clustered at the cell-level. Estimates are also weighted using the number of individuals in each cell from the LFS data. This ensures that cells representing larger demographic groups receive more weight in estimation, so that the cell-level results remain representative of the population.

4.1 Identification

The importance of accounting for endogeneity in the relationship between crime and unemployment rates has been well established in the literature. A criminal history can be a negative signal to employers thus decreasing wages and employment (Freeman, 1999; Bushway, 1996; Fagan and Freeman, 1999; Lott, 1992a,b; Myers, 1983; Waldfogel, 1994). In the case of some professional jobs, and jobs in the public service, employment may not be possible. Incarceration may lead to skill depreciation, and employers hiring those with a criminal past may be less likely to invest in training. Professional networks may also deteriorate while in prison. Those who do find employment may be relegated to secondary labor markets and low wage jobs (Western, 2002). Indirect channels are also possible sources of endogeneity. Any relationship between the justice system and local employment or wealth concentration may be problematic because of the bi-directional relationship between crime and the probability of capture and conviction (Cornwell and Trumbull, 1994; Craig, 1987; Di Tella and Schargrodsky, 2004; Draca et al., 2011; Evans and Owens, 2007; Levitt, 1997, 1998; Mustard, 2003).

This paper addresses endogeneity using IV estimation. Unemployment rates are instrumented with the variable z that captures the exposure of local low-skill labor markets to

[5] The Ottawa-Gatineau CMA straddles the borders of Ontario and Quebec, including both of these cities. In this paper, all values are attributed to Ottawa, which is the more populous of the two.

exogenous changes in demand from the US. This approach provides exogenous variation in labor market conditions that affects those most likely to be at the margin of committing crimes. The first stage equation is given by equation (3):

$$\ln \bar{u}_{jt}^{LS} = \delta z_{mt} + \theta \ln \bar{c}_{jt} + \bar{X}_{jt}'\beta + \tau_t + \alpha_j + T_{rt}'\pi + \epsilon_{jt}. \tag{3}$$

The construction of z can be written the following way:

$$z_{mt} = \sum_{k=1}^{4} I_{mk}(A_{tk}E_{mk}) \tag{4}$$

E_{mk} is the 2006 employment share for low-skill industry k in CMA m. These low-skill employment industries include oil and petroleum extraction, manufacturing and supporting activities (NAICS codes 211, 213111, 213112 and 3211); motor vehicle manufacturing (NAICS codes 3361-3363); forestry, forestry support and lumber and wood products manufacturing (NAICS codes 113, 1153, 321); fishing, fish and seafood farming (NAICS codes 1125,1141). A_{tk} are the aggregate demand shifts over time affecting each of the four low-skill industries. These exogenous changes in demand are captured by the monthly average WTI (West Texas Intermediate) crude oil price, the monthly number of new vehicle sales in the US reported by the Bureau of Economic Analysis, the number of US new home construction starts per month from the Census Bureau, and the monthly size of the New-England seafood catch or "commercial landings" as reported in by the NOAA Fisheries Statistics Division.[6] Binary indicators I flag each CMA's most dominant employer among these low-skill industries.

Standard errors for IV estimates are clustered by CMA because the instrument provides exogenous variation in the demand for low-skill labor specific to the CMA.

4.2 Demand from the US

Demand from the United States has a significant impact on the Canadian economy because the US is Canada's number one trading partner. Automobile manufacturing contributes a substantial amount to this relationship. In 2002, 97% of Canadian exports from motor

[6] Whereas oil prices, vehicle sales and home construction are negatively correlated with unemployment in Canada, the seafood catch is positively related to Canadian unemployment. Therefore when constructing the instrument the seafood catch is multiplied by -1.

vehicle manufacturing and motor vehicle parts manufacturing went to the US. The US demand for Canadian automotive products fluctuated a great deal between 2006 and 2011. Automotive exports declined for five years from 2005-2010, but this trend reversed in 2010 with a 55% increase over the previous year. From 2002-2006 US automobile sales were approximately 16 million units per year. This dropped sharply to a low of 11 million, rebounding to almost 14 million by late 2011 (Bernard, 2013). This industry is a substantial employer in Canada, representing 7.7% of all manufacturing jobs nationwide.

Canada's proven oil reserves are the third largest in the world. Because of the relatively small population, foreign demand for oil plays an important role in production decisions. In 2006, exports reached $38 billion, or 646 million barrels of crude oil. Most of the exported oil comes from Canada's western provinces and is almost exclusively shipped the United States (Natural Resources Canada, 2015). The demand is sensitive to the fluctuation in world oil prices, and in particular the benchmark US price of WTI. Oil and petroleum products are an important source of employment, particularly in the province of Alberta where it accounts for almost 8% of the overall workforce (Government of Alberta, 2015). Over the span of the data used in this paper, US oil prices fluctuated record amounts from approximately $60 US per barrel in early 2007 to a high of around $140 US in mid 2008. Prices plummeted to below $50 US per barrel by early 2009, climbing back to about $ 100 US per barrel by the end of 2011.

Forestry products are also an important component of Canada's natural resource exports. Canada is one of the worlds leading lumber producers containing about 10% of the world's forest cover. Between 2004 and 2010, 59-81% of forestry product exports were destined for the US. Following the slowdown in the US housing market and the associated demand for lumber, 20% of all sawmills in the country closed. Germain (2012) reports that forestry related employment in Canada fell from 50,176 in 2004, to 26,369 in 2009. Starting in 2010 the industry rebounded, increasing employment numbers to 34,532.

Canada is also one of the largest exporters of fish and seafood in the world with roughly 63% of overall seafood trade destined for the US. Fishing and aquaculture are a particularly significant source of employment in Canada's eastern provinces. Of all Atlantic province aquaculture, 60% is exported and approximately 90% of these exports go to the US (Fisheries and Oceans Canada, 2012). In 2008, the harvesting sector of the commercial fishing industry employed 52,107 fish harvesters and crew members, aquaculture employed

4,510 people, and the fish processing industry employed 27,641 workers (Fisheries and Oceans Canada, 2008). One particularly important market for Atlantic Canada's fish and seafood exports is the New-England region of the US, where almost half of all imports are Canadian (National Oceanic and Atmospheric Administration, 2014). The demand for Canadian seafood and fish products can be expected to fluctuate according to the realized catch size in the New-England area, which varies naturally during the period of analysis with weather conditions and fish stocks.

5 Results

Estimates of equation (2) are first presented using OLS estimation, followed by causal IV estimates in Section 5.2.

