The economic value of crime prevention in the City of Vancouver

By
Jonathan Godin

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Approved: Dr. Yigit Aydede
Associate Professor

Approved: Dr. Atul Dar
Professor

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Abstract

This is the first study to use the crime-housing price relationship to attempt to measure the economic cost of crime within a Canadian context. The City of Vancouver, which is home to Canada's hottest real estate market, is used as an area of study. Crime data is obtained from the Vancouver Police Department and the Real Estate Board of Greater Vancouver for a period of nine years (2005-2013). Geographic Information System (GIS) software is then used to redefine the boundaries in order to make the datasets comparable and ultimately construct a unique panel dataset of twenty-two neighbourhoods. This study also proposes a methodology to handle the issue of endogeneity using instrumental variables that may be successfully applied despite the limited neighbourhood-level data that is available in Canada. Once endogeneity is remedied, unbiased coefficients can be obtained, which will make it possible to calculate the economic cost of crime, and thus the value of crime prevention for the City of Vancouver.

April 21, 2015

1. INTRODUCTION

Crime carries a significant cost to society. In fact, the direct costs of crime – that is, public expenditures on the criminal justice system – do not reflect the majority of the total societal costs of crime. A study published on the Department of Justice's website by Zhang (n.d.) estimates that in 2008, the cost of crime in Canada was $99.6 billion. Of this figure, $31.4 billion was in direct costs and $68.2 billion was in intangible costs (p. 8). Similarly, Brantingham, Easton and Furness (2014) estimate that the total cost of crime in Canada was $85.2 billion in 2009, of which only less than a quarter originated from expenditures on police, courts and correction; the majority of the remaining costs were intangible costs (p. 96). Both studies caution that these figures are likely to be underestimates of the true cost of crime to society. Since these figures represent between 5 and 6% of Canada's GDP, it is clear that reducing crime is beneficial not only for the public safety, but also for the region's economy.

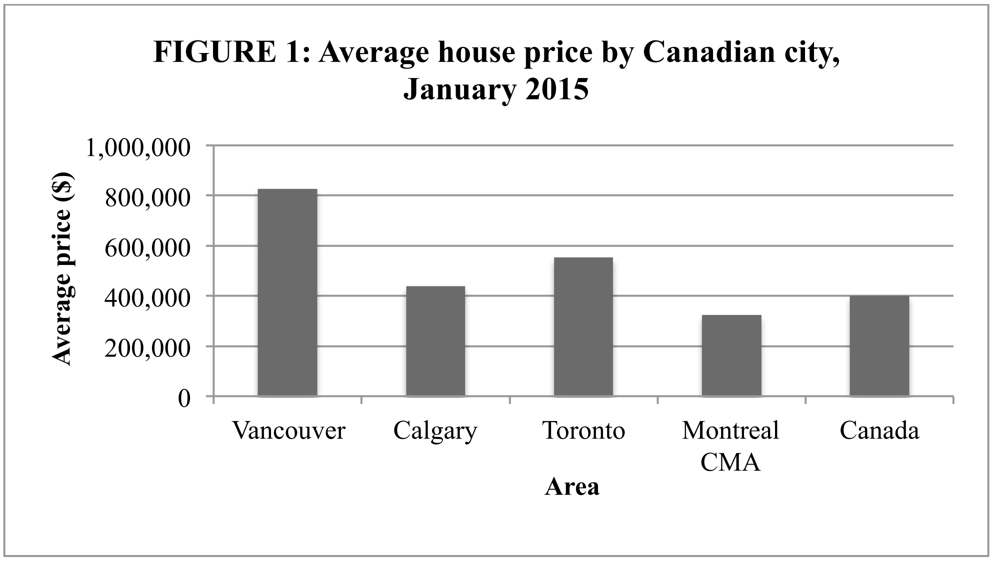
Because crime is predominantly a local issue, studying its costs should likewise be done at the local level. Once the costs of crime are determined, it is possible to determine the value of crime prevention. This valuation will guide public policy decisions on the extent of measures that should be undertaken to reduce crime as well as provide an estimate of the economic benefits of these policies. It will also help narrow the type of crime (property or violent) that has the greatest social cost and should, therefore, be given top priority by policy makers. The difficulty in measuring this cost stems from the fact that "public safety (i.e. the absence of crime) is a non-market good, whose price can only be estimated implicitly" (Ihlanfeldt and Mayock, 2010, p. 303). Previous studies have therefore selected the housing market to implicitly measure the value of crime prevention.[1]

The rationale behind the selection of the housing market is perhaps best explained by Pope and Pope (2012), who state that "crime can be viewed as a neighbourhood disamenity [and] [o]ne market that captures some of these neighbourhood crime disamenities is the housing market" (p. 177). This study, therefore, aims to determine the extent to which crime rates impact housing prices in the City of Vancouver in order to estimate the economic value of reducing crime for the city. This is the first time that the crime-housing price relationship has been used to estimate the value of crime prevention within a Canadian context.

The organization of this paper is as follows. Section 2 discusses the use of this relationship in previous studies, as well as its potential shortcomings. Section 3 outlines the datasets used and the steps that were taken to make them comparable and merge them into a unique panel dataset. Section 4 presents various model specifications and discusses which econometric problems were resolved. It also proposes a methodology to handle the remaining econometric issue – endogeneity – using instrumental variables. Finally, Section 5 highlights the policy implications of this study.

