Domestic Violence Occurrences and the Timing of Welfare Payments

Maxime Cormier

Major paper submitted to the Faculty of Graduate and Postdoctoral Studies
In partial fulfillment of the requirements for the
M.A. degree in Economics

Department of Economics
Faculty of Social Sciences
University of Ottawa

Abstract

This research paper investigates a potential relationship between intimate partner violence and social assistance disbursement policy. In recent research, it is argued that intimate partner violence may be used directly or indirectly as an intrahousehold resource extraction instrument. Moreover, another part of the literature shows that certain types of crimes are strongly concentrated at particular moments of welfare payment cycles, depending on their motive. Using data from fourteen Canadian census metropolitan areas that exhibit relatively high welfare receipt rates, the hypothesis that "first of the month" disbursement drives an increase in domestic violence is tested using a panel model with two-way, clustered fixed effects. I find convincing evidence that occurrences of intimate partner violence are concentrated soon after total welfare benefits are received. I also find a second distinct domestic violence peak in the course of the typical welfare payment cycle.

Table of Contents

1 Introduction 4

2 Background from the economics literature 7

2.1 Welfare payments, consumption and crime 7
2.2 Household bargaining and domestic violence 10

3 Models and methodology 14

3.1 Econometric models 14
3.2 Sources of data 21

4 Empirical results 25

4.1 Regression analysis 25
4.2 Further tests 33
4.3 Potential estimation biases 37

5 Conclusion 39

6 References 41

6.1 Works cited 41
6.2 Other references 42

7 Appendices 44

Appendix A: Social assistance in Canadian provinces 44
Appendix B: Summary statistics 47
Appendix C: Parameter estimates and tests 55

1 Introduction

Social assistance payments are the sole legal source of income of several Canadian households. Some of the recipients of welfare money live by themselves; others must share a common monthly check, which constrains them to pool their main financial resources. Let us consider a household made up at least of two intimate partners whose monthly income is mainly composed of a welfare payment provided by the Government. While members of such a household are likely to have basic needs involving weekly – if not daily – expenditures, social assistance revenues are typically paid monthly at a discrete point in time, near the "first of the month" in many Canadian and American jurisdictions. Welfare checks usually cover the most basic needs of the recipients, who must begin to think of an allocation of the monthly payment upon its reception. If such a decision must be taken collectively, as in the particular case where two intimate partners living on social assistance share the same dwelling space, one might suspect that at times, the necessary bargaining leads to a conflict involving some form of domestic violence. If that is the case, a certain share of all monthly domestic violence occurrences must logically be concentrated at the beginning of social assistance payment cycles. In other words, monthly domestic violence cycles, if such cycles actually exist, might be explained in part by the timing of social assistance payments.

In this paper, I attempt to test the hypothesis that as a consequence of conflicts about the allocation of monthly benefits, domestic violence occurrences involving intimate partners are concentrated at the beginning of payment cycles, soon after total benefits are disbursed by the Government. Doing so, I implicitly verify the hypothesis that violent partners resort to terror as a means of influencing the allocation of financial resources within the household, as put forward in the economics literature pertaining to domestic violence (Grogan *et al.*, 2009; Bloch and Rao, 2002; Tauchen *et al.*, 1991). This is done using Canadian daily data on reported domestic violence incidents in fourteen census metropolitan areas (CMAs), extracted from Statistics Canada's *Incident-based Uniform Crime Report* (UCR2). I find that occurrences of intimate partner violence are concentrated soon after total welfare benefits are disbursed. In addition, I find evidence that a second peak in domestic violence exists.

Relationships between domestic violence and welfare receipt have been investigated by researchers from different disciplines. It has indeed been noticed that towns with higher rates of welfare receipt are strongly associated with higher rates of spousal abuse (Nou and Timmins, 2005). More generally, it has been observed that bargaining for intra-household resources may induce domestic violence. In those cases, violence is said to be used as an *instrument* to make outcomes favourable to the violent intimate partner, whether it happens in North America (Tauchen *et al.*, 1991) or in South America (Grogan *et al.*, 2009). This conception of conjugal violence has been applied to the case of dowries in rural India as well (Bloch and Rao, 2002).

Moreover, in recent research economists have found evidence that the timing of welfare payments does have significant implications on certain categories of criminal activity. Using data from twelve major American cities, Foley (2008) finds that financially motivated criminal activity increases over the course of welfare payment cycles, which indicates that such criminal activity is concentrated at the end of payment social assistance cycles.[1] This provides evidence that some social assistance recipients resort to illegal activities in order to supplement their legal, modest and readily exhausted welfare benefits, thus revealing what Foley refers to as "short-term impatience". With a comparable methodology but focusing on the case of California, a state where social assistance is mostly paid entirely on the first day of each month, Dobkin and Puller (2007) find that hospitalizations and deaths related to drug abuse, contrary to financially motivated crimes, are strongly concentrated at the *beginning* of each month.

The empirical findings of Foley (2008) and Dobkin and Puller (2007) have important policy implications as they suggest that alternative payment policies, in comparison with the classic once-a-month and fixed-date disbursement approach, might smooth down and even help mitigate the occurrences of certain types of incidents and undesirable activities.

The rest of the paper proceeds as follows. An overview of the recent economics literature about monthly social assistance cycles, household bargaining and domestic violence is found in the next section. Section 3 describes in detail the specific methodology necessary to test formally my central research hypothesis, Section 4 displays the relevant empirical results and provides a discussion about the results' statistical validity. My conclusion and policy recommendations are found in Section 5.

---

[1] A welfare payment cycle is the time elapsed between two payments in a given province. Each cycle begins on the day a payment is made to the recipients and ends on the days before the following payment is made.

2 Background from the economics literature

2.1 Welfare payments, consumption and crime

The timing at which welfare recipients spend their monthly benefits or try to supplement them by illegal means has captured the interest of a handful of scholars. The following lines describe some of the key results from the economics literature.

As discussed in the introduction, Foley (2008) demonstrates that while aggregate criminal activity is rather concentrated at the end of welfare payment cycles, the same end-of-the-month concentration is significantly stronger when only financially motivated crimes are considered. Foley uses daily panel data and regresses the daily number of reported incidents on a "time-since-payment index" – which reflects, for each day and each city, the average number of days since social assistance benefits were deposited – and other control variables. Twelve cities from twelve different states are included in the data. One important feature is that three financial aid programs (rather than just one) are taken into account in Foley's framework: *Supplemental Security Income* (SSI), *Temporary Assistance for Needy Families* (TANF) and "food stamps." In some states, payments for all three programs are not made on the same day. In addition, in some cities (and this holds for the entire State where the city is found), which Foley refers to as "staggered payment cities", not all recipients of one given program are paid on the same day of the month.[2] He shows that the end-of-the-month concentration of financially motivated crimes is significantly less in the staggered payment cities and concludes that such a smoothing in criminality might be welcome by police forces for several reasons. Foley alternatively uses a daily crime rate as the dependent variable for both matters of robustness and interpretability of the estimated values.[3] The results of the tests are qualitatively the same as with the methodology using a *count of events* dependent variable.

While financially motivated reported crimes are distinctively concentrated at the end of welfare payment cycles, adverse events related to illegal drug consumption appear to be focused near the *beginning* of those monthly cycles, according to Dobkin and Puller (2007). The two coauthors use daily data from California hospitals. Patient-level data allows them to be sure that a given patient receives welfare benefits and they even know with precision the financial aid programs that the person benefits from. This is an advantageous feature not found in Foley's (2008) data, where criminals and their crimes are anonymous. Dobkin and Puller find monthly drug-related hospitalisation and death peaks of different amplitudes according to the type of drug used and according to the government program that patients benefit from. One of their most conclusive findings concerning hospital admissions is depicted as follows:

> *"The cycles peak between the fifth and seventh day of the month for each substance. Admissions steadily decline in the days after the peak. Cocaine*

[2]For example, recipients living in Saint Louis (Missouri) receive food stamps and needy family assistance benefits between the first and the twenty-second day of the month inclusively, each household being assigned a day of the month *for each* of the two programs). However, Supplemental Security Income benefits are paid on the first of each month everywhere in the US.

[3] One of the main findings made possible with this alternative formulation of the dependent variable is that in cities where every recipient is paid on the first day of each month, financially motivated crime rates are on average 12.5% higher at the end each month relative to the beginning of the same month.

admissions have the most pronounced cycle with a peak on the fifth day of the month that is 37% above the level on the first day of the month." (p. 2144)

One important distinction from Foley's results in Dobkin and Puller (2007) is that the main monthly peak of interest is almost uniquely driven by beneficiaries of SSI, a program aimed at seniors and seriously disabled citizens. No significant peak is found for recipients of "ordinary" welfare benefits. Perhaps another very relevant feature of Dobkin and Puller's paper is that they use the natural experiment of Los Angeles County's 1997 disbursement policy change to test empirically whether "staggered payment" disbursement smoothes down monthly admission peaks relative to "first of the month" disbursement. The test results imply that the staggered schedule strategy set up by Los Angeles County in June 1997, with monthly payments spread out on a period of ten days, effectively shifted the drug-related admission peaks later in the month while smoothing these peaks down. This dual finding, on the one hand, suggests that public utilities such as hospitals can benefit from more staggered payments and, on the other hand, reinforces the statement that beginning of the month admission peaks identified by Dobkin and Puller were actually explained by the timing of government aid disbursement.

In a paper mainly intended to test whether the permanent-income hypothesis holds for social security recipients in the United States, Stephens (2003) shows that monthly expenditure fluctuations for social security beneficiaries are also explained in part by the timing of welfare money disbursement. Investigating fluctuations in daily "instantaneous consumption" expenditure (nondurables, dinners at a restaurant, etc.), Stephens finds that "*...the increase is sharpest on the day of check arrival and is concentrated amongst households for whom Social Security is the primary source of* *income.*" As in Dobkin and Puller's paper (2007), Stephens' data allows him to know the sources of income of the individuals forming his sample. The use of diary data from 1986 to 1996 with a subgroup of social security recipients makes it possible for Stephens to evaluate whether observed temporal patterns in monthly household expenditures are truly related to welfare receipt, which they are. Thus, as in the case of harmful drugs, there is strong evidence that ordinary consumption is significantly concentrated at the beginning of social assistance payment cycles when welfare policy opts for "full wallet" disbursement.

2.2 Intra-household bargaining and intimate partner violence

In this paper, the expression *domestic violence* is used as a synonym for the concept of *intimate partner violence* although the former usually refers to a wider array of situations than the latter, and for matters of accurateness, I shall narrow down my own definition of the concept of intimate partner violence as follows:

> **Intimate partner violence**: Crime committed by a person when attempting to physically or psychologically dominate his or her intimate partner.

A superficial search reveals that economic research did not ignore the phenomenon of intimate partner violence (also called *spousal abuse* in the literature) in the last decades, although only a limited number of economists appear to have made such a delicate issue one of their research topics.

Conjugal violence as an endogenous variable is found in game-theoretical models of non-cooperative family decision-making (Tauchen *et al.* ,1991; Farmer and Tiefenthaler, 1997; Bloch and Rao, 2002; Grogan *et al.*, 2009). Despite significant differences in modeling strategies, one aspect of intimate partner violence is ubiquitous in this literature: the use of violence as an instrument to increase its perpetrator's utility, either directly or indirectly (that is, by resorting to violence to increase his bargaining power regarding intra-household resource allocation, even extra-household resources, as in Bloch and Rao (2002)). Without going into the details of the models, I can at least point out that my paper will be an occasion to verify implicitly that violence is indeed used instrumentally in households, especially given the fact that my focus is on households that in theory are dealing with scarce financial resources.

Pollak (2004) uses a market-for-marriage approach and studies the implications of the intergenerational pattern in domestic violence, repeatedly captured by empirical research. Pollak's dynamic model is quite different from the game-theoretical approach previously described as he assumes that the intergenerational transmission of both spousal abuse and acceptance of a violent spouse is stochastic. For example, the probability of being a violent partner is a function of each individual's family record. Pollak does not treat domestic violence as a choice variable (as in Tauchen *et al.* (1991), for instance), but rather as an exogenous "cultural" trait of certain participants on the marriage market. His objective is mainly to exhibit the advantages and implications of the theoretical model that he develops.

As for empirical research, several papers concerning domestic violence can be found, but since my purpose is not to survey all that has to do with domestic violence in the literature, I shall here focus my attention on the effect of welfare support and welfare reform on domestic violence. Farmer and Tiefenthaler (1997) report that although a negative relationship between women's income and the amount of violence they undergo has been observed, "*...there is little empirical evidence to support the prediction that other alternatives provided for women, such as government transfers* [...] *have a negative* *effect on the violence in intact relationships.*" It is not clear whether the correlation, were it known, would be positive or negative, because of a key underlying aspect of welfare benefits: the ability/non-ability of women to enforce their entitlement when receiving a welfare payment if a collective check is involved (although in theory, government transfers could provide women with more autonomy and increase the chances that they end their violent relationships).