5.1 OLS Results

Demographic characteristics are found to have the expected relationship with theft crime rates. OLS estimates from the most parsimonious specification, which does not include cell-level fixed effects, are presented in column (1) of Table 3. The share of workers with high school education relative to post-secondary education is positively related to theft crimes and statistically significant at the 1% level. An even stronger relationship is found with respect to workers with less than high school education. This correlation is consistent with the finding in the literature that education appears to reduce crime (see Lochner and Moretti (2004) for example). Marital status also correlates with theft crimes. Increases in the share of young married males are associated with decreases in theft crimes. However, the relationship between the share of formerly married individuals (separated and divorced) and theft crimes is not statistically significant. These two coefficients suggest that the potential costs borne by family members in the case of capture and conviction may act as a deterrent

Foreign-born population shares are also related to theft rates. A single percentage point increase in the share of foreign-born males in a cell is associated with a decrease in the theft crime rate by 1.5%. Butcher and Piehl (1998) also find that foreign-born workers commit fewer crimes in the US. Evidence in the literature is mixed, however, including findings from Spain (Alonso-Borrego et al., 2012) and Italy (Bianchi et al., 2012), suggesting that immigration is associated with increased crime rates. Evidence from France suggests that there is no relationship (Aoki and Todo, 2009). One possibility raised by Borjas et al. (2006) is that increased crime rates from US immigration may be due to a displacement effect on native born workers. The strong negative effect in the current results may be explained by features of Canada's immigration system, which admits a significant fraction of high-skill immigrants using a points-based criterion. High-skilled immigrants are likely further from the margin of committing crime than many of the native-born and any displacement of native born workers by these immigrants is also more likely to involve high-skill labor. The suggestion that immigrants to Canada commit fewer crimes because of their higher socioeconomic status is supported by US findings that only those immigrants facing poor labor market outcomes affect crime rates Spenkuch (2014).

Estimates with cell-level fixed-effects in columns (2) and (3) leave most of these factors insignificant. This may reflect very moderate changes in the population shares of foreign-born workers, marital decisions and educational attainment over the five year period in the data. Because the goal of the paper is to identify the effect of unemployment rates on crime, more restrictive specifications are preferred. Estimates conditional on cell fixed-effects are more likely to address the potential for self-selection and unobserved characteristics.

The coefficients on CMA-specific clearance rates have the expected signs and are statistically significant in specifications (2) and (3).[7] However, given the attention paid to the potential endogeneity of deterrence measures in the empirical literature on crime, it is likely that the clearance rates are endogenous. It can be expected that resources given to the justice system may depend, in part, on the extent to which crimes are being committed in a given location. No particular emphasis is placed on these estimates for this reason. Columns (4)-(6) present estimates of comparable specifications without clearance rates for comparison. Estimates are broadly similar.

The correlation between unemployment rates and theft crime rates in Canada is positive. Estimates of the elasticity in specification (1) are not significant, however, a similar

[7]These results are suggest the opposite effect of the estimate in specification (1). Durlauf et al. (2012) show that estimates of deterrent measures may be particularly sensitive to functional form assumptions and may even change sign across specifications.

coefficient in specification (2), is significant at the 5% level. The second specification benefits from the efficiency gains of cell fixed-effects. The coefficient is fairly small in size at approximately 0.06. It is well-established in the literature that OLS estimates of the unemployment-crime relationship may be biased downward because increased crime rates affect unemployment. Almost all similar studies in the literature find much larger coefficients in IV models relative to OLS estimates (Altindag, 2012; Gould et al., 2002; Lin, 2008; Oester and Agell, 2007; Raphael and Winter-Ebmer, 2001). For this reason, the following section turns to IV estimation.

Unemployment rates are commonly used to capture labor market conditions. However, employment rates may provide an important robustness check because they include discouraged workers who are not actively searching for a job. Individuals who have chosen to engage in crime as an alternative to legitimate work may include discouraged workers. One drawback of employment rates in this particular context, where the estimation sample is composed of younger individuals, is that the employment rate cannot distinguish between discouraged workers and students. Table 4 presents estimates of equation 2 using the low-skill employment rate instead of the unemployment rate. Estimates of the covariates are essentially unchanged. The coefficients on employment rates are all negative as expected, although insignificant.

5.2 IV Results

Causal estimates reveal a much stronger relationship between low-skill unemployment and theft-crime rates. In column (1) of Table 5, the elasticity of theft rates with respect to the low-skill unemployment rate is shown to be 0.198. This measured effect is three times larger than the comparable OLS estimate of 0.06 in column (1) of Table 3, although it is not significant. The difference between these two estimated coefficients confirms that OLS estimates are biased downwards. The addition of cell-fixed effects in columns (2) and (3) provide important efficiency gains for the estimator leading to impacts that are statistically significant at the 5% level. These results are consistent with the Becker (1968) model which suggests that decreased opportunity cost will lead those at the margin of offending to commit crimes. The elasticity of theft crimes with respect to unemployment rates is in the rage 0.35-0.39. This impact is quite large given the scale of the unemployment rate.

The impact is more meaningful when evaluating against Canada's average unemployment rate in 2006 of 6.6%. A back-of-the-envelope calculation suggests that an increase in the unemployment rate of one percentage point, from 6.6-7.6%, represents a 12% increment in unemployment and would be associated with an increase in theft crime rates of approximately 4.2-4.7%. Estimates that exclude the potentially endogenous clearance rate variable in columns (4)-(6) are very similar to their counterparts in columns (1)-(3).[8]

Estimated impacts in this paper are slightly higher than the 3.13% increase predicted using a panel of european countries Altindag (2012). Impacts for the US using IV estimates range from a low of 2.5% in Gould et al. (2002) to as high as 16% in Lin (2008). It is worth pointing out that, contrary to the results for Sweden from Oester and Agell (2007), crime rates among younger workers are significantly affected.[9] This may reflect the importance of using a measure of unemployment specific to low-skilled workers. These impacts are likely to be estimated with considerable precision given that the data are specific to gender, age and CMA groups.

Because the IV strategy identifies a Local Average Treatment Effect (LATE), impacts are estimated using variation that arises from the observations directly affected by changes in the instrument. The instrument is therefore providing variation in low-skill employment in industries which are particularly sensitive to demand from the US. The external validity of these estimates may not extend to older workers or to women where low-skill employment may be concentrated in clerical jobs that are not as sensitive to fluctuations in demand. However, this may not be a concern because young low-skill male workers are precisely those who are expected to be at the margin of offending.

First stage results in the lower portion of Table 5 show that the instrument is not weak. The correlation between unemployment rates and the instrument is negative, demonstrating that exogenous increases in the demand for Canadian labor decrease low-skill Canadian unemployment. In particular, the instrument captures the US demand for Canadian lumber, seafood, automotive parts and oil. The instrument is statistically significant at the 1% level in all three specifications. Several statistical tests also support the strength of the instrument. The null hypothesis that the instrument has no effect on low skill unemploy-

[8]IV Specifications without control variables were also estimated but are omitted because they offer no additional information. Coefficient estimates are very similar in size and significance and are available upon request.

[9]Oester and Agell (2007) define youth unemployment rates for those age 18-24.

ment is rejected at the 1% level for all specifications. Angrist and Pischke (2009) (AP) F-tests for the instrument report test statistics in the rage 14-26. Similar results are given for the (AP) underidentification test, rejecting the null hypothesis that only the other first stage covariates provide variation in low-skill unemployment rates.

The causal impact of low-skill employment rates is negative, supporting the Becker (1968) model. Table 6 provides causal estimates for this alternative measure of labor market conditions. The elasticity of theft crimes with respect to the employment rate is much higher than the unemployment rate. Large estimates are partially due to the very high low-skill employment rates among young workers. The double-log functional form fits an exponential relationship leading to larger impacts at higher values of the independent variable. This functional form may be particularly appropriate given because a stronger relationship between crime and unemployment rates would be expected in areas where more young males at the margin of committing crime, precisely because of potential social multiplier effects. The instrument correlates positively and significantly with low-skill employment indicating that it is not a weak instrument for employment among young low-skill males.