As a final point, it should be noted that the selection of City of Vancouver as the study area is not random; rather, it was selected because it is the hottest real estate market in Canada. This is shown in Figure 1, which illustrates the average house price for some of the major cities in Canada in January 2015. The average house price in Vancouver at this time was $827,558, much higher than the Canadian average of $401,143.

[1] For a thorough list and description of previous studies, see Ihlanfeldt and Mayock, 2010, pp. 305-309



Source: Canadian Real Estate Associate

2. THEORY & LITERATURE REVIEW

The theoretical reasoning for this research question rests on the premise that crime is considered a neighbourhood disamenity. This consideration makes it possible to establish the expected nature of the crime-housing price relationship using the law of demand. As Boggess, Greenbaum and Tita (2013) put it: "[c]rime can be considered a *disamenity*, a factor that reduces demand for a community in the same vein that poorly performing schools or a lack of basic municipal services are considered disamenities" (p. 301). According to the law of demand, a decrease in the demand for a good will result in a lower price for that good, *ceteris paribus*. It seems theoretically reasonable to state that homebuyers are willing to pay less for a home in a relatively unsafe neighbourhood compared to an identical home in a safer neighbourhood. This negative crime-housing price relationship is confirmed by many of the existing studies (Thaler, 1978; Gray and Joelson, 1979; Hellman and Naroff, 1979; Rizzo, 1979; Naroff, Hellman, & Skinner, 1980; Dubin and Goodman, 1982; Burnell, 1988; Clark and Cosgrove, 1990; Taylor, 1995; Bowers and Islanfeldt, 2001; Lynch and Rasmussen, 2001; Schwartz, Susin, & Voicu, 2003; Gibbons, 2004; Tita, Petras, & Greenbaum, 2006; Troy and Grove, 2008; Ihlanfeldt and Mayock, 2010; Ceccato and Wilmhemsson, 2011; Pope and Pope, 2012; Buoanno, Montolio and Raya-Vilchez, 2013; Massena, Beltrão and Vetter, 2013).

Despite the wide range of studies on this topic, Ihlanfeldt and Mayock (2010) highlight the shortcomings of 19 studies conducted between 1967 and 2008. Although 15 out of the 19 studies they summarize find a negative, statistically significant relationship between crime and housing prices, the authors are critical of the methodologies employed in many of these studies for two main reasons. For one thing, many (eight) of the previous studies do not make clear which *type* of crime has the highest impact on housing prices because they measure crime using a single variable. This results in there being "little consensus on whether violent crime is more or less important to people than property crime" (p. 304). Therefore, the authors conclude that the model should, at the very least, contain separate variables for violent and property crime. The problem with this "is that violent and property crimes are highly collinear; hence multicollinearity makes it difficult to separate out their specific influences" (p. 304). The solution to this, the authors argue, is to have panel data and first-difference this data.

The other critique that Ihlanfeldt and Mayock (2010) have is that the majority (13 out of the 19) of the studies treat crime as an exogenous variable. They argue that the failure to take into account the endogeneity may result in biased and inconsistent estimates. The issue of endogeneity within the context of this study is discussed in Sections 4-5 and 4-6. For now, it is sufficient to simply state that more recent studies have accounted for the endogeneity of crime using various instrumental variables (Ceccato and Wilmhemsson, 2011; Pope and Pope, 2012; Buoanno et al., 2013; Massena et al., 2013).

Ihlanfeldt and Mayock's (2010) study provides important groundwork. It uses a nine-year panel of crime from Miami-Dade County at the neighbourhood level. The study separates the effect of violent and property crime and finds that while property crime has no impact on housing prices, "the elasticity of house value with respect to the neighbourhood density of violent crime is roughly equal to -0.25" (p. 324). The authors use instrumental variables (related to commercial land use) and validate their instruments. They claim that Gibbons (2004) is the only other one to have successfully done this.

Pope (2008) highlights another challenge with the crime-housing price relationship: the potential of the omitted variable bias, which has particularly plagued cross-sectional studies (p. 602). While Pope and Pope (2012) contend that a "panel design has the potential to ameliorate the issue of omitted variable bias," they acknowledge that it is unlikely to fully solve the problem because "unobserved factors change at the same time as crime changes" (p. 181). Indeed, it is difficult to account for all the factors that can impact housing prices, as these include both individual dwelling characteristics and neighbourhood characteristics. Nonetheless, previous studies have attempted to minimize the likelihood of the omitted variable bias. Buoanno et al. (2013) perform a two-stage approach, which they describe as follows:

> we employ a two-stage procedure in order to assess the impact of crime perception on housing values. In the hedonic first stage, we estimate the hedonic housing price on the basis of a dwelling's physical characteristics, the year and district fixed effects, while in the hedonic second stage, we use

the hedonic housing price at the district level as our dependent variable. (p. 314)

Other studies have simply regressed housing prices on a large number of control variables in addition to the crime variables, such as whether the house has a garage, its proximity to an airport, etc. (Gaviria, Medina, Morales & Núñez, 2010, pp. 113-117). The problem in applying either of these methodologies to this study is that dwelling-specific data is notoriously difficult to acquire in Canada. The best way to handle this problem is, therefore, to build on the method employed by Pope and Pope (2012), who regress changes in the Case-Shiller Index[2] on the change in the crime rate. They maintain that they "do not need to control for physical housing characteristics because the Case-Shiller Index is based on repeat sales for homes where physical housing characteristics are differenced away" (p. 182).