The hypothesis that men use violence as an instrument against their spouses to control intra-household resources is implicitly tested by Grogan *et al.* (2009), who investigate both causes and effects of spousal abuse using data from Nicaragua. The authors' data reveal that in violent households, husbands hide financial resources and make the financial decisions unilaterally in a greater proportion than in non-violent homes. Bloch and Rao (2002) study the mechanism of "dowry violence" by Indian men in rural India and their probit estimation implies that the odds that a woman gets beaten by her husband are greater when her family is rich, since more resources can potentially be extracted through terror. Yet, direct empirical evidence that men use violence purely as a bargaining strategy to redirect their partner's earnings towards their own consumption does not seem to exist, at least in the economic literature.

Last, Nou and Timmins (2005) study a structural change in domestic violence rates potentially caused by major changes in social assistance law in Connecticut. Thus their topic is to my knowledge the closest to mine. They use a panel model, with town-level data for the cross-sectional dimension and yearly data for the temporal dimension. They essentially find that with the passing of new welfare laws forcing non-disabled recipients to join the labour force again after a certain period of time, domestic violence rates fell in Connecticut towns, and it fell more drastically in towns with high welfare receipt rates. They also verify that crime rates for the other crime categories do not display a similar drop in the sampling period. There are many possible interpretations of Nou and Timmins' results, but an obvious one is that the labour market might have given some battered women sufficient autonomy to end their relationship.

3 Models and methodology

3.1 Econometric models

Many aspects of the methodology of this paper are borrowed from Foley (2008) so that my research hypothesis can be tested as an extension of Foley's findings concerning financially motivated criminal activity.The following lines present the econometric specifications that are used to test the hypothesis that when all other relevant factors are fixed, occurrences of domestic violence are focused at the beginning of social assistance payment cycles. To make things more interesting, but also for robustness matters, different models will be specified and estimated, each containing the independent variable of interest under a different form. Following Foley (2008), two different forms of dependent variable will be considered.

Specifications using a *number of days since payment* variable

All specifications to be used in this work consist of panel models with two-way and interacted (*clustered*) fixed effects. That is, city fixed effects, month-year fixed effects and city-month-year clustered fixed effects. The first specification is of the following form:

$$cdv_{t,i} = \beta_1 \cdot ndsp_{t,i} + \beta_2 \cdot (ndsp_{t,i})^2 + z'_{t,i}\gamma + \alpha_i + \theta_{mo\text{-}yr(t)} + \sigma_{i,mo\text{-}yr(t)} + \varepsilon_{t,i} \qquad (1)$$

where $cdv_{t,i}$ is the count of domestic violence incidents at date t in city i; $ndsp_{t,i}$ is the number of days since the last payment of social assistance was made to recipients[4]; α_i is a city-specific fixed effect, $\theta_{mo\text{-}yr(t)}$ is a month-year-specific fixed effect and $\sigma_{i,mo\text{-}yr(t)}$ is a two-way city-month-year fixed effect; $\varepsilon_{t,i}$ is the error term; $\mathbf{z}_{t,i}$ is a vector of control variables to be described below. It can be noticed that the square of the *ndsp* variable has been included in the equation. This is also done by Dobkin and Puller (2007) when regressing drug-related deaths on the number of days since *Supplemental Support Income* was paid and the coefficient of the squared variable proves to be somehow significantly different from zero.

An econometric model as particular as that specified above requires a perhaps unusual set of control variables. Since the statistical unit is *one day in one city* (as opposed, for example, to *one crime*), the selected control variables must contain information about each day-city combination included in my sample that will hopefully account for conjugal violence between intimate partners that are not social assistance recipients or for conjugal violence incidents explained by reasons other than the division of some welfare check. Those controls will essentially be variables that influence the odds that the average intimate partners spend time together in their dwelling space at day t, thus increasing the likelihood of a conflict. One such variable is a *holiday* dummy variable indicating whether a given weekday in a given city is a day off for a great majority of workers. The inclusion of this variable is justified by the idea that if there is a particular increase in domestic violence on a day off, then it must be workers – not welfare recipients – that drive the increase.

[4] In most cities, a welfare payment cycle lasts from 27 to 33 days and this duration varies from month to month (within provinces) mainly because payments must always be made on a banking day. In Newfoundland and Labrador, payment cycles last from 12 to 17 days (all recipients are paid twice a month).

Besides, it is common to include such a holiday variable when using daily crime data. Works such as Foley (2008), Jacob *et al.* (2007) and Dobkin and Puller (2007) have demonstrated that controlling for major holidays is highly relevant. Other variables account for meteorological fluctuations. These have proved to have significant explanatory power in the study of the dynamics of crime.[5] Hence, $z_{t,i}$ is essentially defined as:

$$z_{t,i} := \left(holiday_{t,i},\ temp_{t,i},\ rain_{t,i},\ snow_{t,i}\right)'.$$

Here $holiday_{t,i}$ is a dummy variable which indicates whether date t is a federal or provincial paid holiday in city i or not. The "1" value is only given if t was the actual day when the great majority of workers were off work. For example, $holiday_{t,i} = 1$ on Good Friday (and not Sunday of Easter) for each year and each city. The three other variables in $z_{t,i}$ represent respectively the average temperature over the day within a city (in degrees Celsius), rainfall in millimeters and snowfall in centimeters for each (t, i).

The $\varepsilon_{t,i}$ regression error is assumed to have a negative binomial distribution. This is because the dependent variable in a regression such as (1) is a variable which counts events of a given type. Imposing the usual hypothesis that the regression error is normally distributed would produce results that do not account for the specificities of each city's distribution of *cdv*. It could also be too restrictive to assume that *cdv* has a Poisson distribution. The negative binomial distribution is less restrictive than the Poisson distribution because it does not impose that the mean and the variance be identical (Greene (2008) p. 910). The bar charts found in Figure B.1 (Appendix B) show clear right-side skewness (a characteristic of negative

[5] See for example Foley (2008), Jacob *et al.* (2007), Hipp *et al.* (2004), Farrel and Pease (1994) and Dodge (1988).

binomial distributions) for each city's distribution of daily count of domestic violence incidents. Some of the census metropolitan areas (CMAs) also display a strong prevalence of "0" values. Formal tests of skewness performed separately for each city rejected the null hypothesis of distribution symmetry with a test p-value of 0.000.

Two-way fixed effects must be used for several reasons. I expect city (cross-sectional) fixed effects to account for the size of the city's population, for its unobserved cultural[6] and ethnical differences, for fixed aspects of provincial and municipal legislation against such crimes, and several other unchanging factors. As for the city-month-year interacted fixed effects, they can capture, on the one hand, some of the determinants of domestic violence that change with time in a given city, such as unemployment and *per capita* income (Nou and Timmins, 2005). If a city or a whole province has a "domestic violence awareness month" which has any actual effectiveness, then its effect should be captured by city-month-year dummy variables.

Specification containing a time-since-payment index

An alternative specification that I will be estimating involves a modified version of the *ndsp* independent variable which normalises the length of each "welfare month" to 1. The result is a *time-since-payment index* (*tspi*) indicating with precision the relative position of date *t* in the current welfare payment cycle. The specification which includes *tspi* is as follows:

$$cdv_{t,i} = \beta_{tspi} \cdot tspi_{t,i} + \beta_{tspi^2} \cdot (tspi_{t,i})^2 + z'_{t,i}\gamma + \alpha_i + \theta_{mo\text{-}yr(t)} + \sigma_{i,mo\text{-}yr(t)} + \varepsilon_{t,i} \qquad (2)$$

[6] Here we can think of Pollak's (2004) modeling of conjugal violence as an exogenous trait of society in a given geographic area.

where $tspi_{t,i}$ takes value in the [0 , 1] range[7] and where the other terms are defined as in (1). The $tspi_{t,i}$ variable is similar although not identical to that found in Foley (2008) and in my case, it is simply obtained by dividing the *number of days since payment* variable from specification (1) by the total number of days of the corresponding welfare cycle. The specific contribution of the $tspi_{t,i}$ variable is that Newfoundland and Labrador's welfare payment cycles are artificially given the same length as the other provinces' payment cycles.[8]

Specifications with a series of dichotomous variables

The two previous specifications impose a quadratic relationship between the dependent and the main independent variable. A third specification will allow domestic violence activity to have more complicated temporal patterns within each welfare payment cycle. The idea is to divide each payment cycle in 10 periods, each consisting of approximately 3 days, and see where in the typical welfare payment cycle peaks are actually found.

To achieve this, a set of dichotomous variables indicating for each (t, i) whether $tspi_{t,i}$ is between two given values is created and included in the specification instead of the *ndsp* or *tspi* terms. The resulting econometric model is as follows:

$$cdv_{t,i} = \Sigma_j \delta_j \cdot D^j_{t,i} + z'_{t,i} \gamma + \alpha_i + \theta_{mo\text{-}yr(t)} + \sigma_{i,mo\text{-}yr(t)} + \varepsilon_{t,i} \qquad (3)$$

where $j \in \{1, 2, 3, 4, 5, 7, 8, 9, 10\}$. Table 3.1 reports the definition of each of the dichotomous variables contained in the sum operator in (3). The [0.5, 0.6]

---

[7] The *tspi* variable is worth 0 on a day when a payment is made and reaches 1 the last day before a new payment is made. Ten days after a payment, if the next payment will be made in 20 days, then $tspi_{t,i}$ is equal to 0.3333.

[8] The average number of days between two payments is less in St. John's (see Appendix table B.2).

range (representing from 1 to 4 "middle of the cycle" days) is deliberately omitted in order to prevent perfect multicolinearity and thus it serves as the base category. The other variables are as defined above.

Table 3.1 Definition of the period-related dichotomous variables

Dummy variable	Values taken by $tspi_{t,i}$ for D^j to equal 1
D^1	[0.0, 0.1[
D^2	[0.1, 0.2[
D^3	[0.2, 0.3[
D^4	[0.3, 0.4[
D^5	[0.4, 0.5[
D^7	]0.6, 0.7]
D^8	]0.7, 0.8]
D^9	]0.8, 0.9]
D^{10}	]0.9, 1.0]

Of course, in accordance with the hypothesis that I wish to test in this paper, I expect the few first δ_j's to be significantly greater than the δ_j's corresponding to the middle and end of the month. The estimation of model (3) will be of particular interest because if domestic violence incidents actually decrease in the course of payment cycles, it will indicate whether this type of crime decreases monotonically within welfare cycles or if other increases arise before the end of the typical payment cycle. It is also a means of verifying whether a second order polynomial is a reasonable functional form to impose in specifications (1) and (2).

An alternative dependent variable: ***Temporal rate of incidents***

Specifications (1), (2) and (3) imply that the *count* of daily incidents – a discrete variable – is being regressed on a series of exogenous variables. Foley (2008) uses an alternative form of the dependent variable which he calls *crime rate*. It is defined as the daily count of incidents, for a given type of crime, divided by the average daily number of incidents of the same type in the sampling period. Since a *crime rate* usually refers to a ratio between incidents and population, I shall refer to Foley's alternative dependent variable as a *temporal rate of incidents*.

A consequence of the use of such a temporal crime rate is that it results in an average value of 1 within each city represented in the data. A temporal crime rate above (respectively under) 1 indicates more than average (respectively less than average) criminal activity on date t in city i.

The temporal domestic violence rate ($dvr_{t,i}$) will be used in the following specifications:

$$dvr_{t,i} = B_{ndsp} \cdot ndsp_{t,i} + z'_{t,i}\,\Gamma + \phi_i + \psi_{mo\text{-}yr(t)} + \xi_{i,mo\text{-}yr(t)} + e_{t,i} \quad (4)$$

$$dvr_{t,i} = B_{tspi} \cdot tspi_{t,i} + z'_{t,i}\,\Gamma + \phi_i + \psi_{mo\text{-}yr(t)} + \xi_{i,mo\text{-}yr(t)} + e_{t,i} \quad (5)$$

$$dvr_{t,i} = \Sigma_j\, \eta_j \cdot D^j_{t,i} + z'_{t,i}\,\Gamma + \phi_i + \psi_{mo\text{-}yr(t)} + \xi_{i,mo\text{-}yr(t)} + e_{t,i} \quad (6)$$

where ϕ_i, $\psi_{mo\text{-}yr(t)}$ and $\xi_{i,mo\text{-}yr(t)}$ are the analogs of α_i, $\theta_{mo\text{-}yr(t)}$ and $\sigma_{i,mo\text{-}yr(t)}$ in (1) to (3). Although (4) and (5) are very similar, specification (5) is of great interest because of its concrete interpretation of the B_{tspi} parameter: $B_{tspi} < 0$ would indicate that occurrences of intimate partner violence fall by an average of $100B_{tspi}$ percentage points in the course of a welfare cycle, all other things being equal. That interpretation would not hold if the squared term from specification (2) was inserted into specification (5), which explains its absence here. Specification (6) is simply the counterpart of specification (3) using *dvr* for an endogenous variable.