6 Conclusion

This paper provides the first causal evidence from Canada that unemployment rates increase crime. Impacts are measured using unique cell-level data where observations are groups of workers by age, gender and CMA. The approach to the data relates cell-level theft rates directly to cell-level unemployment rates. Elasticity estimates are slightly lower than those from the US literature which primarily uses data aggregated to the county or state level. This data is also advantageous relative to the few sources of microdata on crime available for the US because it covers all crimes nationwide and is relatively recent. The findings confirm the positive and economically significant relationship between unemployment and theft crime that has been documented in the prior literature.

Slightly lower impacts for Canada relative to the US suggest that higher incarceration rates may not reduce theft rates if these crimes are used as a supplement for legitimate employment. This finding may be particularly important as the US grapples to deal with overcrowding in its correctional facilities. Meaningful reductions in property crime may be achieved by improving labor market options for young males. This is an important policy alternative to police spending and punitive sentencing laws, not only because it can reduce crime, but also because it has the potential to increase economic output.

One potentially important difference between Canada and the US is the level of social assistance. Slightly lower impacts in Canada may be partially attributed to institutions such as public healthcare. Social support systems effectively extend the budget constraint of low income and unemployed individuals, moving them further from the margin of offending. The empirical strategy in this paper eliminates the potential effects of many social assistance differences that exist across provinces and over time within Canada, however, it cannot eliminate the influence of institutional arrangements in one country which are not present in the other. The elasticity of crime with respect to social assistance among the unemployed remains an important topic for future research.

Table 1: Cell Counts by Number of Crimes and Gender

Count	Male	Female	Total
0	34,510	42,258	76,768
1-5	15,713	6,420	22,133
6-10	7,079	7,098	14,177
11-15	7,118	10,942	18,060
16-24	2,128	4,011	6,139
25-34	2,337	3,873	6,210
35-50	3,978	6,284	10,262
50-100	3,187	4,627	7,814
100-200	4,039	13,005	17,044

Source: UCR 2007-2011. Count represents the number of crimes reported in a monthly cell-level observation. Cells defined as combination of CMA, age and gender.

Table 2: Mean Characteristics of Young Males by Unemployment Rates

	Below Median Unemployment Rate			**Above Median Unemployment Rate**		
	Mean	SD	n	Mean	SD	n
Low Skill Unemployment Rate	7.185	1.552	14,308	12.361	2.343	14,371
Theft Crime Count	366.2	1362	9222	730.7	2500	12,281
Clearance Rate	0.653	0.135	9224	0.620	0.138	12,291
Share Married	0.090	0.136	14,308	0.098	0.156	15,179
Share Widow/Sep/Divorced	0.001	0.010	14,308	0.001	0.011	15,179
Share Foreign Born	0.086	0.112	14,308	0.093	0.125	15,179
Share $<$ HS Education	0.378	0.380	14,308	0.357	0.370	15,179
Share HS Education	0.242	0.206	14,308	0.214	0.204	15,179

Source: Males age 15-25 from Canadian LFS and UCR 1997-2012. Low skill employment and unemployment rates are calculated monthly for workers with $\leq$ high school education from LFS data using population weights. Clearance rate is the share of crimes cleared by charge, specific to theft-crimes and calculated at the CMA level. Theft crime counts are monthly at the cell level (CMA, gender and age in years). Share >HS education omitted.

Table 3: Unemployment Rates and Theft Crime in Canada, 2007-2011

	ln Theft Crime Rate (1)	ln Theft Crime Rate (2)	ln Theft Crime Rate (3)	ln Theft Crime Rate (4)	ln Theft Crime Rate (5)	ln Theft Crime Rate (6)
ln Low Skill Unemp. Rate	0.061 (0.048)	0.060** (0.027)	0.038 (0.033)	0.058 (0.047)	0.063** (0.027)	0.051 (0.035)
ln Clearance Rate	0.087 (0.081)	-0.089** (0.042)	-0.167*** (0.048)			
Share Married	-0.235* (0.131)	0.006 (0.067)	0.036 (0.070)	-0.237* (0.131)	0.006 (0.067)	0.035 (0.070)
Share Wid/Sep/Div	-1.319 (1.010)	-0.364 (0.599)	-0.172 (0.593)	-1.312 (1.010)	-0.399 (0.601)	-0.130 (0.596)
Share Foreign Born	-1.409*** (0.117)	-0.066 (0.064)	-0.087 (0.067)	-1.400*** (0.119)	-0.063 (0.064)	-0.084 (0.068)
Share $<$ HS Edu.	0.732*** (0.068)	0.030 (0.060)	-0.023 (0.062)	0.730*** (0.067)	0.032 (0.060)	-0.023 (0.062)
Share HS Edu.	0.492*** (0.101)	-0.033 (0.053)	-0.105* (0.056)	0.488*** (0.102)	-0.029 (0.053)	-0.103* (0.056)
Time Dummies	YES	YES	YES	YES	YES	YES
Prov. Trend	YES	YES	NO	YES	YES	NO
Cell Fixed-effects	NO	YES	YES	NO	YES	YES
n_j	15,774	15,774	15,774	15,777	15,777	15,777
n_ℓ		352	352		352	352

OLS estimates for males age 16-25. All specifications include time-dummies to capture non-linear trends at the national level which may be spuriously correlated with theft crime rates. Source: Monthly Cell level data from Canadian LFS and UCR surveys for the period 2007-2011. Cells defined as combination of CMA and age. Low skill unemployment rate is defined from the LFS for workers with High school education or less. Clearance rate specific to the CMA and theft crimes. Estimates weighted with the number of observations per cell. Standard errors clustered at the cell level. Monthly time dummies control for seasonality. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4: Employment Rates and Theft Crime in Canada, 2007-2011

	ln Theft Crime Rate (1)	ln Theft Crime Rate (2)	ln Theft Crime Rate (3)	ln Theft Crime Rate (4)	ln Theft Crime Rate (5)	ln Theft Crime Rate (6)
ln Low Skill Emp. Rate	-0.698	-0.340	-0.254	-0.698	-0.371	-0.367
	(0.441)	(0.249)	(0.284)	(0.442)	(0.250)	(0.297)
ln Clearance Rate	0.083	-0.091*	-0.170***			
	(0.080)	(0.042)	(0.049)			
Share Married	-0.237*	0.006	0.035	-0.238*	0.006	0.034
	(0.131)	(0.067)	(0.070)	(0.131)	(0.067)	(0.070)
Share Wid/Sep/Div	-1.316	-0.359	-0.177	-1.309	-0.332	-0.135
	(1.008)	(0.603)	(0.595)	(1.012)	(0.605)	(0.599)
Share Foreign Born	-1.410***	-0.064	-0.086	-1.402***	-0.602	-0.083
	(0.117)	(0.064)	(0.067)	(0.119)	(0.064)	(0.068)
Share $<$ HS Edu.	0.732***	0.031	-0.022	0.730***	0.033	-0.022
	(0.068)	(0.060)	(0.062)	(0.068)	(0.060)	(0.062)
Share HS Edu.	0.491***	-0.032	-0.105*	0.487***	-0.029	-0.022*
	(0.101)	(0.053)	(0.056)	(0.102)	(0.053)	(0.056)
Time Dummies	YES	YES	YES	YES	YES	YES
Prov. Trend	YES	YES	NO	YES	YES	NO
Cell Fixed-effects	NO	YES	YES	NO	YES	YES
n_j	15774	15774	15774	15777	15777	15777
n_ℓ		352	352		352	352