As was stated previously, the ultimate goal of this study is to use the crime-housing price relationship to estimate the aggregate value of crime prevention. In other words, this paper aims to determine the value of crime prevention for the entire City of Vancouver, not just for the average household. Massena et al. (2013) present their conclusion in such a way. Specifically, they state that: "increasing the sense of security in the home by one standard deviation would increase average home values by US$1,513 … or about US$13.6 million if applied to all 18.0 million households in the study area" (p. 30). The present study aims to assess whether similar conclusions follow for Vancouver.

[2] As explained in Pope and Pope (2012): "[The Case-Shiller (CSI)] indices are estimated using arithmetic weighting of repeat sales … Housing prices of home that have sold at least twice are collected from primarily metropolitan areas across the country. … Furthermore, the indexes are not affected by differences in average housing quality across zip codes. The CSI is widely considered the most accurate measure of single-family home price changes in the areas that it covers" (p. 181).

It should be noted that while hedonic price models are the most commonly used method, they are not without criticism, and it is important to be aware of their potential shortcomings. Boggess et al. (2013) contend that the impact of crime on housing *sales*, as opposed to housing *prices*, is a better method for calculating the indirect costs of crime (p. 304). They point out the two major deficiencies with using a hedonic price model. The first problem relates to the demand-side of the housing market. They argue that since hedonic price models measure prices based on a "subset of houses that are transacted over a given period of time, … an increase in crime in a neighbourhood may make the neighbourhood less attractive to potential buyers relative to other similarly priced neighbourhoods." This could result in a reduction in sales (i.e. demand) in the neighbourhood, and "price indexes dependent on transactions would fail to capture this reduction in demand" (Boggess et al., p. 303).

The second problem relates to the supply-side of the housing market. They argue that housing values are limited in their effectiveness to measure the indirect cost of crime because the impact of a reduction in demand (caused by an increase in crime) differs across neighbourhoods as it depends on the elasticity of supply. A "crime-induced decrease in demand" has a greater impact on housing prices in neighbourhood with an inelastic supply (i.e. a low vacancy rate) than in neighbourhoods with a more elastic supply (i.e. a high vacancy rate). The result: "models that rely on measuring the impact of crime on housing prices underestimate the impact of crime in neighbourhoods with a large supply of available or vacant houses" (Boggess et al., 2013, p. 304).

While there is certainly some validity to their claims, data limitations and time constraints make it unfeasible to attempt to use the quantity of housing sales as opposed to housing prices in this paper. Additionally, the use of the Multiple Listing Service (MLS) Benchmark Price – the price used to calculate the MLS Home Price Index (MLS HPI) – may mitigate the impact of these two problems because the MLS HPI is not a simple price index. It fuses repeat-sales and hedonic price model approaches and is calculated using state-of-the-art statistical techniques. Furthermore, as mentioned above, the vast majority of the literature uses a price-based model, and so it seems unlikely that this approach is completely invalid.

With all of this in mind, the coefficient signs of the explanatory crime rate variables are expected to be negative. However, the coefficient signs for violent crime are expected to be *more* negative than those for property crime. The reasoning behind this is that violent crimes cause more psychic harm than property crime, and therefore people are more inclined to avoid the former relative to the latter (Ihlanfeldt and Mayock, 2010, p. 325). As a result, their willingness to pay for a house will decrease more with violent crimes than property crimes.

3. DATA SOURCES

3-1. Crime data

The explanatory variables of interest in this model are the crime rates. Crime data from 2005 to 2013 is obtained from the Vancouver Police Department (VPD), which publishes monthly data on nine different crimes: sex offences, assaults, robbery, breaking and entering, theft from automobile, theft, arson, mischief and offensive weapons. These crime statistics are available publicly and are broken down by into 24 neighbourhoods in

Vancouver. The boundaries, as well as the types of crime reported, are consistent for the study period, which makes the data comparable across years.

This dataset has been manipulated in three ways. Firstly, the nine offences were grouped together under the header of one of two broader categories: violent crime and property crime. This allows the study to determine the different impact of these two categories of crime on housing prices, as was done in previous studies (Ihlanfeldt and Mayock, 2010; Pope and Pope, 2012). The classification of the offence under violent or property crime is shown in Table 1.

TABLE 1: Classification of offences

Violent Crimes	Property Crimes
Sex offences	Breaking and Entering
Assaults	Theft of Motor Vehicle
Robbery	Theft from Auto
Offensive weapons	Theft <> $5k
	Arson
	Mischief

Secondly, because these two variables (violent crime and property crime) are likely to be highly collinear, the absolute change between years is taken, as suggested by Ihlanfeldt and Mayock (2010, p. 304).