Following Foley (2008), I will resort to ordinary least squares (OLS) to estimate specifications (4) to (6), despite the fact that the distribution of *dvr* within each city is skewed on the right side, suggesting non-normality of the distributions.

In this paper, heteroscedasticity in the regression errors could arise for various reasons, such as an incorrect functional form. Although I are less concerned with finding the best functional form than finding statistical validity for the estimates of my parameters of interest, all regressions will come with robust standard errors that allow for the large number of city-month-year clusters that I wish to use.

3.2 Sources of Data

In this subsection, the data required to estimate econometric models (1) to (6) are discussed separately according to the source of data.

Intimate partner violence data

The daily count of domestic violence occurrences, which corresponds to the dependent variable in the first half of my econometric specifications, is extracted form Statistics Canada's *Incident-based Uniform Crime Report* (UCR2) for the years 2005 to 2007, which represents a total of 1095 days for each city that I have included in the sample. Only cases where the reported crime was committed by an intimate partner toward the complementary intimate partner and inside or near the dwelling unit were accounted for. Cases of murder were excluded for two reasons. First, it was not this paper's purpose to make the assumption that violent partners resort to murder to influence intra-household resource allocation. Second, Statistics Canada, which provided the data, assured me that reported cases of murder which could have been the result of domestic violence as defined in this paper are seldom in the UCR2 database in the sampling period.

The sample is composed only of fourteen Canadian census metropolitan areas (CMAs), all selected on the basis that 9% or more of all households living in these regions received social assistance money in the census year 2006.[9] Unfortunately, due to problems of data transmission between Statistics Canada and the CMAs' police stations, full territory coverage is not always achieved, ranging from 27% to 100% of each CMA's population in the data. Nonetheless, there is still at least 90% coverage for 11 CMAs out of 14.[10]

Time since the last payment of social assistance was made

The *number of days since payment* variable and the *time since payment* index are constructed from each city's provincial delivery date policy. A summary of how the delivery date of social assistance payments is determined in each city included in the sample is found in appendix Table A.1. As can be seen, among the six provinces represented in the data, only Newfoundland and Labrador truly has a distinct delivery schedule. I verified each province's "disbursement rule" using governmental websites and calling the relevant

---

[9] Setting the threshold at 10% as in Foley (2008) would have forced me to drop major cities such as Toronto, Montreal and Calgary, each of these having 9% of households on social assistance in 2006. See appendix Table A.2 for the list of city-specific receipt rates.

[10] The reported incidents for St. John (NB), Edmonton (AL) and Saskatoon (SK) in the sampling period are respectively representative of 27%, 70% and 83% of those CMAs' population.

provincial ministries. I also verified that the delivery date policy did not change in any of the provinces during the sample period (2005 to 2007).

Meteorological data

The data associated with the meteorological circumstances are taken from *Environment Canada*'s Weather Office and are easily accessed on the agency's website. Most values were measured at each city's main airport. For days when values such as snowfall are not available, missing values correspond to those measured at other Environment Canada meteorological stations within 20 kilometres. For the census metropolitan area (CMA) of Saint-Catharines-Niagara in Ontario, the temperature data are taken from *Weather Underground* and the daily snowfall and rainfall are proxy-ed by the CMA of Hamilton's corresponding values from Environment Canada's Weather Office.[11]

Paid holidays

To create the *holiday* dummy variable, a list of official federal and province-specific paid holidays was drawn up. There are five federal paid holidays[12] and the corresponding dates for 2005 to 2007 can easily be inferred. As for provincial holidays, they vary from one province to another. Appendix table B.1 presents the complete list of statutory provincial holidays accounted for in the data.

Appendix Table B.2 presents relevant descriptive statistics for the main variables and for each CMA included in the sample. The distinctiveness of Newfoundland-and-Labrador's average value of the number-of-days-since-

[11] Hamilton is 45 kilometres away from the city of Saint Catharines, so its daily weather measures can only be used as proxies for those of the Saint-Catharines-Niagara metropolitan area.
[12] These are: New Year's Day, Good Friday, Queen's Day, First of July and Christmas Day.

payment (*ndsp*) variable is brought to the reader's attention, along with the very low average value of the daily count of domestic violence incidents (*cdv*) in the CMA of Saint John, New Brunswick, due to poor coverage of New Brunswick CMAs in *Statistics Canada*'s UCR2 database.

4 Empirical results

4.1 Regression analysis

The estimation results found in Appendix C are all consistent with my hypothesis that incidents of intimate partner abuse are highly concentrated on the first days that follow social assistance disbursement when other factors are held constant. The estimation results for specifications (1) and (2) are found in appendix Table C.1, those of specifications (4) and (5) are in Table C.2. Finally, those of specifications (3) and (6) appear respectively in tables C.3 and C.4.

In appendix Table C.1, columns A, B, E and F present the parameter estimates of specification (1) using different combinations of fixed-effects, while columns C, D, G and H exhibit the parameter estimates of specification (2) using the same combinations of fixed effects. Both of these groups of regressions confirm that on average, occurrences of domestic violence do decrease with respect to time between two social assistance disbursement dates. In all columns, the second and third estimates together imply that domestic violence activity decreases at a decreasing rate in the course of welfare payment cycles (because the estimates of β_2 in (1) and β_{tspi^2} in (2) both have positive signs) and this holds at levels of significance inferior to 0.5%. The estimation results presented in column H, where the daily number of incidents is regressed on the time-since-payment index, is illustrated in Figure 4.1. The shape of the parabola in Figure 4.1 suggests that after an initial jump at the beginning of the payment cycle, domestic violence gradually decreases but increases somewhat before the delivery of a new welfare check. The existence and relative amplitude of this possible reversal of tendency is investigated in the next subsection.

Figure 4.1 **Daily number of domestic violence occurrences in the course of a typical welfare payment cycle**

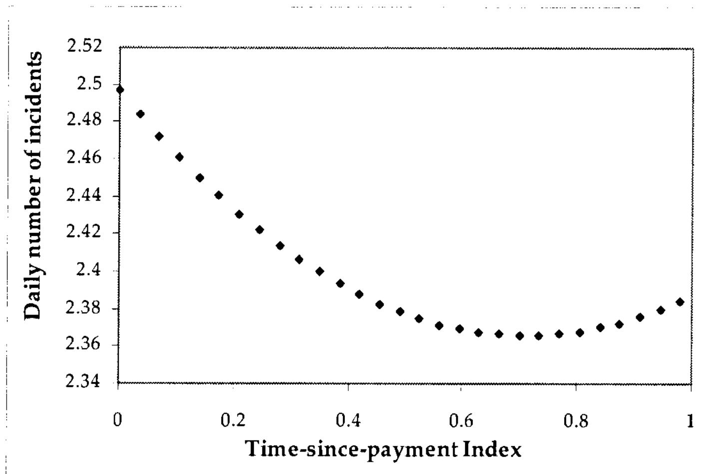


Figure 4.1 shows the temporal pattern of domestic violence activity as a quadratic function of the time-since-payment index over the course of one typical welfare payment cycle. Note that the "1" value on the horizontal axis corresponds to the last day before welfare money is disbursed by the government, whereas "0" corresponds to cashing day.

We see from appendix Table C.1 that using a time-since-payment index (*tspi*), which normalizes each payment cycle's length to 1, does not improve the fit compared to simply regressing the number of incidents on the number of days that passed since a payment was made (and control variables). The log-pseudolikelihood score of the latter method (column F) is practically the same when the former is applied (column H). This is not surprising as for each CMA except St. John's (NFL), changing the *ndsp* dependant variable for *tspi* boils down to a change in measurement units. However, plotting domestic violence occurrences against time passed for the average payment cycle, as is done in Figure 4.1, makes more sense if all cycles are adjusted as if they had the same length.

The estimation of specification (5) is found under various forms in appendix Table C.2, but our attention shall be on the fifth column. Column E's second estimated value, which is significant at the 2% level, implies that as a result of the timing of welfare payments, intimate partner violence is lower by about 11% at the very end of the average welfare cycle relative to disbursement day. Reasons why that percentage might be understating the actual value will be discussed in subsection 4.3. Let me just point out for now that if a sudden 11% increase arises in the *whole* population in the data's CMAs, then the value that would be obtained if I studied the temporal violence rate within the subpopulation of welfare recipients could only be greater than 11%. As for the second estimate in column F, its -0.004 value means that an additional day after a payment implies an average decrease of 0.4% in the daily violence rate if all other things are held constant.

Table C.2 also displays the outcome of different methods of controlling for the fact that most workers of city *i* are at home at date *t*. The use of day-of-the-week fixed effects combined with a *paid holiday* dummy variable most likely produces the best fit judging by the regressions' R-squared. Also, columns C to F of Table C.2 show an interesting fact: the coefficient on the *Saturday* dummy variable is greater than the *holiday* and *Sunday* dummy variables. So Saturdays appear to be the intra-week peak in intimate partner violence as a whole.

The results of the estimation of specifications (3) and (6) are respectively found in appendix tables C.3 and C.4. Each "welfare month" has been divided in ten periods to produce the nine period-specific dichotomous variables which appear in (3) and (6). The temporal pattern of domestic violence resulting from the timing of social assistance disbursement is represented graphically in appendix Figure C.1. The fact that in each regression the first two dichotomous variables have greater coefficients than the seven other dichotomous variables, plus the fact that their p-values are null is additional evidence that welfare disbursement drive an increase in domestic violence incidents at the very beginning of payment cycles. Interestingly, the choice of dependent variable (number of incidents versus temporal rate of incidents) shifts the monthly "peaks".[13] The estimates of (6) in column D of Table C.4 imply that the daily rate of domestic violence is at its highest level at period 1 of welfare payment cycles, being higher by 0.126 at period 1 than at period 10[14], consistent with the 11% drop revealed in Table C.2 (column E).

The explanatory power of the control variables varies substantially from one control variable to another, but also from one regression to another (with same numbers of observations). There is no doubt that controlling for the fact that date *t* is not a working day for most individuals is highly relevant according to my results. No matter what method is used to control for "days off", the related parameter estimates have null p-values, as seen in tables C.1 to C.4. The positive sign on the coefficients of holiday and week-end variables imply that domestic violence is higher on days when the great

[13] Compare, for example, the coefficients of the "Dummy *j*" variables in column D in Table C.3 and column D in Table C.4. With *count of incidents* as a dependent variable, the peaks are at periods 2, 7 and 9, whereas with *temporal domestic violence rate* the peaks appear at periods 1 and 8.

[14] The 0.126 value corresponds to the difference between the coefficients of period 1 dummy and the period 10 dummy.

majority of workers are not at their workplace, a result that makes intuitive sense. Similarly, the *temperature* variable has a significant, positive effect on domestic violence incidents (tables C.2 and C.3) even though I am already taking seasonal trends into account by controlling for months and city-month pairs. Interestingly, that positive effect on violence is precisely what is predicted by the sociological literature's "temperature-aggression theory" for violent crime[15], also observed by researchers in criminology and psychology (Hipp *et al.*, 2004). Moreover, this is consistent with Farrell and Pease (1994), who find that police calls for "domestic disputes" in Merseyside (North-West England) increase by more than 25% during the warmest weeks of the summer (in addition with a smaller two-week peak during Christmas vacation).

Conversely, the predictive power of the two other meteorological variables, snowfall and rainfall, is not robust to the different modelling options that I have examined. In specifications (1) and (2), the insertion of city-month-year fixed effects clearly reduces to a great extent the individual significance of the coefficients of *snow* and *rain*, as can be observed in Table C.1. Strangely, tables C.3 and C.4 show that including city-month-year effects increases the p-value of *snowfall* if the number of incidents acts as a dependent variable, but lowers that same p-value if the temporal rate of incidents is considered instead. Even the sign of the coefficient of the *snowfall* variable is not robust to the form of my dependent variable nor to the composition of the sample. One notices, however, a low p-value for *snowfall*'s coefficient estimate in specifications (4), (5) and (6) along with a negative sign on the coefficient (see columns E and F of Table C.2 and column D of Table C.4). As for *rainfall*, the inclusion of city-month-year fixed effects produces an

[15] This theory states that "... uncomfortably hot temperatures increase the frustration of individuals, leading to aggressive behaviour." (Hipp *et al.*, 2004).

increase in its coefficient's p-value so drastic that its relevance also becomes doubtful. Rainfall and snowfall being strongly associated respectively with non-winter and winter months, it is likely that these meteorological factors simply act as proxies for a hidden seasonal trend in domestic violence, captured better by city-month-year fixed effects, as suggested by the p-value disparities driven by the insertion of these effects. Hence, I consider that with city-month-year effects and average daily temperatures in this paper's panel model, the presence of *rain* and *snow* becomes unessential.