OLS estimates for males age 16-25. All specifications include time-dummies to capture non-linear trends at the national level which may be spuriously correlated with theft crime rates. Source: Monthly Cell level data from Canadian LFS and UCR surveys for the period 2007-2011. Cells defined as combination of CMA and age. Low skill employment rate is defined from the LFS for individuals age 15-65 with High school education or less. Clearance rate specific to the CMA and theft crimes. Estimates weighted with the number of observations per cell. Standard errors in parentheses clustered at the cell level. Monthly time dummies control for seasonality. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5: The Effect of Unemployment Rates on Theft Crime in Canada, 2007-2011

Second Stage	ln Theft Crime Rate (1)	ln Theft Crime Rate (2)	ln Theft Crime Rate (3)	ln Theft Crime Rate (4)	ln Theft Crime Rate (5)	ln Theft Crime Rate (6)
ln Low Skill Unemp. Rate	0.198	0.335**	0.390**	0.185	0.358**	0.441***
	(0.373)	(0.131)	(0.159)	(0.372)	(0.138)	(0.166)
ln Clearance Rate	0.096	-0.065***	-0.097			
	(0.223)	(0.077)	(0.093)			
Share Married	-0.225*	-0.002***	0.045	-0.337*	-0.003	0.046
	(0.132)	(0.063)	(0.066)	(0.135)	(0.062)	(0.067)
Share Wid/Sep/Div	-1.259	-0.411***	-0.115	-1.259	-0.396	-0.086
	(0.944)	(0.451)	(0.487)	(0.945)	(0.449)	(0.490)
Share Foreign Born	-1.447***	-0.089***	-0.116*	-1.434***	-0.089*	-0.118*
	(0.160)	(0.053)	(0.062)	(0.174)	(0.053)	(0.063)
Share $<$ HS Edu.	0.732***	0.019***	-0.039	0.730***	0.019	-0.042
	(0.126)	(0.07)	(0.080)	(0.127)	(0.070)	(0.081)
Share HS Edu.	0.497***	-0.041***	-0.117**	0.492***	-0.039	-0.118**
	(0.165)	(0.046)	(0.046)	(0.170)	(0.046)	(0.047)
First Stage	ln Low Skill Unemp. Rate	ln Low Skill Unemp. Rate	ln Low Skill Unemp. Rate	ln Low Skill Unemp. Rate	ln Low Skill Unemp. Rate	ln Low Skill Unemp. Rate
Z	-0.206***	-0.187***	-0.143***	-0.207***	-0.193***	-0.160***
	(0.051)	(0.037)	(0.038)	(0.052)	(0.034)	(0.033)
ln Clearance Rate	-0.063	-0.083	-0.198*			
	(0.095)	(0.075)	(0.100)			
Share Married	-0.078	0.030	-0.026	-0.077	0.029	-0.028
	(0.059)	(0.024)	(0.035)	(0.058)	(0.024)	(0.035)
Share Wid/Sep/Div	-0.392	0.178	-0.155	-0.039	0.202	-0.106
	(0.345)	(0.277)	(0.270)	(0.329)	(0.292)	(0.285)
Share Foreign Born	0.274**	0.086**	0.084*	0.268**	0.089**	0.089*
	(0.122)	(0.042)	(0.046)	(0.123)	(0.043)	(0.047)
Share $<$ HS Edu.	-0.001	0.04	0.046	0.001	0.042	0.046
	(0.033)	(0.028)	(0.044)	(0.032)	(0.029)	(0.047)
Share HS Edu.	-0.041	0.027	0.033	-0.038	0.030	0.036
	(0.060)	(0.027)	(0.048)	(0.060)	(0.028)	(0.052)
Time Dummies	YES	YES	YES	YES	YES	YES
Prov. Trend	YES	YES	NO	YES	YES	NO
Cell Fixed-effects	NO	YES	YES	NO	YES	YES
n_j	15,774	15,774	15,774	15,777	15,777	157,77
n_ℓ		352	352		352	352
F	6.20***	9.30***	10.09***	6.93***	9.17***	5.53***
$F^A P$ (32df)	16.15***	26.30***	14.20***	15.71***	33.03***	23.12***
U-ID^{AP}	16.75***	27.27***	14.72***	16.29***	34.25***	23.96***

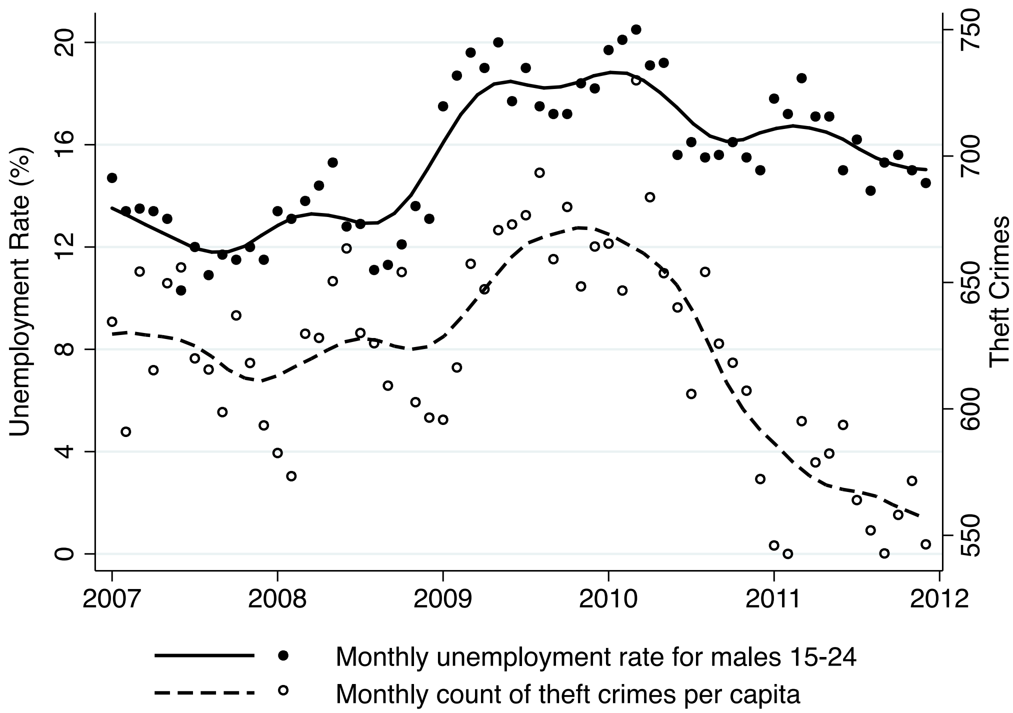
2SLS Estimates for males age 16-25. All specifications include time-dummies to capture non-linear trends at the national level which may be spuriously correlated with theft crime rates. Source: Monthly Cell level data from Canadian LFS and UCR surveys for the period 2007-2011. Cells defined as combination of CMA and age. Low skill unemployment rate is defined from the LFS for workers with High school education or less. Clearance rate specific to the CMA and theft crimes. Estimates weighted with the number of observations per cell. Standard errors in parentheses clustered at the CMA level. Monthly time dummies control for seasonality. F^{AP} and U-ID^{AP} are the tests for excluded instruments and underidentification suggested by Angrist and Pischke (2009). Instrumental variable Z interacts the CMA level employment shares in key industries for low skilled males with exogenous changes at the aggregate level from world trade prices and proxies for US import demand. Coefficients and SE's for z scaled up by 100,000. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6: The Effect of Employment Rates on Theft Crime in Canada, 2007-2011