Finally, crime *rates*, as opposed to crime *levels*, are used. This is in line with previous studies (Tita, Petras and Greenbaum, 2006; Pope and Pope, 2012; Boggess, Greenbaum and Tita, 2013). Consequently, the dataset is expressed as the number of crimes per 1,000 people in each neighbourhood. A limitation in this regard is that the population for each area is only calculated in Census years, and so is only available for 2006 and 2011. To partially remedy this, the average of the population reported in the two

Census years is used. This results in a more accurate figure of the true population in each neighbourhood during the study period.

There are two main limitations to this dataset. The first is that is does not include the number of homicides for each neighbourhood. While homicide data is publicly available for the City of Vancouver at a more aggregate level, due to the sensitive nature of the data, it is not publicly available at the neighbourhood level. Requests to obtain homicide data for each neighbourhood were denied by the VPD.

The second limitation relates to the nature of this dataset: police-reported data. It is well documented within the literature with that police-reported crime data is subject to underreporting (Gibbons, 2004; Tita et al., 2006; Buoanno et al., 2013). Criminologists often refer to this as the *dark figure of crime*, and it is for this reason that victimization surveys are considered to be a closer depiction of reality. Unfortunately, victimization surveys are not available at the geographical level and for the time period required for this study. Gibbons concludes that, in the absence of available data, this is simply a limitation that we must live with (p. F446).

3-2. Housing price data

Housing price data is obtained from the Real Estate Board of Greater Vancouver (REBGV), which provided the Multiple Listing Service (MLS) Benchmark Prices – the prices used to calculate the MLS Home Price Index (MLS HPI). This dataset contains a benchmark price for the average home in each of 39 sub-areas (neighbourhoods) within the City of Vancouver and is calculated on a monthly basis. This dataset contains the MLS Benchmark Price from 2005 to 2013. Since monthly changes in household prices are unlikely to be explained by changes in crime, the monthly values are converted to annual values. While it is possible to convert the Benchmark Price figures to an index, doing so does not provide any additional insight, and so the Benchmark Prices are used.

Because the construction of the MLS Benchmark Price uses various econometric techniques, its use reduces the extent of data correction that must be applied in this study.[3] Its construction ensures that multicollinearity is not a problem in the final regression by using Stepwise regression and Variance Inflation Factors (VIF). It also uses the Akaike Information Criterion (AIC) and the RESET test to correctly specify the model. The data is corrected for heteroskedasticity and spatial autocorrelation. Furthermore, the determination of how to divide the City of Vancouver into sub-areas that are "small enough to ensure homogeneity and large enough to ensure that there are sufficient sales volume" is done carefully by using two approaches (Multiple Listing Service, 2014, p. 6). Firstly, sub-areas are grouped according to socio-demographic attributes, notably Education Level and Average Income. Secondly, Geographical Information Systems (GIS) are used to take into account physical neighbourhood characteristics, such as proximity to schools, water or main streets. The boundaries for each sub-area are consistent over the study period, and therefore the Benchmark Prices are comparable between years. In the main regression to obtain this Benchmark Price, 48 control variables are used to take into account individual dwelling characteristics.[4] Since many of these control variables contain information that is not easily accessible, the use

[3] For a complete description of the methodology used to construct the MLS Benchmark Price, see the MLS® Home Price Index Methodology by the Multiple Listing Service (2014).
[4] See Appendix A for a full list of the control variables used when calculating the MLS Benchmark Price

of the MLS Benchmark Price also greatly reduces the amount of data that must be acquired for this study.

The choice of this data source is motivated by a study by Pope and Pope (2012), which regresses the change in the Case-Shiller Index on the change in the crime rate and a number of control variables. While there is no equivalent index in Canada that tracks home prices at the micro-level needed for this study,[5] the MLS HPI provides many of the same benefits that come from using the Case-Shiller Index.