Table 4.1 summarizes the main relevant qualitative comparisons to be made between Foley's parameter estimates (2008) and this paper's estimation results. All estimates except that of *rainfall*'s coefficient are fairly significantly different from zero in both researches. Interestingly, except for the *temp* and *rain* variables, the estimated parameters have opposite signs.

Table 4.1 Comparison of signs of estimated parameters with those of Foley (2008)

Independent variable	**Effect on reported financially motivated crimes** (Foley, 2008)	**Effect on reported conjugal violence occurrences** (this paper)
Time since payment	(+)	(-)
Holiday dummy	(-)	(+)
Temperature	(+)	(+)
Rainfall*	(-)	(-)

* The *rainfall* variable in this paper is at best significant at a level of 8% when using the daily number of incidents as a dependent variable and controlling for city-month-year fixed effects. Its presence in Table 4.1 is only motivated by the robustness of its sign to the various econometric settings considered in this research.

Focussing on the holiday and meteorological variables, their sign corroborates either one of the "temperature-aggression theory" or the "routine activities theory", which links certain seasons and weather conditions with probabilities for potential victims and criminals of being at home, at work, in vacation, etc. (Hipp *et al.*, 2004). The negative sign on *rainfall* in this paper is however difficult to explain by means of one of those two theories as both relate more to temperature than precipitation.

Separation of the sample in two groups of CMAs

The census metropolitan areas in the sample do not have the same welfare receipt rate. For example, 8.9% of the Toronto CMA families lived on social assistance in 2006 compared to 13.7% in the CMA of Edmonton, as shown in appendix Table A.2. Although the gap between those two rates seems rather slight at first glance, is it worth investigating whether the effect of the timing of welfare payments on domestic violence changes with the city's welfare receipt rate. Recalling that one flaw of my data about domestic violence is that it is "anonymous" (I do not know the sources of income of the authors and victims of the reported incidents), a more prominent effect in the higher welfare receipt rate group would be additional evidence of the appropriateness of my research hypothesis.

One means of making this verification is to sort the fourteen CMAs in the data according to their welfare receipt rate (see appendix Table A.2) and split them in two sub-samples: the seven cities with the highest welfare receipt rate and the seven others. Then, one can observe if the relevant parameters (the coefficients on *tspi*, on the first *period-j* dummies, etc.) are statistically significant in both regressions or not.[16] The results of such regression are found in appendix tables C.5 to C.7.

[16] Interacting a *high-rate-CMAs* dummy with the time-since-payment index did not yield conclusive results, which explains why only sub-sample regressions are found in appendix tables C.5 to C.7.

Clearly from Table C.5, domestic violence activity falls more sharply in the high receipt rate group than in the low receipt rate group: column A and column F's estimates for β_{tspi} are greater, in absolute value, than column C and G's estimates. Referring to column F, the temporal violence rate decreases by an average of 0.17 in the seven CMAs with the highest receipt rates, compared to 0.05 in the lower-rate group; the coefficient in column G is not actually significantly different than zero. However, it appears from Table C.5 that the second order polynomial of specifications (1) and (2) is a better choice for the low-rate group, judging by the p-values of the relevant coefficients in columns A to D. One must be aware though that the lower-rate group contains the three most populous CMAs in the sample and that this hidden factor might explain the disparity in the fits.

Appendix tables C.6 and C.7 tell a similar story. In Table C.6, we see that in the higher-rate CMAs, domestic violence incidents are relatively more concentrated at period 1 than at period 2, the opposite of the lower-rate group. The same fact is somehow observed when the temporal rate of incidents is used (Table C.7): although the marginal effect of "being at period 1" is greater in the lower-rate group, we can see that the real period 1 focus is only in the higher-rate CMAs. In addition, the difference between the estimates of the η^1 and η^{10} in Table C.7 show a 24% jump for the higher-rate group, compared to a negligible 0.5% jump in the lower-rate group. Hence, Tables C.5 to C.7 display additional evidence that the subpopulation of social assistance recipients drives a rapid increase in domestic violence in the first few days following welfare disbursement.

4.2 Further tests

In the previous subsection, Figure 4.1 shows a within-month time path for domestic violence incidents which suggests two intermediate conclusions. First, the transition from one welfare cycle to the following cycle seems to present an important instantaneous break in intimate partner violence. Second, it appears that a small increase happens before the end of each cycle. In this subsection, I investigate separately the statistical validity of both phenomena using relevant tests of hypothesis.

End-of-the-month break

The estimates corresponding to the δ_j's in specifications (3) and the η_j's (6) found in appendix tables C.3 and C.4 suggest intra-month temporal patterns similar to those found in Figure 4.2, which gives a rough idea of how domestic violence appears to fluctuate in the course of two consecutive social assistance payment cycles.

Figure 4.2 Domestic violence occurrences over the course of two typical payment cycles

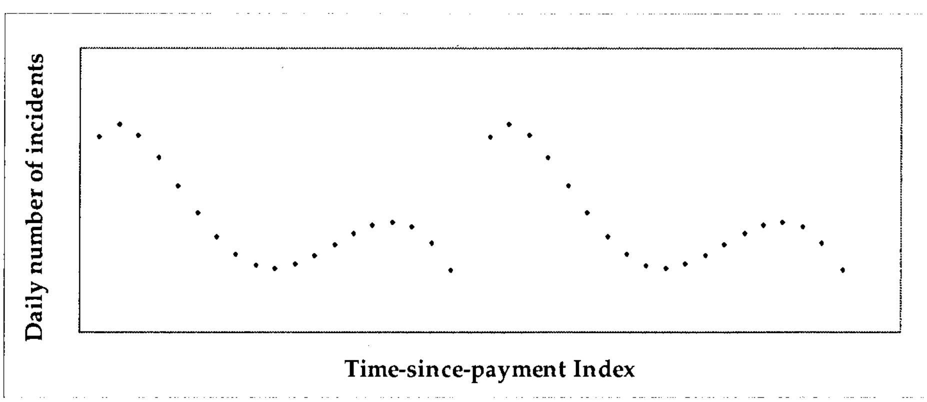


Figure 4.2 illustrates roughly the pattern found tables C.3 and C.4's regression results for two consecutive social assistance payment cycles. The results suggest a rapid increase in domestic violence when welfare benefits are received, followed by a drop and a peak that arises a few days before the reception of another payment.

The hypothesis that there exists a break can be readily tested using basic Wald tests on relevant parameter differences. These are equivalent to bilateral t-tests. Recalling that specifications (3) and (6) contain a dichotomous variable for each of the ten parts of the typical welfare cycle, I can resort to a null hypotheses as simple as "H_0: $\delta_1 - \delta_{10} = 0$" (absence of a break), tested against the alternative hypothesis "H_1: $\delta_1 - \delta_{10} \neq 0$". Appendix Table C.8 shows the result of this test with respect to the type of dependent variable and with respect to the sample composition. Panel A and Panel C are based respectively on the estimates found in column D of appendix Table C.3 and column D of appendix Table C.4.

In panels A and B, there is no doubt that there is a break as the tests' p-values for the rejection of H_0 are as low as they can be. As for Panel C, where the alternative dependent variable is used, the null is rejected at the 5% level of significance when the full sample is used. In the 12-city sample[17] though, the p-value reaches 0 (Panel D). This improvement is probably due to the exclusion of the CMA of St-John's (NFL and Labrador), where welfare recipients are paid twice a month rather than just once, which possibly reduces the effect of "full wallet" on domestic violence.

An important phenomenon to underline is the relative asymmetry between the results of panels A and B versus those of panels C and D. In panels A and B, the test statistics are larger when "$H_{0,2}$: $\delta_2 - \delta_{10} = 0$" is tested than when the "real" no-break hypothesis, "$H_{0,1}$: $\delta_1 - \delta_{10} = 0$", is tested, while in panels C and D, the opposite is found. This is because the position of the beginning-of-the-month "peak" differs according to the choice

[17] The CMAs of St. John (NB) and St. John's (NFL) are excluded because I only have poor territorial coverage of the former and because the province where the latter is found pays the beneficiaries twice as often as the other provinces of the sample, which is likely to mitigate the end-of-the-cycle break in intimate partner violence.

of dependent variable, as observed in the previous subsection. We see in appendix Table C.3 that it is the second dummy variable that has the largest coefficient estimate when the number of incidents is the dependent variable. However, when it is the temporal rate of incidents that is considered, the largest coefficient is associated with the *first* dummy variable. So dividing each city's daily number of incidents by the city-specific daily average in the sampling period (to obtain a temporal rate of incidents) can potentially modify certain results.

I conclude that there is indeed a break in domestic violence when social assistance payments are received by beneficiaries. This is further evidence that intimate partner violence increases in reaction to once-a-month and "full wallet" disbursement of welfare.

Investigating the existence of a second peak

I now attempt to verify that there really exists an increase in domestic violence in the second half of welfare payment cycles, as can be seen in Figure 4.2. Appendix Table C.3's estimation results for specification (3) show a peak at periods 7 and 9 of the payment cycle and this peak is significantly different than zero at the 10% level of significance (see column D). As for the estimation of specification (6), the peak now appears to be at $tspi \approx 0.75$ (period 8)[18] according to Table C.4. There is stronger evidence of a peak, with a level of significance less than 3% for the eighth period's marginal effect (see column D).

The second peak observed in welfare payment cycles does seem to be real and one might want to verify whether its amplitude is comparable to that of

[18] Appendix tables C.6 and C.7 show that the peaks can be at the same "place" with both dependent variables if the sample is separated in two groups of CMAs.

the peak found in the beginning of the payment cycle, as appears to be the case in appendix Table C.3. Testing "H_0: $\delta_j - \delta_k = 0$" with $j = 1, 2$ and $k = 7, 9$ in specification (3) and "H_0: $\eta_1 - \eta_8 = 0$" in specification (6) will provide this question with an answer. According to the test results found in appendix Table C.8, the first null hypotheses are easily rejected, the test p-values being very low. Unfortunately, this result is not robust to the choice of dependent variable: as we can see from panels C and D of Table C.8, the null hypothesis that $\eta_1 - \eta_8 = 0$ cannot be rejected, even at a 15% level of significance. So although the estimate of η_1 in specification (6) is irrefutably greater than the estimate of η_8 (see table C.4), my data do not allow me to draw a solid conclusion about the relative "height" of the second monthly peak in domestic violence. Perhaps this is due to the implicit hypothesis that the regression error is normally distributed (which affects the p-values) despite the fact that the distribution of the temporal rate of incidents (the dependent variable) is most likely not distributed normally within the CMAs.[19] Another explanation would be that the use of a *temporal rate of incidents* for a dependent variable might be less appropriate in this paper, which uses CMA-level data with large population size disparities, than in works like Foley (2008), whose data is based on cities with perhaps more comparable numbers of residents. The CMA-specific standard errors for the *temporal rate of incidents* (*dvr*) found in appendix Table B.1 are quite informative on that matter.

All in all, while I cannot conclude successfully that the second peak of conjugal violence is of smaller amplitude than the beginning-of-the-month

[19] Tauchen *et al.* (1991) use bounded influence regressions when using the number of violent incidents undergone by a same woman within a given period. It appears that t-tests based on the bounded influence regressions have more favourable outcomes than those based on OLS regressions. However, the possibility that the implicit normality hypothesis in inappropriate should not play a large role here according to econometric theory.

peak, the test results imply that the existence of that second peak is difficult to deny. Its exact position varies from period 7 to period 9 of each payment cycle, depending on the form of the dependent variable and on the cities in the sample. Given that it does not arise right before welfare money is disbursed (*i.e.* at period 10[20]) but rather *several days before* recipients have access to their financial aid, I conclude that the second increase in intimate partner violence in the course of the typical welfare cycle is probably explained by the lack of financial resources that social assistance recipients are likely to face a few weeks after receiving their monthly payment.

4.3 Potential estimation biases

The domestic violence peaks that I have found in this paper are indeed statistically significant. In this subsection I argue that both peaks might be greatly understated due to various sources of bias related to the nature of my data.

First, there is a strong case for a bias in *who* reports acts of violence they undergo to the police. It is possible that social assistance recipients are less likely than non-recipients to report violence to the police after being victimized. If welfare receipt and the propensity to report domestic violence to the police are negatively related within CMAs, then the observed beginning-of-payment-cycles concentration is clearly understated, as well as the second violence peak. Rates of reported incidents per 1000 families are found in appendix Table B.3. The values suggest a weak negative correlation between reported incidents per family in a CMA and the welfare receipt rate.

[20] A period 10 peak is found for the lower-rate CMAs when using the temporal rate of incidents (Table C.7, column B). However, this is not the case in higher-rate CMAs (column A).

Second, the peaks are likely to be understated since the crime data that I use is anonymous: there is an implicit combination of two populations, the biggest one (non-welfare-recipients) having perhaps no monthly cycle in domestic violence, so that the "full-wallets" effect attributable to the subpopulation of welfare recipients is most likely diluted. Thus, the 11% and 12% increases in domestic violence found when estimating specifications (5) and (6) are probably much greater within the population of families receiving welfare benefits.