Second Stage	ln Theft Crime Rate (1)	ln Theft Crime Rate (2)	ln Theft Crime Rate (3)	ln Theft Crime Rate (4)	ln Theft Crime Rate (5)	ln Theft Crime Rate (6)
ln Low Skill Emp. Rate	-2.395	-3.415**	-3.811**	-2.257	-3.640**	-4.386**
	(4.474)	(1.460)	(1.722)	(4.514)	(1.559)	(1.879)
ln Clearance Rate	0.082	-0.602	-0.109			
	(0.221)	(0.077)	(0.098)			
Share Married	-0.230*	-0.008	0.030	-0.231*	-0.009	0.029
	(0.132)	(0.064)	(0.069)	(0.134)	(0.064)	(0.070)
Share Wid/Sep/Div	-1.250	-0.396	-0.160	-1.248	-0.382	-0.134
	(0.948)	(0.456)	(0.507)	(0.948)	(0.453)	(0.510)
Share Foreign Born	-1.453***	-0.095*	-0.117*	-1.442***	-0.096*	-0.120*
	(0.158)	(0.055)	(0.064)	(0.172)	(0.054)	(0.064)
Share < HS Edu.	0.730***	0.019	-0.035	0.728***	0.020	-0.037
	(0.128)	(0.071)	(0.079)	(0.128)	(0.071)	(0.081)
Share HS Edu.	0.494***	-0.043	-0.118**	0.489***	-0.041	-0.119**
	(0.165)	(0.047)	(0.046)	(0.170)	(0.047)	(0.048)
First Stage	ln Low Skill Emp. Rate	ln Low Skill Emp. Rate	ln Low Skill Emp. Rate	ln Low Skill Emp. Rate	ln Low Skill Emp. Rate	ln Low Skill Emp. Rate
Z	0.017***	0.018***	0.015***	0.017***	0.019***	0.016***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
ln Clearance Rate	-0.0001	0.009	0.017*			
	(0.010)	(0.007)	(0.008)			
Share Married	0.004	-0.005*	-0.001	0.004	-0.005*	-0.001
	(0.006)	(0.003)	(0.003)	(0.006)	(0.003)	(0.003)
Share Wid/Sep/Div	0.038	-0.013	0.004	0.037	-0.016	-0.0002
	(0.037)	(0.027)	(0.026)	(0.037)	(0.029)	(0.028)
Share Foreign Born	-0.025**	-0.010**	-0.009*	-0.025**	-0.011**	-0.009*
	(0.011)	(0.004)	(0.005)	(0.011)	(0.004)	(0.005)
Share < HS Edu.	-0.001	-0.004	-0.004	-0.001	-0.004	-0.004
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
Share HS Edu.	0.002	-0.003	-0.004	0.002	-0.004	-0.004
	(0.006)	(0.003)	(0.004)	(0.006)	(0.003)	(0.004)
Time Dummies	YES	YES	YES	YES	YES	YES
Prov. Trend	YES	YES	NO	YES	YES	NO
Cell Fixed-effects	NO	YES	YES	NO	YES	YES
n_j	15,774	15,774	15,774	15,777	15,777	15,777
n_ℓ		352	352		352	352
F	5.65***	5.33***	5.37***	6.33***	5.49***	3.03***
$F^A P$ (32df)	12.11***	16.16***	10.00****	12.02***	18.75***	13.85***
U-ID^{AP}	12.56***	16.76***	10.36***	12.46***	19.45***	14.35***

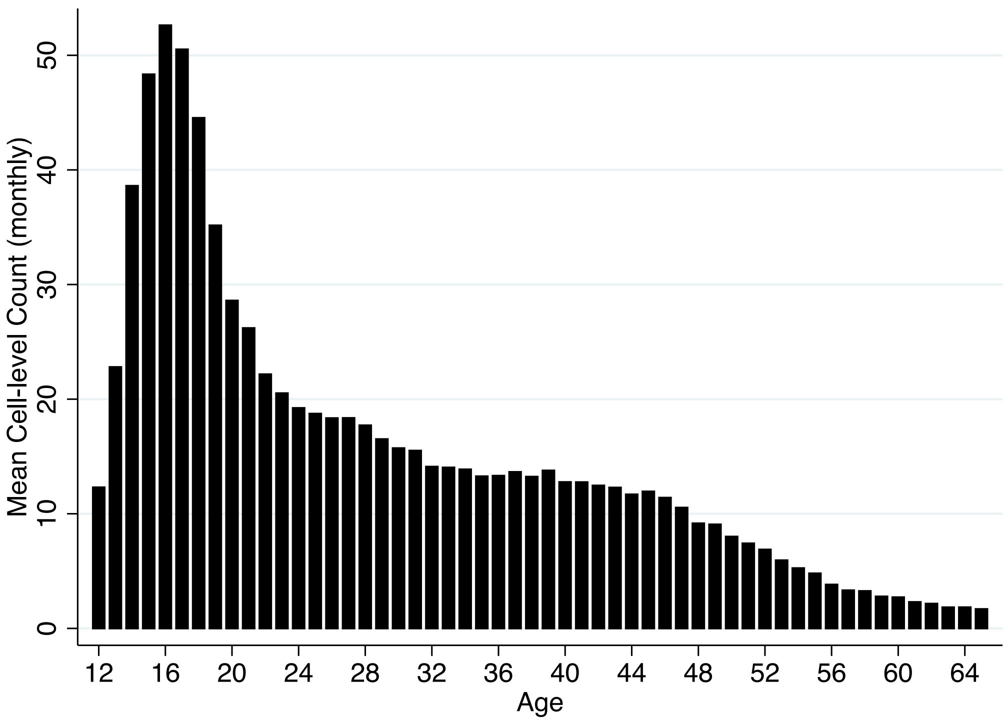
2SLS Estimates for males age 16-25. All specifications include time-dummies to capture non-linear trends at the national level which may be spuriously correlated with theft crime rates. Source: Monthly Cell level data from Canadian LFS and UCR surveys for the period 2007-2011. Cells defined as combination of CMA and age. Low skill employment rate is defined from the LFS for individuals age 15-65 High school education or less. Clearance rate specific to the CMA and theft crimes. Estimates weighted with the number of observations per cell. Standard errors in parentheses clustered at the CMA level. Monthly time dummies control for seasonality. F^{AP} and U-ID^{AP} are the tests for excluded instruments and underidentification suggested by Angrist and Pischke (2009). Instrumental variable Z interacts the CMA level employment shares in key industries for low skilled males with exogenous changes at the aggregate level from world trade prices and proxies for US import demand. Coefficients and SE's for z scaled up by 100,000. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Figure 1: Aggregate Unemployment and Thefts in Canada 2007-2012



Source: Statistics Canada Cansim Tables 282-0001 and UCR microdata. Crimes include well-reported theft related violations where 80% or more of all incidents are reported to police. Details provided in the text section 3.