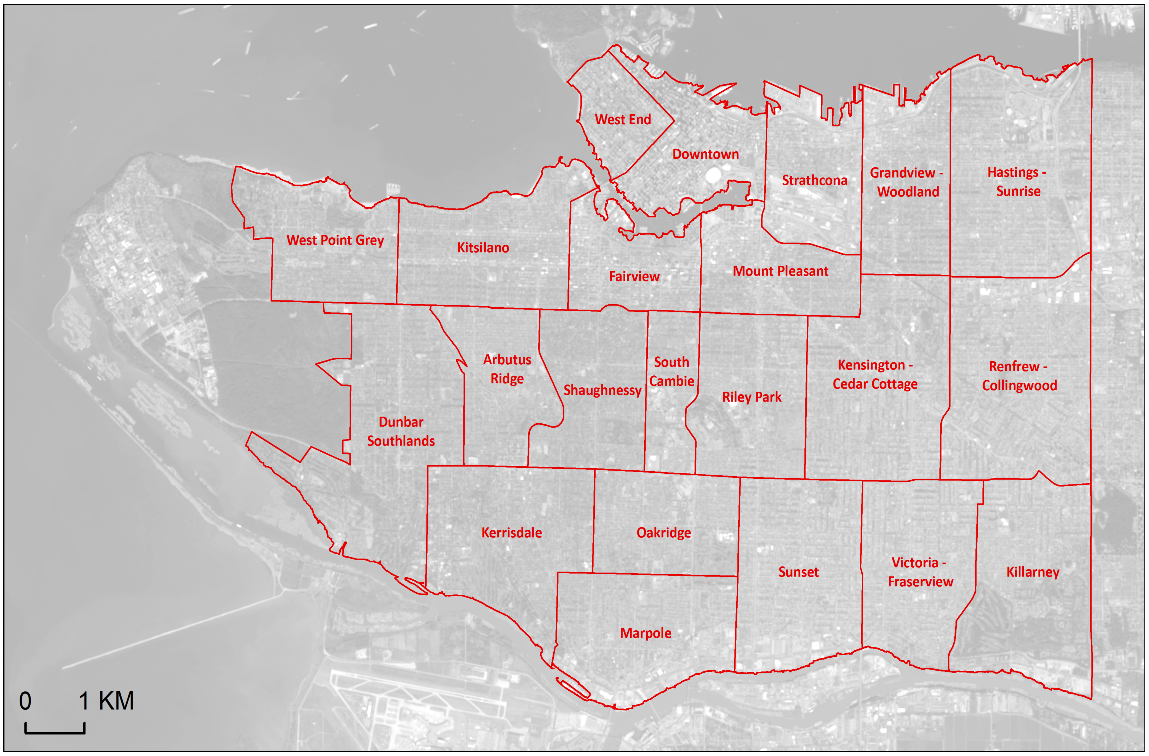
The use of the dataset is not without any shortcomings. Most notably, while the Benchmark Price is a more accurate figure than a simple average, the fact remains that it is a single number. By nature, one figure cannot possibly take into account all of the information that would be captured if individual dwelling prices were used.

3-3. Redefining the boundaries using GIS to create a panel dataset

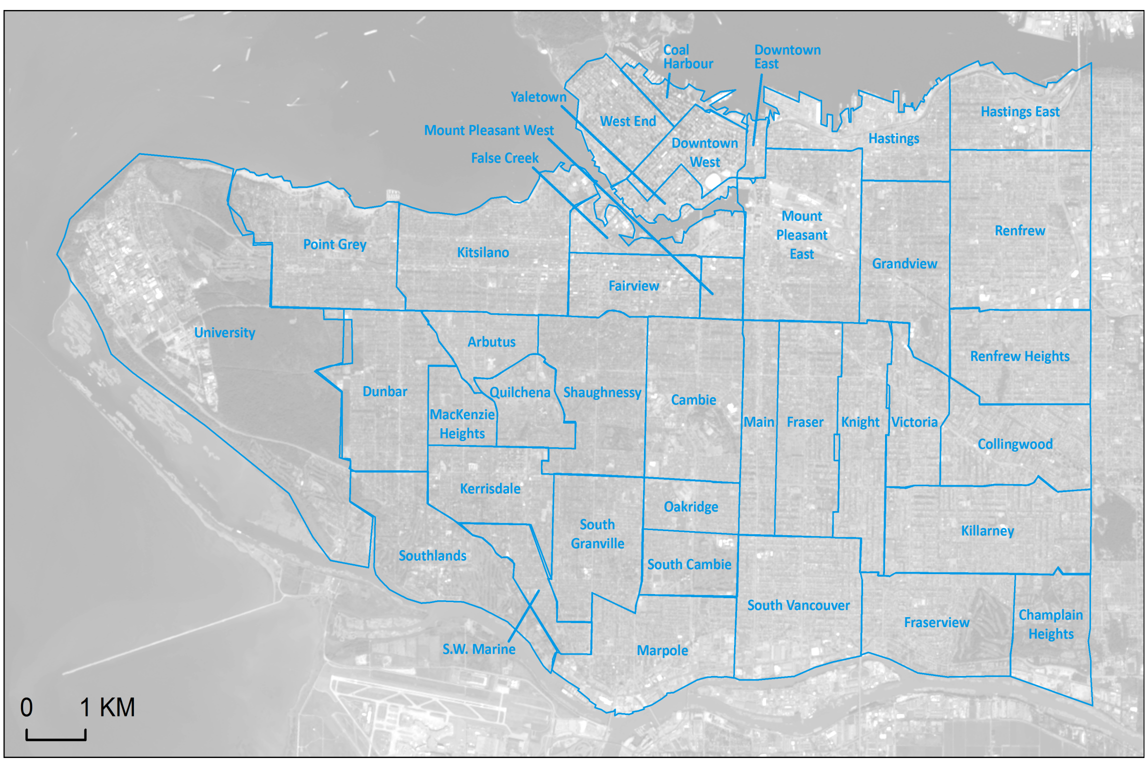
The biggest challenge in creating a panel data set from these two data sources (VPD and REBGV) is that while boundaries for both housing price data and crime data are consistent over time, the boundaries *between* the two datasets differ. In other words, the 39 neighbourhood boundaries chosen by the REBGV differ from the 24 neighbourhood boundaries used by the VPD. Map 1 and Map 2 make this point clear. To deal with this issue, and to make the datasets comparable, the boundaries are redefined.

[5] In terms of methodology, the closest index available in Canada is the Teranet–National Bank House Price Index™; however, this index is only available for the major cities and is not broken down to the neighborhood level required for this study.