Third, I resorted to CMA-level data in my analysis. Using town-level data might have improved the regression analysis. CMA data is *aggregated,* so that it doesn't allow controlling for unobserved heterogeneity within each CMA when studying criminal activity, as town-level data would. Cornwell and Trumbull (1994) report that such a source of endogeneity can substantially bias the marginal effects of the regressors. However, this is especially a problem when estimating the economic model of crime, which is not the objective of this paper. Also, except for the meteorological variables, it is not the case that there is heterogeneity in the CMAs: welfare policy is provincial and paid holidays are either federal or provincial. Thus, if ignoring heterogeneity within CMAs did not bias my results, town-level data might have allowed me to exploit disparities in the cross-sectional dimension of the data. Nou and Timmins (2005) use county specific panel data in their analysis, as well as Dobkin and Puller (2007).

5 Conclusion

In this paper, my purpose was to test the hypothesis that social assistance disbursement as it is done in Canada drives a rapid increase in domestic violence occurrences. The empirical results support that hypothesis. In addition, I find an unexpected second peak within the typical welfare payment cycle. Contrary to the beginning-of-the-payment-cycle peak, that second peak might be explained by the exhaustion of financial resources around the third week of the payment cycles. Both peaks are statistically significant and may even be understated due to data-related methodological obstacles.

My results have immediate policy implications. Staggering welfare payments between recipients at every month, as is done in some states in the US, would facilitate the police forces' intervention by smoothing monthly cycles in domestic violence. Increasing the number of payments per month, as in Newfoundland-and-Labrador, could help protect victims of conjugal violence by creating a rationing of intra-household financial resources and by reducing the potential gain of violent strategies on the part of intimate partners benefiting from social assistance. What's more, combining financial aid with modern "food stamps" or other in-kind aid is an option worth exploring.

Future research investigating intimate partner violence and welfare receipt could improve the analysis by resorting to town-level data, which would allow taking advantage of municipality-specific effects, but also by using data specific to the population of social assistance recipients. Alternative data sets, provided by hospitals, centers for battered women[21], etc., could relevantly complement my work.

[21] Statistics Canada reports that only 25% of Canadian women taking refuge in a shelter for victimized women in 2008 had reported the violent acts undergone to the police.

6 References

6.1 Works Cited

Bloch, Francis and Vijayendra Rao (2002): "Terror as a bargaining instrument: A case-study of dowry violence in rural India", *American Economic Review* 92(4), pp 1029-1043

Cornwell, Christopher and William N. Trumbull (1994): "Estimating the Economic Model of Crime with Panel Data", *The Review of Economics and Statistics* 76(2), pp 360-366

Dobkin, Carlos and Stephen Puller (2007): "The effects of government transfers on monthly cycles in drug abuse, hospitalization, and mortality", *Journal of Public Economics* 91(11-12), pp 2137-2157

Dodge, Richard W. (1988): "The seasonality of crime victimization", U.S. Department of Justice, Bureau of Justice Statistics, 12 pp

Foley, C. Fritz (2008): "Welfare payments and crime", *National Bureau of Economic research,* NBER working paper #14074, 44 pp

Farmer, Amy and Jill Tiefenthaler (1997): "An Economic Analysis of Domestic Violence", *Review of Social Economy* 55(3), pp 337-358

Farrell, Graham and Ken Pease (1994): "Crime seasonality - Domestic disputes and residential burglary in Merseyside 1988-90.", *British Journal of Criminology* 34(4), pp 487-498

Greene, William H. (2008): "Econometric analysis", 6th edition, *Prentice-Hall,* 1216 pp

Grogan, Louise, Julia Witt and Asha Sadanand (2009): "Domestic violence and intrahousehold resource allocation", working paper, 34 pp

Hipp, John R., Daniel J. Bauer, Patrick J. Curran and Kenneth A. Bollen (2004): "Crimes of opportunity or crimes of emotion? Testing two explanations of seasonal change in crime", *Social Forces* 82(4), pp 1333-1372

Jacob, Brian, Lars Lefgren, and Enrico Morretti (2007): "The Dynamics of Criminal Behavior: Evidence from Weather Shocks", *Journal of Human Resources* 42(3), pp 489-527.

Nou, Jennifer and Christopher Timmins (2005): "How do changes in welfare law affect domestic violence? An Analysis of Connecticut Towns, 1990–2000", *Journal of Legal Studies* 34, pp 445-469

Pollak, Robert A. (2004): "An intergeneration model of domestic violence", *Journal of Population Economics* 17(2), pp 311-329

Stephens, Melvin Jr. (2003): "3rd of tha month: Do social security recipients smooth consumption between checks?" *American Economic Review* 93(1), pp 406-422

Tauchen, Helen V., Ann Dryden Witte and Sharon K. Long (1991): "Domestic violence: a nonrandom affair", *International Economic Review* 32(2), pp 491-511

6.2 Other references[22]

Alberta Ministry of Employment and Immigration: Alberta Works (Income Support), February 2009. http://employment.alberta.ca/documents/FCH/FCH_yourguide.pdf

Environment Canada, Weather Office: "National climate data and information archive". http://www.climate.weatheroffice.ec.gc.ca/climateData/canada_e.html

House of Assembly of Newfoundland and Labrador, Income and Employment Support, 2009. http://www.assembly.nl.ca/Legislation/sr/Regulations/rc040144.htm#20_

[22] All WEB pages listed have been consulted for the last time on August 5th, 2009.

New Brunswick Department of Social Development, Social Assistance: "Intake and continuing eligibility", 2007. http://www.gnb.ca/0017/ Policy%20Manual/ POL-E/policy4.htm#payment

Ontario Ministry of Labour: "Paid Public Holidays in Canadian Jurisdictions", 2008. http://www.labour.gov.on.ca/english/es/ family/pp_holidays.html

Ontario Ministry of Community and Social Services, Ontario Works: "Ontario Works policy directives", 2008. http://www.mcss.gov.on.ca/ mcss/english/pillars/ social/directives/ow_policy_directives.htm

Saskatchewan Ministry of Social Services: "Saskatchewan assistance handbook", 2008. http://www.socialservices.gov. sk.ca/sap-handbook.pdf

Sauvé, Julie and Mike Burns (2009): "Residents of Canada's shelters for abused women, 2008", Statistics Canada Catalogue no. 85-002-X, *Juristat* 29(2), 21 pp. http://www.statcan.gc.ca/pub/85-002x/2009002/article/10845-eng.htm#a8

Ministère de l'Emploi et de la Solidarité Sociale du Québec, Programme d'Aide Sociale : "Versement du montant d'aide financière", 2009. http://www.mess. gouv .qc.ca/solidarite-sociale/programmes-mesures/ assistance-emploi/versement-aide-financiere/#5

Weather Underground: "History for St. Catharines, ON", 2009. www.wunderground.com

APPENDIX A

Social Assistance in Canadian Provinces

Table A.1

Delivery date of social assistance payments, by province

Canadian province	CMAs in the sample	Delivery date(s)
Alberta	Calgary, Edmonton.	4th last banking day of the month or first banking day before.
Saskatchewan	Regina, Saskatoon.	3rd last banking day of the month or first banking day before.
Ontario	Toronto, Kingston, Windsor, St-Catharines-Niagara, Sudbury.	3 or 4 days before the 1st of the month and must be a banking day.
Quebec	Montreal, Trois-Rivieres, Sherbrooke.	1st day of the month or first banking day before if 1st is not a banking day.
New-Brunswick	Saint-John	1st day of the month or first banking day before if 1st is not a banking day.
Newfoundland-and-Labrador	Saint-John's	1st and 16th days of the month or first banking day before in both cases.

Table A.2

Social assistance receipt rate, by census metropolitan region, 2006

CMA	Number of families living in the CMA	Receipt rate
Toronto, Ontario	2221700	8.9%
Montreal, Quebec	1709960	9.1%
Saint John, New Brunswick	55790	9.8%
St. Catharines-Niagara, Ontario	174530	9.9%
Calgary, Alberta	478750	9.9%
Saskatoon, Saskatchewan	103110	10.0%
Regina, Saskatchewan	89630	10.1%
Sherbrooke, Quebec	91200	10.6%
St. John's, NFL and Labrador	79320	10.7%
Windsor, Ontario	138370	10.8%
Kingston, Ontario	67550	10.9%
Grand Sudbury, Ontario	72590	11.8%
Trois-Rivieres, Quebec	71280	12.3%
Edmonton, Alberta	462370	13.7%

The rates are computed by me and based on the following source: *Statistics Canada*, Table 111-0014: Family characteristics, by family type and sources of income, annual, *CANSIM* database, *E-STAT*.

APPENDIX B

Summary statistics

Figure B.1

Bar plot for daily number of reported domestic violence incidents, by city

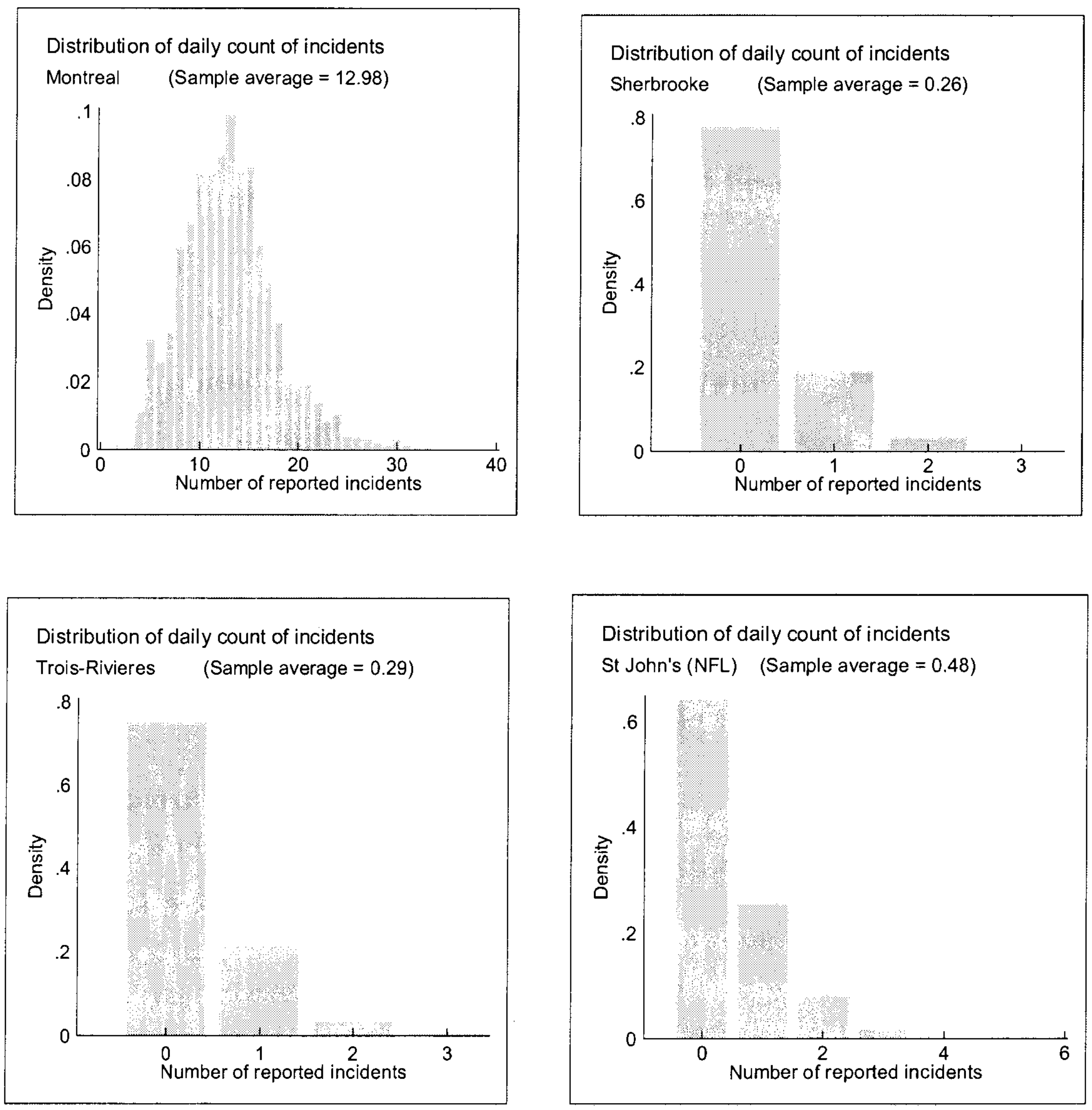


Figure B.1

Bar plot for daily number of reported domestic violence incidents, by city (continued)