Figure 2: Cell-level Incidence of Theft Crimes by Age of Accused



Source: Canadian UCR and LFS data, 2007-2011. Cells defined as combination of CMA and age. Overall average count per cell is 22.98 offenses per month. Zero crime cell-level observations are excluded.

References

Alonso-Borrego, C., N. Garoupa, and P. Vázquez (2012). Does immigration cause crime? evidence from Spain. *American Law and Economics Review 14*(1), 165–191.

Altindag, D. T. (2012). Crime and unemployment: Evidence from Europe. *International Review of Law and Economics 32*(1), 145–157.

Andresen, M. A. (2012). Unemployment and crime: A neighborhood level panel data approach. *Social science research 41*(6), 1615–1628.

Angrist, J. D. and J.-S. Pischke (2009). *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press.

Aoki, Y. and Y. Todo (2009). Are immigrants more likely to commit crimes? Evidence from France. *Applied Economics Letters 16*, 1537–1541.

Avio, K. L. and C. S. Clark (1978). The supply of property offences in Ontario: Evidence on the deterrent effect of punishment. *Canadian Journal of Economics 11*(1), 1–19.

Becker, G. (1968). Crime and punishment: An economic approach. *The Journal of Political Economy 76*(2), 169–217.

Bernard, A. (2013). Recent trends in Canadian automotive industries. Analytical Paper 11-626-X 26, Statistics Canada.

Bernhardt, D., S. Mongrain, and J. Roberts (2012). Rehabilitated or not: An informational theory of parole decisions. *Journal of Law, Economics, & Organization 28*(2), 186–210.

Bianchi, M., P. Buonanno, and P. Pinotti (2012). Do immigrants cause crime? *Journal of the European Economic Association 10*(6), 1318–1347.

Borjas, G. J., J. Grogger, and G. H. Hanson (2006). Immigration and African-American employment opportunities: The response of wages, employment, and incarceration to labor supply shocks. Technical Report w12518, National Bureau of Economic Research.

Buonanno, P. (2006). Crime and labour market opportunities in Italy (1993–2002). *Labour 20*(4), 601–624.

Bushway, S. D. (1996). The impact of a criminal history record on access to legitimate employment. Dissertation, Carnegie Mellon University.

Butcher, K. F. and A. M. Piehl (1998). Cross-city evidence on the relationship between immigration and crime. *Journal of Policy Analysis and Management 17*(3), 457–493.

Card, D. (1990). Unexpected inflation, real wages, and employment determination in union contracts. *American Economic Review 80*(4), 669–688.

Carmichael, F. and R. Ward (2001). Male unemployment and crime in England and Wales. *Economics Letters 73*(1), 111–115.

Cornwell, C. and W. N. Trumbull (1994). Estimating the economic model of crime with panel data. *Review of Economics and Statistics 76*(2), 360–366.

Craig, S. G. (1987). The deterrent impact of police: An examination of a locally provided public service. *Journal of Urban Economics 21*(3), 298–311.

Cullen, J. and S. Levitt (1999). Crime, urban flight, and the consequences for cities. *The Review of Economics and Statistics 81*(2), 159–169.

Curry, P. A., A. Sen, and G. Orlov (2013). Crime, apprehension, and clearance rates: Panel data evidence from Canadian provinces. Working Paper 2336202, SSRN.

Di Tella, R. and E. Schargrodsky (2004). Do police reduce crime? estimates using the allocation of police forces after a terrorist attack. *The American Economic Review 94*(1), 115–133.

Draca, M., S. Machin, and R. Witt (2011). Panic on the streets of London: Police, crime, and the July 2005 terror attacks. *The American Economic Review 101*(5), 2157–2181.

Durlauf, S. N., C. Fu, and S. Navarro (2012). Assumptions matter: Model uncertainty and the deterrent effect of capital punishment. *American Economic Review: Papers and Proceedings 102*(3), 487–492.

Edmark, K. (2005). Unemployment and crime: Is there a connection? *The Scandinavian Journal of Economics 107*(2), 353–373.

Ehrlich, I. (1973). Participation in illegitimate activities: A theoretical and empirical investigation. *The Journal of Political Economy 81*(3), 521–565.

Evans, W. N. and E. G. Owens (2007). COPS and crime. *Journal of Public Economics 91*(1), 181–201.

Fagan, J. and R. B. Freeman (1999). Crime and work. *Crime and Justice 25*, 225–290.

Fisheries and Oceans Canada (2008). Canadian fisheries statistics 2008. Technical Report DFO/2011-1732, Strategic Policy Sector.

Fisheries and Oceans Canada (2012). Aquaculture in canada 2012. First report of the aquaculture sustainability reporting initiative.

Fougère, D., J. Pouget, and F. Kramarz (2009). Youth unemployment and crime in France. *Journal of the European Economic Association 7*(5), 909–938.

Freeman, R. B. (1999). The economics of crime. In O. Ashenfelter and D. Card (Eds.), *Handbook of Labor Economics*, Volume 3, pp. 3529–3571. Amsterdam: North-Holland.

Furlong, W. J. and S. L. Mehay (1981). Urban law enforcement in Canada: An empirical analysis. *Canadian Journal of Economics 14*(1), 44–57.

Gannon, M. (2001). Crime comparisons between Canada and the United States. Juristat Catalogue Number 85-002-XPE, Statistics Canada.

Germain, B. (2012). An overview of the lumber industry in Canada, 2004 to 2010. Analytical Paper 11-621-M 89, Statistics Canada.

Glaeser, E., J. Scheinkman, and B. Sacerdote (2003). The social multiplier. *Journal of the European Economic Association 1*, 345–353.

Gould, E. D., B. A. Weinberg, and D. B. Mustard (2002). Crime rates and local labor market opportunities in the United States: 1979–1997. *Review of Economics and Statistics 84*(1), 45–61.

Government of Alberta (2015). Mining and oil and gas extraction industry. Industry profiles.

Grogger, J. (1998). Market wages and youth crime. *Journal of Labor Economics 16*(4), 756–791.

Hartnagel, T. F. and G. W. Lee (1990). Urban crime in Canada. *Canadian Journal of Criminology 32*, 591–606.

Holzer, H. (2007). Collateral costs: The effects of incarceration on the employment and earnings of young workers. Discussion paper, IZA.

Levitt, S. D. (1997). Using electoral cycles in police hiring to estimate the effect of police on crime. *American Economic Review 87*(3), 270–290.

Levitt, S. D. (1998). Why do increased arrest rates appear to reduce crime: Deterrence, incapacitation, or measurement error? *Economic Inquiry 36*(3), 353–372.