MAP 1: VPD boundaries dividing Vancouver into 22 neighbourhoods



MAP 2: REBGV boundaries dividing Vancouver into 39 neighbourhoods



In order to accurately redefine the boundaries, GIS files were obtained for the boundaries set by both the VPD[6] and the REBGV. GIS software is then used to fit the REBGV neighbourhoods into the VPD neighbourhoods. The nature of the datasets makes it necessary to redefine the boundaries in this way (as opposed to fitting the VPD neighbourhoods into the REBGV ones). This is because while the crime dataset provides a precise figure for the number of crimes that were committed in each of the 22 VPD-defined neighbourhoods, it does not specify the exact location of each crime. For this reason, the crime dataset can only be used within the context of the VPD-boundaries, whereas the housing dataset can be manipulated to fit within these boundaries. Specifically, once the boundaries are redefined, a weighted average of the original Benchmark Prices in the areas defined by the REBGV is calculated in order to create a Benchmark Price for the newly defined area. This is expressed by Equation (1):

$$\boldsymbol{BP_{it=w_{kt}}M_{kt}} \tag{1}$$

Where BP_{it} represents the MLS Benchmark price for the VPD-defined area i in year t, w represents the weight of the REBGV area k in year t, and M_{kt} represents the Benchmark price of the REBGV area k in year t.[7]

After redefining the boundaries, we are left with a nine-year panel (2005-2013) with twenty-two neighbourhoods, for a total sample size of 198 observations (N=198).

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[6] To be precise, the GIS files obtained are actually for the 22 Local Planning Areas boundaries set by the City of Vancouver. These boundaries are almost identical to those set by the VPD, which has 24 neighbourhoods. The VPD boundaries contain two additional neighbourhoods because (1) they include Stanley Park as a neighbourhood, whereas the City does not and (2) they create a separate neighbourhood for *Musqueam*, whereas the City of Vancouver includes *Musqueam* under the *Dunbar Southlands* region. The first difference does not impact the results, as there is no housing price data available for Stanley Park. Therefore, the area is simply omitted from the study. To handle the second difference, the number of crimes in the VPD-defined neighbourhoods *Dunbar-Southlands* and *Musqueam* are combined. Thus, this panel dataset uses 22 neighbourhoods, as defined by the City of Vancouver but consistent with the VPD dataset.

[7] See Appendix B for the weights of all REBGV neighbourhoods for each VPD neighbourhood.

4. EMPIRICAL METHODOLOGY

In order to obtain reliable results, it is necessary to address several econometric problems that are present in the assembled panel dataset. This section first describes the corrective measures undertaken to remedy some of these problems. It then outlines an econometric issue that was not resolved – endogeneity – and proposes a method that could potentially be used to correct the issue.

Table 2 presents the descriptive statistics for the all of the variables in the dataset. The average Benchmark Price in this study area is \$826,377, though it ranges from \$243,774 to \$2,748,516. The average number of violent crimes is 17.27 per 1,000 residents, though it ranges from 1.25 per 1,000 residents to 88.02 per 1,000 residents. Similarly, the average number of property crimes is 52.49 per 1,000 residents and ranges from 36.99 per 1,000 residents to 205.80 per 1,000 residents.

TABLE 2: Descriptive Statistics

	Observations	Mean	Std. Dev.	Min	Max
Benchmark price (\$)	198	826,377	487,383	243,774	2,748,516
Violent crime rate (per 1,000 residents)	198	11.67	17.27	1.25	88.02
Property crime rate (per 1,000 residents)	198	52.49	36.99	16.79	205.80

Table 3 contains the OLS regression results for specifications (I) through (IV). A discussion of each model follows. Specification (IV) is the final model in this study, although there remain econometric problems that must be solved before its results can be deemed reliable.

Column (1) of Table 3 show the untreated results using specification (I):

$$\boldsymbol{BP_{it} \;=\; \alpha + \beta_1 C_{it}^{V} + \beta_2 C_{it}^{P} + \varepsilon_{it}} \tag{I}$$

This specification states that the MLS Benchmark Price *BP* for the neighbourhood *i* in the time period *t* is represented as a linear function of property crime rate C^p, violent crime rate C^V and a random error term. The results show that only property crime has a statistically significant negative impact on housing prices. However, this conclusion is not valid as there are several econometric issues that must be dealt with.

TABLE 3: OLS Estimates of the Effect of Crime on Housing Prices ($)
Dependent Variable: MLS Benchmark price for (1) and ΔMLS Benchmark Price for (2)-(5)