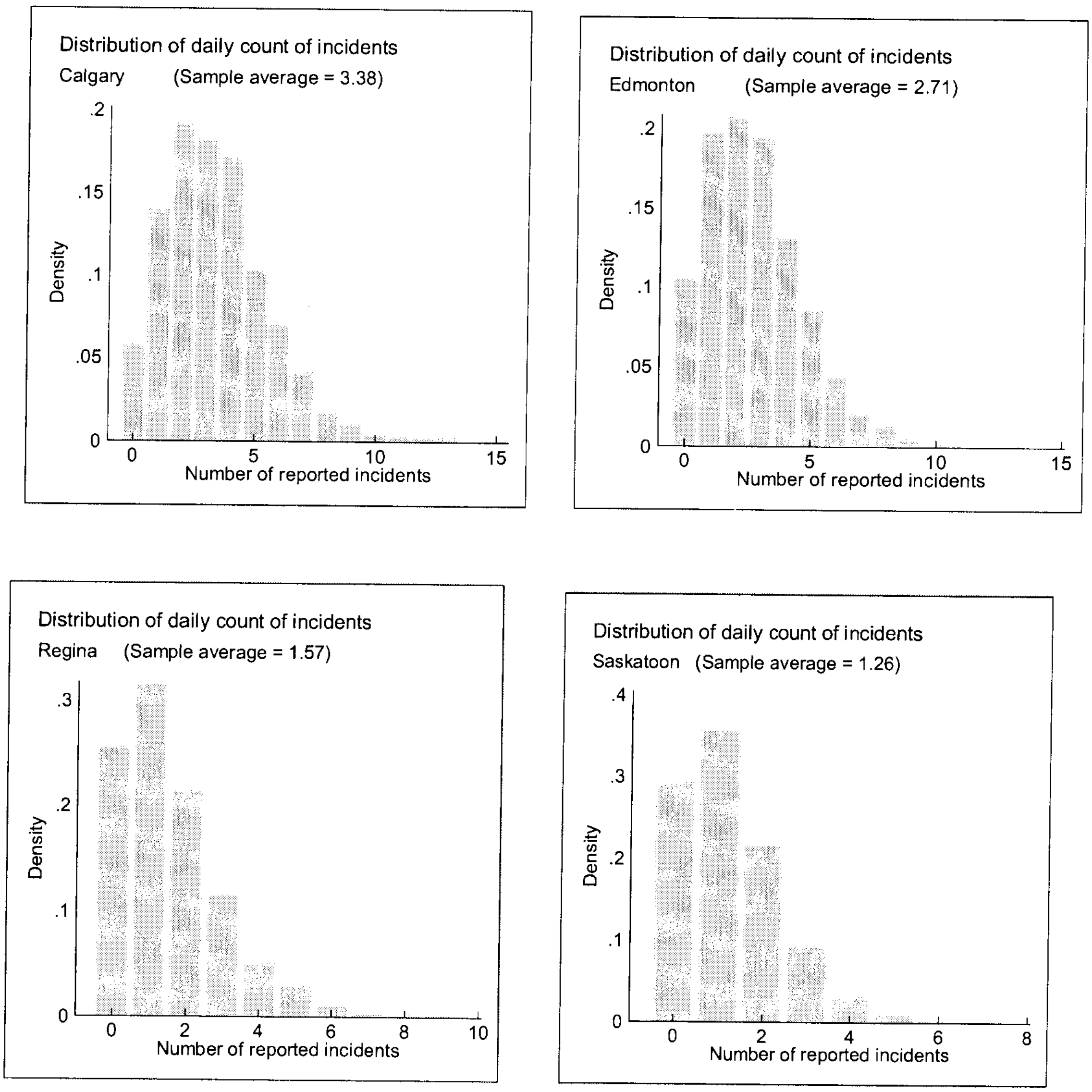


Figure B.1

Bar plot for daily number of reported domestic violence incidents, by city (continued)

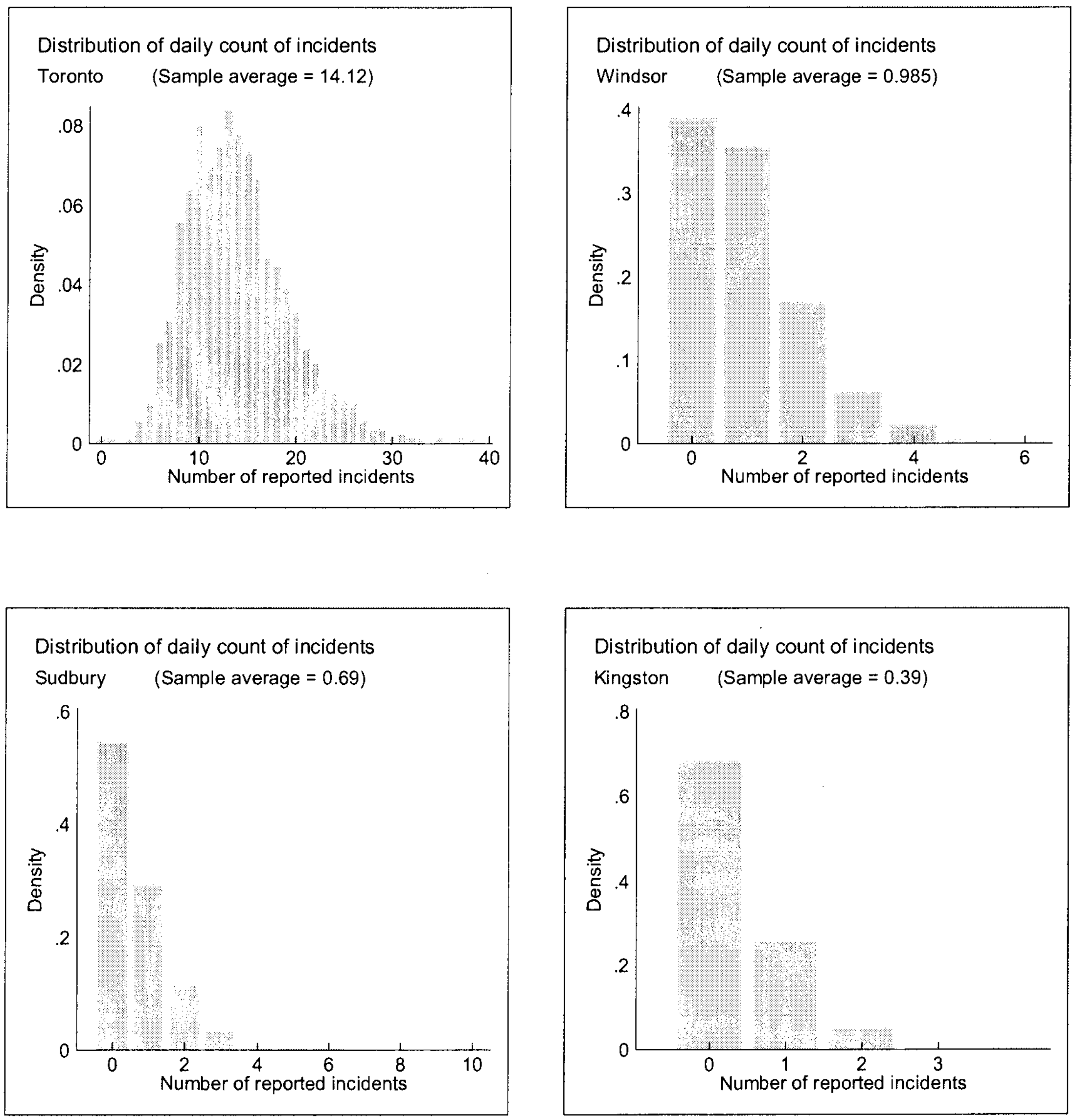
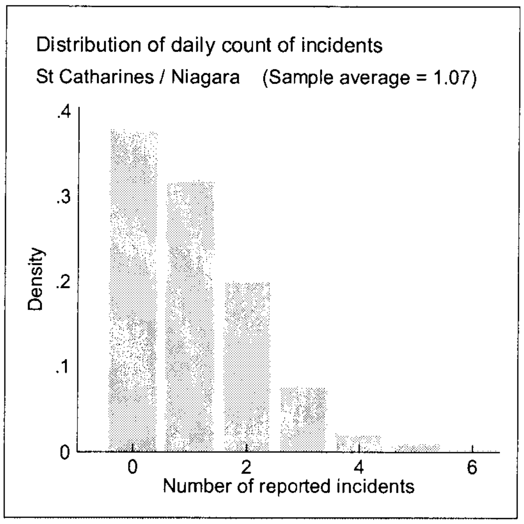


Figure B.1

Bar plot for daily number of reported domestic violence incidents, by city (continued)



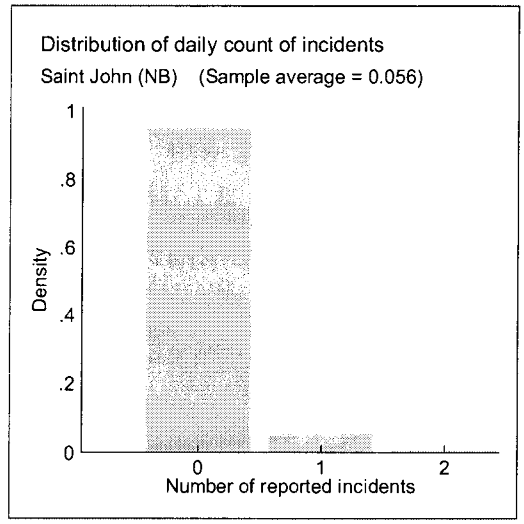


Table B.1
Provincial statutory paid holidays in Canada

Province	Statutory paid holidays
Alberta	Family Day Victoria Day Thanksgiving Remembrance Day
Saskatchewan	Family Day (since the year 2007) Victoria Day Saskatchewan Day Thanksgiving Remembrance Day
Ontario	Victoria Day Thanksgiving Boxing day
Quebec	National Patriot's Day Quebec's National Holiday Thanksgiving
New Brunswick	New Brunswick Day Remembrance Day
Newfoundland and Labrador	Remembrance Day

Table B.2

Mean values of variables with standard errors, by city

CMA \ Variable	*cdv*	*dvr*	*ndsp*	*tspi*	*temp*	*rain*	*snow*	*holiday*
Calgary (AL)	3.38 (2.24)	1 (0.662)	14.71 (8.85)	0.50 (0.30)	5.02 (9.88)	1.12 (4.96)	0.32 (1.22)	0.024 (0.152)
Edmonton (AL)	2.71 (1.92)	1 (0.709)	14.71 (8.85)	0.50 (0.30)	2.94 (11.41)	0.91 (3.05)	0.32 (1.25)	0.024 (0.152)
Regina (SK)	1.57 (1.47)	1 (0.938)	14.71 (8.86)	0.50 (0.30)	3.46 (13.02)	1.12 (3.46)	0.20 (0.78)	0.025 (0.155)
Saskatoon (SK)	1.25 (1.15)	1 (0.915)	14.71 (8.86)	0.50 (0.30)	2.88 (13.00)	(1.09) (4.83)	(0.26) (1.48)	0.025 (0.155)
Sudbury (ON)	0.69 (0.96)	1 (1.402)	14.75 (8.86)	0.50 (0.30)	5.19 (12.27)	1.66 (4.30)	0.61 (2.32)	0.021 (0.143)
Kingston (ON)	0.39 (0.63)	1 (1.627)	14.75 (8.86)	0.50 (0.30)	7.80 (11.24)	2.24 (6.34)	0.33 (1.42)	0.021 (0.143)
Toronto (ON)	14.12 (5.39)	1 (0.382)	14.75 (8.86)	0.50 (0.30)	9.29 (10.89)	1.76 (4.83)	0.28 (1.22)	0.021 (0.143)
Windsor (ON)	0.98 (1.04)	1 (1.054)	14.75 (8.86)	0.50 (0.30)	10.83 (10.67)	2.33 (6.30)	0.38 (1.79)	0.021 (0.143)
St .Catharines-Niagara (ON)	1.07 (1.10)	1 (1.028)	14.75 (8.86)	0.50 (0.30)	9.83 (10.32)	2.09 (5.45)	0.42 (1.88)	0.021 (0.143)
Montreal (QC)	12.98 (4.70)	1 (0.362)	14.76 (8.87)	0.50 (0.30)	7.52 (11.73)	2.67 (7.36)	0.58 (2.77)	0.022 (0.146)
Sherbrooke (QC)	0.26 (0.52)	1 (1.977)	14.76 (8.87)	0.50 (0.30)	5.23 (11.59)	2.93 (7.18)	0.58 (2.26)	0.022 (0.146)
Trois-Rivieres (QC)	0.29 (0.55)	1 (1.850)	14.76 (8.87)	0.50 (0.30)	6.64 (11.59)	2.08 (5.71)	0.69 (2.69)	0.022 (0.146)
St. John (NB)	0.06 (0.24)	1 (4.328)	14.76 (8.87)	0.50 (0.30)	5.67 (9.70)	3.04 (8.66)	0.49 (2.10)	0.018 (0.140)
St. John's (NFL)	0.49 (0.76)	1 (1.561)	7.16 (4.48)	0.50 (0.31)	5.72 (8.23)	3.28 (8.03)	1.05 (4.36)	0.016 (0.127)
All CMAs	2.87 (4.97)	1 (1.651)	14.20 (8.84)	0.50 (0.30)	6.28 (11.44)	2.02 (6.01)	0.47 (2.16)	0.022 (0.145)

For a description of the variables, see subsection 3.1. The reader should notice the disparities in the first two columns' mean values and standard errors, which inform us that the CMAs in the data differ considerably in population size.