Lin, M. (2008). Does unemployment increase crime? Evidence from US data 1974–2000. *Journal of Human Resources 43*(2), 413–436.

Lochner, L. and E. Moretti (2004). The effect of education on crime: Evidence from prison inmates, arrests, and self-reports. *The American Economic Review 94*(1), 155–189.

Lott, J. R. (1992a). An attempt at measuring the total monetary penalty from drug convictions: The importance of an individual's reputation. *Journal of Legal Studies 21*, 159–187.

Lott, J. R. (1992b). Do we punish high income criminals too heavily. *Economic Inquiry 30*, 583–608.

Machin, S. and C. Meghir (2004). Crime and economic incentives. *Journal of Human Resources 39*(4), 958–979.

McGregor, J. (2015). The biggest mass layoffs of the past two decades. *The Washington Post*.

Mustard, D. B. (2003). Reexamining criminal behavior: The importance of omitted variable bias. *Review of Economics and Statistics 85*(1), 205–211.

Mustard, D. B. (2010). How do labor markets affect crime? New evidence on an old puzzle. Discussion Paper 4856, IZA.

Myers, S. (1983). Estimating the economic model of crime: Employment versus punishment effects. *Quarterly Journal of Economics 98*(1), 157.

National Oceanic and Atmospheric Administration (2014). New England imports (1,000 metric tons) of selected fishery products from Canada and all other countries. Northeast region trade summary.

Natural Resources Canada (2015). About crude oil and petroleum products.

Oester, A. and J. Agell (2007). Crime and unemployment in turbulent times. *Journal of the European Economic Association 5*(4), 752–775.

Phillips, L., H. Votey, and D. Maxwell (1972). Crime, youth and the labor market. *Journal of Political Economy 80*(3), 491–504.

Raphael, S. and R. Winter-Ebmer (2001). Identifying the effect of unemployment on crime. *Journal of Law and Economics 44*(1), 259–283.

Reilly, B. and R. Witt (1996). Crime, deterrence and unemployment in England and Wales: An empirical analysis. *Bulletin of Economic Research 48*(2), 137–159.

Rosenmerkel, S., M. Durose, and D. Farole (2009). Felony sentences in state courts, 2006 – statistical tables. National judicial reporting program, US Department of Justice, Bureau of Justice Statistics.

Spenkuch, J. L. (2014). Understanding the impact of immigration on crime. *American Law and Economics Review 16*(1), 177–219.

Statistics Canada (2015). Adult criminal courts, guilty cases by mean and median length of custody, annual.

Trumbull, W. (1989). Estimates of the economic model of crime using aggregate and individual level data. *Southern Economic Journal 56*(2), 423–439.

Trussler, T. (2012). Demographics and homicide in Canada: A fixed-effects analysis of the role of young males on changing homicide rates. *Western Criminology Review 13*(1), 53–67.

Waldfogel, J. (1994). The effect of criminal conviction on income and the trust 'reposed in the workmen'. *Journal of Human Resources 29*(1), 62–81.

Western, B. (2002). The impact of incarceration on wage mobility and inequality. *American Sociological Review 67*, 526–546.

Western, B. and B. Pettit (2000). Incarceration and racial inequality in men's employment. *Industrial and Labor Relations Review 54*(1), 3–16.

Wilson, J. Q. and J. Petersilia (2011). *Crime and Public Policy*. Oxford UK: Oxford University Press.

Appendix

This section provides additional details about the UCR and LFS data and the merging procedure used to create the synthetic panel. I am grateful for access to this data, which was made possible by a Statistics Canada Research Data Center pilot project.

The UCR is administered yearly nationwide with essentially all police forces responding by jurisdiction. The UCR data are divided in three files. The “Incident” file provides the time, location and violations of each report, the “Charged / Suspect-Chargeable” file identifies the accused and the “victim” file provides details about any victims. The files are merged using the respondent (police force identifier) codes which are unique. The data are provided as yearly files, but incident dates are recorded. This makes it possible to separate the data into a monthly record. Only the 33 largest CMAs are reported for confidentiality reasons. CMAs data available in the UCR data are St. John’s, Halifax, Moncton, Saint John, Saguenay, Québec City, Sherbrooke, Trois-Rivières, Montréal, Ottawa-Gatineau, Kingston, Peterborough, Oshawa, Toronto, Hamilton, St.Catharines-Niagara, Kitchener-Cambridge-Waterloo, Brantford, Guelph, London, Windsor, Barrie, Greater Sudbury, Thunder Bay, Winnipeg, Regina, Saskatoon, Calgary, Edmonton, Kelowna, Abbotsford-Mission, Vancouver, and Victoria. The Ottawa-Gatineau CMA, which is reported separately by its Quebec and Ontario parts in this data, is merged and listed under Ontario where the majority of its citizens reside.

The data are collapsed to mean values in cells based on age and CMA. Because the LFS and UCR files are not linkable at the individual level, this strategy provides data corresponding to narrowly defined demographic groups. These cells are the most narrow groups possible because other offender demographics, such as racial indicators, are suppressed from researchers by Statistics Canada because data quality concerns. Observations in the LFS are collapsed to means using the LFS final weights, within each age-CMA cell. The weighting yields representative cells which should be a better match for the population theft crime counts from the UCR. The data are limited to individuals over the age of 15 because the LFS only samples working age persons. The data are also limited to include males less than 25 years of age in order to focus the analysis on the population group that is most likely to commit crime.

Using detailed violation codes and CMA population counts from the Statistics Canada

Cansim database, monthly theft crime rates (per 100,000 CMA population) are generated for each cell. CMA population, which is based on Census 2006 boundaries, is only available annually as of July 1. Monthly changes are imputed as equal shares of the annual change. Because the population counts are not available for gender/age splits, the denominator for crime rates is common so that the sum of theft crime rates across all synthetic individuals yields the total crime rate for a given CMA.

For many criminal incidents, more than one offense is committed by an accused. The violation codes used in this paper correspond to the most serious violation. For example, an intoxicated individual who steals a car might be charged with automobile theft and driving while intoxicated. In this case, the crime would be reported as the former. In determining the seriousness of an offense, the following criteria are used by the CCJS: i) person or violations against the person take precedence over non-violations against the person; ii) greatest maximum penalty prescribed by law; iii) homicide violations take precedence over other violations with the same maximum penalty; iv) if above three rules do not break 'ties' then the most serious violation within an incident is at the discretion of the reporting police department. To obtain theft rates, the four-digit violation codes are grouped into major crime categories. The grouping used in this paper omits the major categories of break and enter and automobile theft because of low responses in the "Suspect-Chargeable file." Robbery is also excluded because it is considered to be a violent offense rather than a property crime.