	(1)	(2)	(3)	(4)	(5)
Violent Crime Rate (t)	-5,873				
	(-1.30)				
Property Crime Rate (t)	-5,837				
	(-5.05)				
ΔViolent Crime Rate (t)		1,633	11,726	12,172	1,616
		(0.47)	(1.19)	(1.87)	(2.42)
ΔProperty Crime Rate (t)		1,573	6,681	6,714	6,105
		(1.89)	(2.65)	(4.81)	(5.98)
ΔViolent Crime Rate (t-1)			8496.545	8,899	1,256
			(0.86)	(3.08)	(0.21)
ΔProperty Crime Rate (t-1)			2198.95	2,318	3,114
			(1.49)	(1.81)	(4.68)
ΔViolent Crime Rate (t-2)			-6413.394	-6,415	-2,442
			(-0.86)	(-1.32)	(-0.58)
ΔProperty Crime Rate (t-2)			-682.9477	-503	1,487
			(-0.47)	(-0.31)	(1.06)
ΔViolent Crime Rate (t-3)			-8071.186	-8,100	-4,019
			(-0.96)	(-5.41)	(-1.33)
ΔProperty Crime Rate (t-3)			-1,992	-1,811	-1,999
			(-1.35)	(-1.05)	(-2.84)
ΔViolent Crime Rate (t-4)			8,760	8,755	7,397
			(1.18)	(2.64)	(1.12)
ΔProperty Crime Rate (t-4)			-1,138	-1,020	-1,911
			(-0.64)	(-0.51)	(-1.60)
Driscoll-Kraay SEs used?	No	No	No	Yes	Yes
Year and Region fixed effects?	No	No	No	No	Yes
R-squared	0.1565	0.0193	0.2444	0.1337	0.6636
F-statistic				8.66	85.68

4-1. Nonstationary variables

The Levin-Lin-Chu and Harris-Tsavalis tests conclude that all three variables contain unit roots. In order to remedy this issue, the data is first-differenced. These tests then confirm that the data has become stationary. Column (2) of Table 3 shows the results of running a regression with specification (II):

$$\Delta \boldsymbol{BP_{it}} \ = \ \boldsymbol{\alpha} + \boldsymbol{\beta_1} \Delta \boldsymbol{C_{it}^{V}} + \boldsymbol{\beta_2} \Delta \boldsymbol{C_{it}^{P}} + \boldsymbol{\varepsilon_{it}} \tag{II}$$

First-differencing the data has rendered the coefficients statistically insignificant, which suggests that crime has no impact on housing prices.

4-2. Lagged values

The impact of the change in crime on housing prices is not expected to be immediate. Ihlanfeldt and Mayock (2010) found that "the full impact of a spike of crime on housing price will occur with a lag" (p. 316). Consequently, they include both the current change and four lags. These lags are represented by j in specification (III):

$$\Delta \boldsymbol{BP_{it}} \ = \ \boldsymbol{\alpha} + \sum_{j=0}^{4} \boldsymbol{\beta_j} \Delta \boldsymbol{C_{i,t-j}^{V}} + \sum_{j=0}^{4} \boldsymbol{\delta_j} \Delta \boldsymbol{C_{i,t-j}^{P}} + \boldsymbol{\varepsilon_{it}} \tag{III}$$

Column (3) in Table 3 displays the results of this regression. The change in property crime rate in the current time period is the only variable with a statistically significant coefficient in this model. Unfortunately, this coefficient is positive, which goes against expectations.

4-3. Serial correlation, heteroskedasticity and cross-sectional dependence

Specification (III) contains many econometric problems. Wooldridge's test for autocorrelation in panel data confirms the presence of serial correlation.[8] Furthermore, plotting the predicted residuals against the independent crime variables confirms the

[8] For a full description of Wooldridge's test for autocorrelation, see Drukker (2003).

presence of heteroskedasticity. This is likely due to the fact that despite all the neighbourhoods being located in the City of Vancouver, they still differ on a number of factors, such as size, population density and median income. Finally, De Hoyos and Sarafidis (2006) warn that panel data may suffer from cross-sectional dependence:

> panel-data models are likely to exhibit substantial cross-sectional dependence in the errors, which may arise because of the presence of common shocks and unobserved components that ultimately become part of the error term, spatial dependence, and idiosyncratic pairwise dependence in the disturbances with no particular pattern of common components or spatial dependence. (p. 482)

Pesaran's test of cross-sectional independence indicates that cross-sectional dependence is present. This is likely due to the fact that the neighbourhoods are at a close proximity from each other and are highly economically integrated. As a result, there is a strong interdependency between neighbourhoods.

In order to remedy these issues, Driscoll and Kraay standard errors are used. These standard errors are robust to heteroskedasticity, autocorrelation and cross-sectional dependence.[9] The results of this correction are presented in Column (4) of Table 3. They indicate that the change in property crime in the current time period, the change in violent crime in the previous time period (t-1) and the change in violent crime in the t-4 period all have a statistically significant, positive impact on housing prices. At the same time, the change in violent crime in the t-3 period has a statistically significant, negative impact on housing prices, as expected.

[9] For a full description of Driscoll and Kraay standard errors as used in this study, see Hoechle (2007).

4-4. Fixed effects

One more correction is applied to specification (III). In order to control for unobserved differences between the regions, a fixed effects regression is used. While the MLS Benchmark Price contains a number of control variables, some differences between neighbourhoods likely remain unaccounted for. Data limitations are one of the factors that make it impossible to control for all differences between neighbourhoods.[10]

Additionally, there are likely to be unobserved differences between the years in this study that are difficult to measure (e.g. policy changes). To handle this, year dummies are included the model. Specification (IV) presents the fixed-effects regression:

$$\Delta \boldsymbol{BP}_{it} = \boldsymbol{\alpha}_i + \boldsymbol{\gamma}_t + \sum_{j=0}^{4} \boldsymbol{\beta}_j \Delta \boldsymbol{C}^{V}_{i,t-j} + \sum_{j=0}^{4} \boldsymbol{\delta}_j \Delta \boldsymbol{C}^{P}_{i,t-j} + \boldsymbol{\varepsilon}_{it} \tag{IV}$$

Where $\boldsymbol{\alpha}_\mathbf{i}$ represents regional fixed effects and $\boldsymbol{\gamma}_\mathbf{t}$ represents year dummies.