Table B.3

Reported incidents per 1000 families by city, 2006

CMA	Sample value	Estimated true value	CMA	Sample value	Estimated true value
Toronto (ON)	2.19	2.40	Sherbrooke (QC)	1.15	1.15
Montreal (QC)	2.75	2.76	St. John's (NF)	1.95	1.95
Saint John (NB)	0.45	1.67	Windsor (ON)	2.80	3.08
St.Cath.-Niagara (ON)	2.62	2.62	Kingston (ON)	2.29	2.29
Calgary (AL)	2.67	2.92	Sudbury(ON)	3.33	3.33
Saskatoon (SK)	4.60	5.54	Trois-Rivieres (QC)	1.53	1.53
Regina (SK)	5.99	6.61	Edmonton, Alberta	2.15	3.07
7 lower-rate CMAs	2.55	2.73	**7 higher-rate CMAs**	2.19	2.66
Full sample	2.49	2.71			

Table B.2 displays annual domestic violence rates per 1000 households in all 14 CMAs of the data. The values in the *Sample value* column are computed directly from the sample's values for the daily number of incidents in each CMA. The *Estimated true value* column shows extrapolations of the *Sample value* column values that accounts for the incomplete coverage. "7 lower-rate CMAs" and "7 higher-rate CMAs" are respectively the sub-samples containing the seven CMAs with the lowest rates of welfare receipt and the seven CMAs with the highest rates in our data. For the year 2006, the domestic violence rate (based on events reported to the police) and the welfare receipt rate have a negative correlation of about -0.11 in our data. This means that more domestic violence is reported to the police in regions with lower welfare receipt rates.

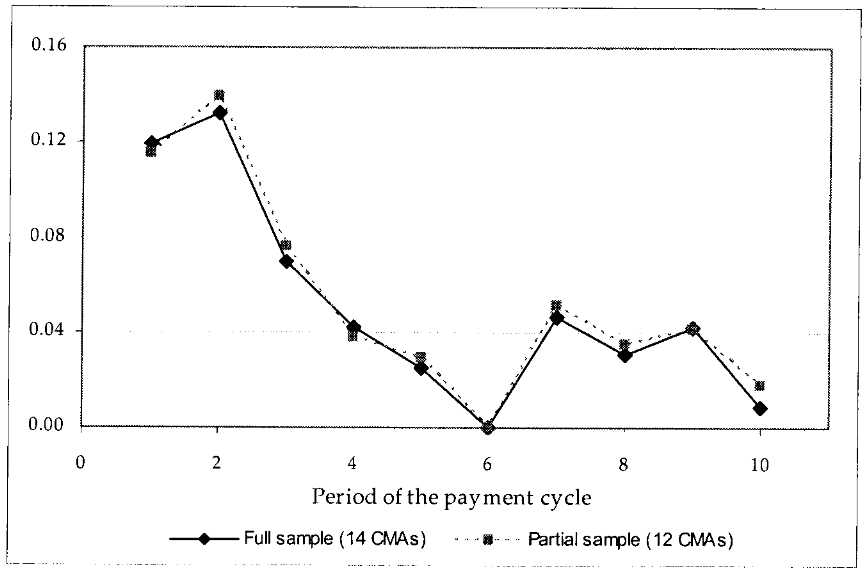
APPENDIX C

Parameter estimates and tests

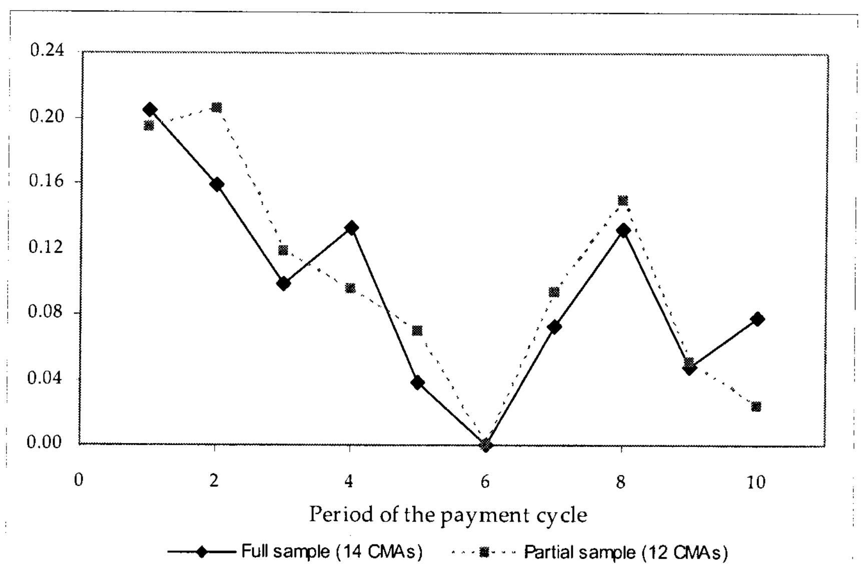
Figure C.1

The marginal effect of "being at period *j*" of the typical welfare payment cycle

Panel A Marginal effect of period *j* dummy on daily count of domestic violence incidents



Panel B Marginal effect of period *j* dummy on daily temporal domestic violence rate



Panel A of Figure C.1 uses marginal effects taken from column D of Table C.3 and the third column of Table C.6. Panel B uses estimates from column D of Table C.4 and the third column of Table C.7. All period and period 2 peaks have p-values less than 1%. In Panel A, period 7 and 9 peaks have p-values ranging between 4 and 9%, while the period 8 peaks in Panel B have p-values of 2.1% (full sample) and 0.3% (partial sample).

Table C.1

The marginal effects of the timing of social assistance disbursement on intimate partner violence: Specifications (1) and (2)

	Dependent variable:			Daily count of reported incidents				
	A	B	C	D	E	F	G	H
Constant	2.67301	2.50314	2.67078	2.50402	2.60943	2.53620	2.60791	2.53606
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Number of days since payment	-0.01267	-0.01227			-0.01232	-0.01194		
	0.000	0.000			0.000	0.000		
(Number of days since payment)^2	0.00033	0.00029			0.00032	0.00028		
	0.000	0.000			0.000	0.000		
Time-since-payment index			-0.35443	-0.37001			-0.34939	-0.36332
			0.000	0.000			0.000	0.000
(Time-since-payment index)^2			0.26408	0.26568			0.26198	0.26048
			0.000	0.000			0.000	0.000
Average temperature		0.00540		0.00539		0.00611		0.00605
		0.000		0.000		0.000		0.000
Rain		-0.00156		-0.00159		-0.00129		-0.00132
		0.056		0.108		0.116		0.109
Snowfall		0.00373		0.00372		0.00156		0.00156
		0.124		0.144		0.557		0.557
Paid holiday dummy		0.31570		0.31493		0.31961		0.31887
		0.000		0.000		0.000		0.000
City-year fixed effects	YES*	YES*	YES*	YES*	NO	NO	NO	NO
City-month-year fixed effects	NO	NO	NO	NO	YES*	YES*	YES*	YES*
Day of the week fixed effects	NO	YES	NO	YES	NO	YES	NO	YES
Log-*pseudo* likelihood score	-22166.147	-21506.568	-22166.866	-21506.578	-21837.248	-21192.497	-21837.984	-21192.529

This table displays the estimates of specifications (1) and (2) with two different types of two-way fixed effects. The numbers found under the parameter estimates in smaller prints are the corresponding p-values. " YES* " indicates that the standard errors on which the table's p-values rely are robust standard errors that take into account the large number of clusters employed to include the fixed effects that are indicated. The *Time-since-payment index* is 0 on payment day and 1 the last day before another payment is made. In each column, the number of observations is 15 330.

Table C.2

The marginal effect of the timing of social assistance disbursement on intimate partner violence: Specifications (4) and (5)

	Dependent variable:		Temporal rate of incidents			
	A	B	C	D	E	F
Constant	1.009914	0.96564	0.96508	0.93575	0.92787	0.93463
	0.000	0.000	0.000	0.000	0.000	0.000
Time-since-payment index	-0.10288	-0.11948	-0.11794	-0.10989	-0.10998	
	0.018	0.006	0.006	0.011	0.011	
Number of days since payment						-0.00401
						0.008
Average temperature		0.00548	0.00563	0.00594	0.00605	0.00601
		0.079	0.071	0.056	0.052	0.053
Rain		-0.00019	-0.00023	-0.00040	-0.00040	-0.00981
		0.956	0.947	0.907	0.906	0.907
Snowfall		-0.00948	-0.00958	-0.00956	-0.00977	-0.00981
		0.045	0.043	0.044	0.039	0.039
Holiday/week-end dummy		0.38920				
		0.000				
Paid holiday dummy			0.27931	0.26783	0.27806	0.27823
			0.000	0.001	0.000	0.000
Friday dummy				0.148703	0.15824	0.15895
				0.001	0.002	0.002
Saturday dummy			0.41075	0.44042	0.45030	0.45100
			0.000	0.000	0.000	0.000
Sunday dummy			0.37796	0.40714	0.41691	0.41747
			0.000	0.000	0.000	0.000
City-month-year fixed effects	YES*	YES*	YES*	YES*	YES*	YES*
Day of the week fixed effects	NO	NO	NO	NO	YES	YES
R-squared	0.0462	0.0583	0.0583	0.0592	0.0596	0.0596

This table displays the estimates of specifications (4) and (5) with two different types of two-way fixed effects. The numbers found under the parameter estimates in smaller prints are the corresponding p-values. " YES* " indicates that the standard errors on which the table's p-values rely are robust standard errors that take into account the large number of clusters employed to include the fixed effects that are indicated. The Time-since-payment index is 0 on payment day and 1 the last day before another payment is made.
In each column, the number of observations is 15 330.

Table C.3

The marginal effects of the timing of social assistance disbursement on intimate partner violence: Specifications (3)

Dependent variable:	Daily count of incidents			
	A	B	C	D
Constant	2.34858	2.45531	2.38453	2.39328
	0.000	0.000	0.000	0.000
Period 1	0.11969	0.11218	0.11576	0.11304
	0.000	0.000	0.000	0.000
Period 2	0.13251	0.17682	0.13157	0.13303
	0.000	0.000	0.000	0.000
Period 3	0.06974	0.05689	0.06955	0.07165
	0.003	0.028	0.004	0.003
Period 4	0.04175	0.06005	0.04070	0.03603
	0.076	0.014	0.082	0.124
Period 5	0.02498	0.04787	0.02295	0.02787
	0.291	0.120	0.338	0.245
Period 7	0.04624	0.05295	0.04591	0.04392
	0.043	0.077	0.071	0.085
Period 8	0.03082	0.03597	0.03074	0.03159
	0.183	0.165	0.174	0.162
Period 9	0.04196	0.06019	0.03919	0.04005
	0.069	0.029	0.090	0.084
Period 10	0.00853	0.05311	0.00808	0.01468
	0.706	0.049	0.713	0.503
Average temperature	0.00541		0.00590	0.00627
	0.000		0.000	0.000
Rain	-0.00143		-0.00116	-0.00127
	0.101		0.155	0.121
Snowfall	0.00404		0.00188	0.00169
	0.105		0.499	0.532
Holiday/week-end dummy	0.40224		0.40201	
	0.000		0.000	
Paid holiday dummy				0.31651
				0.000
City-year fixed effects	YES*	NO	NO	NO
City-month-year fixed effects	NO	YES*	YES*	YES*
Day of the week fixed effects	NO	NO	NO	YES
Log-*pseudo* likelihood	-21521.983	-21823.105	-21206.586	-21186.455

This table displays the estimates of specification (3) with two different types of two-way fixed effects.
The numbers found under the parameter estimates in smaller prints are the corresponding p-values. " YES* " indicates that the standard errors on which the corresponding p-values rely are robust standard errors that take into account the large number of clusters employed to include the fixed effects that are indicated.
In each column, the number of observations is 15 330.