Table A.1: Unemployment Rates and Theft Crime in Canada using Extended Measure of Theft Crimes, 2007-2011

	ln Theft Crime Rate (1)	ln Theft Crime Rate (2)	ln Theft Crime Rate (3)	ln Theft Crime Rate (4)	ln Theft Crime Rate (5)	ln Theft Crime Rate (6)
ln Low Skill Unemp. Rate	0.089*	0.037	-0.0004	0.079*	0.036	0.001
	(0.047)	(0.027)	(0.033)	(0.047)	(0.027)	(0.034)
ln Clearance Rate	0.309***	0.042	-0.017			
	(0.095)	(0.055)	(0.052)			
Share Married	-0.596***	0.028	0.073	-0.606***	0.028	0.073
	(0.119)	(0.072)	(0.074)	(0.129)	(0.072)	(0.074)
Share Wid/Sep/Div	-1.479	-0.729	-0.409	-1.373	-0.731	-0.409
	(0.971)	(0.690)	(0.686)	(0.979)	(0.688)	(0.687)
Share FB	-1.112***	-0.068	-0.093	-1.093***	-0.068	-0.092
	(0.097)	(0.064)	(0.066)	(0.099)	(0.064)	(0.066)
Share $<$ HS Edu.	0.825***	0.043	-0.002	0.819***	0.042	-0.002
	(0.064)	(0.059)	(0.062)	(0.064)	(0.059)	(0.062)
Share HS Edu.	0.542***	-0.042	-0.114**	0.528***	-0.043	-0.114**
	(0.090)	(0.051)	(0.053)	(0.092)	(0.051)	(0.053)
Time Dummies	YES	YES	YES	YES	YES	YES
Prov. Trend	YES	YES	NO	YES	YES	NO
Cell Fixed-effects	NO	YES	YES	NO	YES	YES
n_j	18,635	18,635	18,635	18,635	18,635	18,635
n_ℓ		352	352		352	352

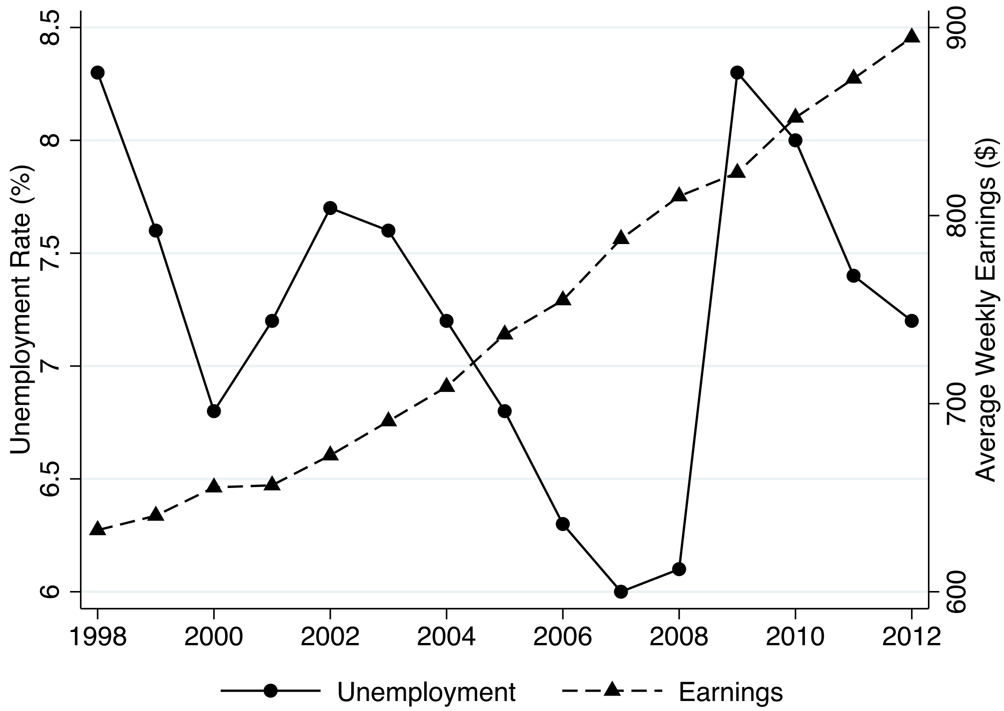
Fixed-effects estimates for males age 16-25. All specifications include time-dummies to capture non-linear trends at the national level which may be spuriously correlated with theft crime rates. Source: Monthly Cell level data from Canadian LFS and UCR surveys for the period 2007-2011. Cells defined as combination of CMA and age. Low skill unemployment rate is defined from the LFS for workers with High school education or less. Clearance rate specific to the CMA and theft crimes. Estimates weighted with the number of observations per cell. Standard errors in parentheses clustered at the cell level. Monthly time dummies control for seasonality. $^{*}p < 0.1,\ ^{**}p < 0.05,\ ^{***}p < 0.01$.

Table A.2: Employment Rates and Theft Crime in Canada using Extended Measure of Theft Crimes, 2007-2011

	ln Theft Crime Rate (1)	ln Theft Crime Rate (2)	ln Theft Crime Rate (3)	ln Theft Crime Rate (4)	ln Theft Crime Rate (5)	ln Theft Crime Rate (6)
ln Low Skill Emp. Rate	-0.947** (0.441)	-0.305 (0.253)	-0.127 (0.284)	-0.910** (0.441)	-0.295 (0.255)	-0.135 (0.293)
ln Clearance Rate	0.305*** (0.094)	0.041 (0.055)	-0.015 (0.062)			
Share Married	-0.599*** (0.119)	0.028 (0.072)	0.073 (0.074)	-0.607*** (0.120)	0.028 (0.072)	0.073 (0.074)
Share Wid/Sep/Div	-1.478 (0.973)	-0.728 (0.691)	-0.408 (0.689)	-1.371 (0.981)	-0.730 (0.689)	-0.408 (0.687)
Share FB	-1.111*** (0.097)	-0.068 (0.064)	-0.094 (0.066)	-1.094*** (0.098)	-0.069 (0.064)	-0.094 (0.066)
Share < HS Edu.	0.824*** (0.064)	0.043 (0.059)	-0.003 (0.616)	0.818*** (0.064)	0.042 (0.059)	-0.003 (0.062)
Share HS Edu.	0.540*** (0.090)	-0.042 (0.051)	-0.115** (0.053)	0.527*** (0.092)	-0.043 (0.051)	-0.115** (0.053)
Time Dummies	YES	YES	YES	YES	YES	YES
Prov. Trend	YES	YES	NO	YES	YES	NO
Cell Fixed-effects	NO	YES	YES	NO	YES	YES
n_j	18,635	18,635	18,635	18,635	18,635	18,635
n_ℓ		352	352		352	352

Fixed-effects estimates for males age 16-25. All specifications include time-dummies to capture non-linear trends at the national level which may be spuriously correlated with theft crime rates. Source: Monthly Cell level data from Canadian LFS and UCR surveys for the period 2007-2011. Cells defined as combination of CMA and age. Low skill employment rate is defined from the LFS for individuals aged 15-65 with High school education or less. Clearance rate specific to the CMA and theft crimes. Estimates weighted with the number of observations per cell. Standard errors in parentheses clustered at the cell level. Monthly time dummies control for seasonality. $^{*}p < 0.1,\ ^{**}p < 0.05,\ ^{***}p < 0.01$.

Figure A.1: Annual Unemployment and Earnings in Canada 1998-2012



Source: Statistics Canada Cansim Tables 281-0053, 281-0063, 282-0008. The unemployment rate is the number of unemployed persons civilian, non-institutionalized persons 15 years of age and over expressed as a percentage of the labour force. Earnings data are based on gross payroll before source deductions, expressed in current (2015) Canadian dollars.