Table C.4

The marginal effects of the timing of social assistance disbursement on intimate partner violence: Specification (6)

Dependent variable:	Temporal rate of incidents			
	A	B	C	D
Constant	0.78007	0.84887	0.81134	0.77340
	0.000	0.000	0.000	0.000
Period 1	0.21032	0.20718	0.21106	0.20475
	0.000	0.000	0.000	0.000
Period 2	0.15271	0.19998	0.15383	0.15936
	0.001	0.001	0.009	0.007
Period 3	0.08872	0.08515	0.09181	0.09886
	0.210	0.130	0.102	0.077
Period 4	0.13936	0.15521	0.13710	0.13256
	0.039	0.039	0.069	0.077
Period 5	0.02579	0.04310	0.02698	0.03798
	0.649	0.383	0.575	0.430
Period 7	0.07709	0.09004	0.07542	0.07259
	0.140	0.085	0.149	0.162
Period 8	0.12223	0.13231	0.12563	0.13218
	0.051	0.021	0.029	0.021
Period 9	0.04703	0.06681	0.04812	0.04798
	0.312	0.182	0.323	0.323
Period 10	0.06164	0.10171	0.06331	0.07835
	0.466	0.086	0.290	0.191
Average temperature	0.00409		0.00544	0.00599
	0.000		0.084	0.057
Rain	-0.00019		-0.00006	-0.00027
	0.936		0.986	0.937
Snowfall	-0.00599		-0.00917	-0.00946
	0.273		0.048	0.043
Holiday/week-end dummy	0.38961		0.38743	
	0.000		0.000	
Paid holiday dummy				0.27300
				0.000
City-year fixed effects	YES*	NO	NO	NO
City-month-year fixed effects	NO	YES*	YES*	YES*
Day of the week fixed effects	NO	NO	NO	YES
R-squared	0.0194	0.0473	0.0592	0.0605

This table displays the estimates of specification (6) with two different types of two-way fixed effects.
The numbers found under the parameter estimates in smaller prints are the corresponding p-values. " YES* " indicates that the standard errors on which the corresponding p-values rely are robust standard errors that take into account the large number of clusters employed to include the fixed effects that are indicated.
In each column, the number of observations is 15 330.

Table C.5

The marginal effects of the timing of social assistance disbursement on intimate partner violence: Alternative samples [specifications (2)and (5)]

Dependent variable:	Daily count of incidents					Temporal rate of incidents		
	7 cities - high		7 cities - low		12 cities	7 cities - high	7 cities - low	12 cities
	A	B	C	D	E	F	G	H
Constant	0.04452	0.05787	2.49229	2.53819	2.53855	1.12532	0.86587	0.94732
	0.342	0.253	0.000	0.000	0.000	0.000	0.000	0.000
Time-since-payment index	-0.15611	-0.24154	-0.09337	-0.38791	-0.36829	-0.17066	-0.04969	-0.14682
	0.001	0.109	0.000	0.000	0.000	0.003	0.446	0.000
(Time-since-payment index)^2		0.08583		0.29503	0.26404			
		0.559		0.000	0.000			
Average temperature	0.00748	0.00742	0.00601	0.00580	0.00609	0.00476	0.00703	0.00427
	0.017	0.018	0.000	0.000	0.000	0.282	0.112	0.083
Rain	-0.00285	-0.00286	-0.00108	-0.00111	-0.00150	-0.00276	0.00233	-0.00339
	0.310	0.308	0.197	0.189	0.070	0.351	0.714	0.071
Snowfall	-0.00691	-0.00687	0.00332	0.00337	0.00249	-0.00653	-0.01569	-0.00339
	0.288	0.292	0.246	0.220	0.354	0.278	0.045	0.743
Paid holiday dummy	0.37710	0.37550	0.31449	0.30788	0.31971	0.39392	0.16990	0.35737
	0.000	0.000	0.000	0.000	0.000	0.004	0.031	0.000
Friday dummy	0.11308	0.11303	0.06414	0.06404	0.07150	0.09838	0.21555	0.11267
	0.023	0.023	0.004	0.004	0.001	0.125	0.007	0.004
Saturday dummy	0.42112	0.42113	0.39644	0.39624	0.39857	0.33964	0.55872	0.42730
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Sunday dummy	0.44764	0.44762	0.38567	0.38547	0.31971	0.33964	0.43599	0.37869
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Number of observations	7665	7665	7665	7665	13140	7665	7665	13140
City-month-year fixed effects	YES*	YES*	YES*	YES*	YES*	YES*	YES*	YES*
Day of the week fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Log-*pseudo* likelihood/ R-squared	-7921.001	-7920.8655	-13269.113	-13260.498	-19999.446	0.0576	0.0623	0.0700

This table displays the estimates of specifications (2) and (5) with 3 alternative sub-samples for each specification. "7 cities - high" and "7 cities - low" are respectively the sub-samples containing the seven CMAs with the highest rates of welfare receipt and the seven CMAs with the lowest rates in our data. In columns A and C, the squared term of specification (2) is excluded to allow for comparison with columns F and G. The subsamples that comprise 12 cities simply exclude the CMAs of St. John and St. John's (see comment under Table C.8). The numbers found under the parameter estimates in smaller prints are the corresponding p-values. " YES* " indicates that the standard errors on which the table's p-values rely are robust standard errors that take into account the large number of clusters employed to include the fixed effects that are indicated.
The Time-since-payment index is 0 on payment day and 1 the last day before another payment is made.

Table C.6

The marginal effects of the timing of social assistance disbursement on intimate partner violence: Alternative samples [specification (3)]

Dependent variable:	Daily count of incidents		
	7 cities - high	7 cities - low	12 cities
Constant	-0.08087	2.39394	2.39148
	0.128	0.000	0.000
Period 1	0.15888	0.10430	0.11519
	0.001	0.000	0.000
Period 2	0.05424	0.14882	0.13969
	0.370	0.000	0.000
Period 3	0.07934	0.07185	0.07642
	0.223	0.006	0.002
Period 4	0.10234	0.02363	0.03771
	0.075	0.353	0.111
Period 5	0.04611	0.02501	0.02920
	0.467	0.353	0.226
Period 7	-0.03493	0.05935	0.05126
	0.541	0.036	0.046
Period 8	0.10463	0.01803	0.03453
	0.074	0.457	0.130
Period 9	-0.01406	0.05100	0.04152
	0.793	0.046	0.076
Period 10	-0.04364	0.02643	0.01780
	0.442	0.265	0.420
Average temperature	0.00752	0.00605	0.00633
	0.018	0.000	0.000
Rain	-0.00277	-0.00108	-0.00145
	0.319	0.197	0.080
Snowfall	-0.00700	0.00342	0.00268
	0.281	0.226	0.329
Holiday dummy	0.38877	0.30316	0.31730
	0.000	0.000	0.000
Number of observations	7665	7665	13140
City-month-year fixed effects	YES*	YES*	YES*
Day of the week fixed effects	YES	YES	YES
Log-*pseudo* likelihood	-7914.9752	-13250.87	-19992.208

This table displays the estimates of specifications (3) with three alternative sub-samples for each specification. "7 cities - high" and "7 cities - low" are respectively the sub-samples containing the seven CMAs with the highest rates of welfare receipt and the seven CMAs with the lowest rates in our data. The subsamples that comprise 12 cities simply exclude the CMAs of St. John and St. John's (see comment under Table C.8). The numbers found under the parameter estimates in smaller prints are the corresponding p-values. " YES* " means that the standard errors on which the table's p-values rely are robust standard errors that take into account the large number of clusters employed to include the fixed effects that are indicated.

Table C.7

The marginal effects of the timing of social assistance disbursement on intimate partner violence: Alternative samples [specification (6)]

Dependent variable:	Temporal rate of incidents		
	7 cities - high	7 cities - low	12 cities
Constant	0.97218	0.71029	0.77310
	0.000	0.000	0.000
Period 1	0.19798	0.21003	0.19468
	0.007	0.003	0.000
Period 2	0.13577	0.18520	0.20538
	0.096	0.029	0.009
Period 3	0.06402	0.12879	0.11892
	0.417	0.106	0.011
Period 4	0.10663	0.15689	0.09523
	0.150	0.231	0.034
Period 5	0.04357	0.03300	0.06932
	0.566	0.582	0.104
Period 7	-0.00030	0.14311	0.09344
	0.997	0.046	0.033
Period 8	0.18358	0.07714	0.14964
	0.036	0.303	0.003
Period 9	-0.01210	0.10307	0.05136
	0.868	0.109	0.242
Period 10	-0.04443	0.20491	0.02436
	0.529	0.036	0.563
Average temperature	0.00488	0.00674	0.00441
	0.271	0.137	0.074
Rain	-0.00273	0.00255	-0.00324
	0.359	0.686	0.085
Snowfall	-0.00686	-0.01476	-0.00140
	0.252	0.055	0.798
Holiday dummy	0.40086	0.15415	0.35603
	0.003	0.050	0.000
Number of observations	7665	7665	13140
City-month-year fixed effects	YES*	YES*	YES*
Day of the week fixed effects	YES	YES	YES
R-squared	0.0594	0.0637	0.0718

This table displays the estimates of specifications (6) with three alternative sub-samples for each specification. "7 cities - high" and "7 cities - low" are respectively the sub-samples containing the seven CMAs with the highest rates of welfare receipt and the seven CMAs with the lowest rates in our data. The subsamples that comprise 12 cities simply exclude the CMAs of St. John and St. John's (see comment under Table C.8). The numbers found under the parameter estimates in smaller prints are the corresponding p-values.
" YES* " means that the standard errors on which the table's p-values rely are robust standard errors that take into account the large number of clusters employed to include the fixed effects that are indicated.

Table C.8

Parametric tests on monthly domestic violence peaks' relative amplitude

Panel A
All 14 CMAs in the sample
Dependent variable: Daily number of incidents

Null hypothesis tested	Test statistic (and p-value)
$\delta_1 - \delta_{10} = 0$	19.70 (0.0000)
$\delta_1 - \delta_9 = 0$	10.49 (0.0012)
$\delta_1 - \delta_8 = 0$	13.23 (0.0003)
$\delta_1 - \delta_7 = 0$	7.60 (0.0059)
$\delta_2 - \delta_{10} = 0$	24.93 (0.0000)
$\delta_2 - \delta_9 = 0$	14.47 (0.0001)
$\delta_2 - \delta_8 = 0$	15.11 (0.0001)
$\delta_2 - \delta_7 = 0$	11.96 (0.0005)

Panel B
12 CMAs (St. John and St. John's excluded)
Dependent variable: Daily number of incidents

Null hypothesis tested	Test statistic (and p-value)
$\delta_1 - \delta_{10} = 0$	19.07 (0.0000)
$\delta_1 - \delta_9 = 0$	10.57 (0.0012)
$\delta_1 - \delta_8 = 0$	12.82 (0.0003)
$\delta_1 - \delta_7 = 0$	6.40 (0.0114)
$\delta_2 - \delta_{10} = 0$	26.12 (0.0000)
$\delta_2 - \delta_9 = 0$	15.98 (0.0001)
$\delta_2 - \delta_8 = 0$	15.95 (0.0001)
$\delta_2 - \delta_7 = 0$	11.58 (0.0007)

Panel C
All 14 CMAs in the sample
Dependent variable: Temporal rate of incidents

Null hypothesis tested	Test statistic (and p-value)
$\eta_1 - \eta_{10} = 0$	4.06 (0.0445)
$\eta_1 - \eta_9 = 0$	8.79 (0.0033)
$\eta_1 - \eta_8 = 0$	1.49 (0.2227)
$\eta_1 - \eta_7 = 0$	4.85 (0.0282)
$\eta_2 - \eta_{10} = 0$	1.51 (0.2201)
$\eta_2 - \eta_9 = 0$	3.06 (0.0807)
$\eta_2 - \eta_8 = 0$	0.22 (0.6392)
$\eta_2 - \eta_7 = 0$	2.46 (0.1173)

Panel D
12 CMAs (St. John and St. John's excluded)
Dependent variable: Temporal rate of incidents

Null hypothesis tested	Test statistic (and p-value)
$\eta_1 - \eta_{10} = 0$	15.86 (0.0001)
$\eta_1 - \eta_9 = 0$	9.88 (0.0018)
$\eta_1 - \eta_8 = 0$	0.84 (0.3604)
$\eta_1 - \eta_7 = 0$	4.32 (0.0383)
$\eta_2 - \eta_{10} = 0$	15.03 (0.0001)
$\eta_2 - \eta_9 = 0$	9.99 (0.0017)
$\eta_2 - \eta_8 = 0$	1.07 (0.3026)
$\eta_2 - \eta_7 = 0$	5.62 (0.0182)

Above are basic Wald test statistics and the corresponding p-values in parentheses. Panel A and Panel B values are based on the negative binomial specification as estimated in column D of appendix Table C.3, while Panel C and Panel D values are based on the OLS estimates that appear in column D of Table C.4. In panels B and D, the CMAs of St. John and St. John's are excluded because I only have poor coverage of the former and because the province where the latter is found pays the beneficiaries twice as often as the other provinces of the sample, which is likely to mitigate the end-of-the-cycle break in intimate partner violence.