For both cross-sectional fixed effects and time fixed-effects models, a Hausman test indicates that the efficient random effects estimators were different than the consistent fixed-effects estimators, and so applying a fixed-effects model is appropriate.

Specification (IV) is the final model in this study and its results are displayed in Column (5) of Table 3. This model explains 66.36% of the variation in housing prices – much higher than any of the other specifications. The change in violent crime in the current time period and the change in property time in both the current and previous time period have a positive impact on housing prices. The change in property crime in the t-3 time period has a negative impact on housing prices. Despite the improved R^2, the results

[10] Many neighbourhood-specific control variables are available for Census years (2006 and 2011). However, because there is no equivalent data for non-Census years, these variables cannot be included in the dataset.

from this model cannot be interpreted with confidence due to the very likely presence of endogeneity within the model, as discussed in the following sections.

4-5. Finding an appropriate Instrumental Variable (IV)

The fact that crime is endogenous in the crime-housing price model is well documented in the literature (Ihlanfeldt and Mayock, 2010). Various attempts have been made by economists to find a suitable IV to deal with the endogeneity problem (Rizzo, 1979; Naroff et al, 1980; Burnell, 1988; Buck, Hakim and Spiegel et al., 1993; Gibbons, 2004; Tita et al., 2006; Ihlanfeldt and Mayock; Ceccato and Wilmhemsson, 2011; Pope and Pope, 2012; Buoanno et al., 2013; Massena et al., 2013). Finding an appropriate IV is no easy task, for it is necessary to also validate the instrument in a convincing matter. Additionally, while an ideal instrument may exist in theory, one is limited by the available data. The fact that this study targets a city in Canada, as opposed to a more data-rich country such as the U.S., makes this point particularly important. To further complicate this matter, the small geographical level that is used in this study results in there being even less data being available, as neighbourhood-level data is much scarcer than data at the city, provincial or national level. It is therefore extremely challenging to find an appropriate IV, and doing so is beyond the scope of this paper.

It is, however, worthwhile to note that Pope and Pope (2012) employ a promising method. Their approach is to "execute a nearest-neighbor matching algorithm that identifies for each [neighborhood], a [neighbourhood] from a different [Metropolitan Statistical Area] that is the closest match based on … total crime rates" (p. 182). This new area is located elsewhere in the country and serves as an instrument.[11]

Selecting an appropriate matching area to apply this method is also outside the scope of this study. However, further studies should certainly consider Toronto as a potential matching area. It is the second hottest real estate market in the country (see Figure 1) and neighbourhood-level MLS Benchmark Prices are published monthly by the Toronto Real Estate Association (TREA) for 66 neighbourhoods. Crime data is also available from the Toronto Police at the disaggregated level of 17 divisions.[12] The boundaries could be redefined using a similar GIS-method that was applied in this study.

4-6. Identifying the direction of the bias

As this paper does not handle the issue of the endogeneity of crime, the results presented in Table 3 are not instrumented and likely biased. While correcting endogeneity is beyond the scope of this paper, an attempt is made here to identify the expected *direction* of the bias. Ihlanfeldt and Mayock (2010) pinpoint five mechanisms through which crime is endogenous (p. 310). This section outlines their findings and discusses which of these mechanisms are most likely to apply within the context of this study.

The first three mechanisms result in a positive bias of the estimators. Firstly, criminals tend to be attracted to neighbourhoods with more expensive homes as there is a higher potential payoff. This would tend to affect the property crime variables, and it would help explain why two of the three statistically significant, positive coefficients in

[11] For a more complete description of this methodology, see Pope and Pope (2012). For a more formal discussion on this empirical methodology on the method of matching estimators, see Abadie, Drukker, Herr, and Imbens (2004).
[12] See the annual Statistical Reports published on the Toronto Police Service's website, which include (1) the estimated population for each division each year (2) the area of each division and (3) a breakdown of the number of crimes in each division into 15 different types of crime.

specification (IV) relate to property crimes. There is likely no greater payoff in committing a violent crime in a more affluent neighbourhood relative to a poorer one, so this mechanism is not expected to impact the violent crime variables.

Secondly, it is well documented that reporting rates are higher in more prosperous neighbourhoods. Since the limitations of police-reported data are inherently part of the model used in this study, it seems plausible that this would affect both of the crime variables. In fact, Pope and Pope (2012) find that their instrumented coefficients are more negative than their OLS coefficients and attribute this difference to "measurement errors in the crime data" (p. 186).

Thirdly, certain dwelling characteristics, such as large windows or a secluded backyard, that make a property more attractive can also make it an easier target for crime. In other words, these characteristics impact both the dependent variable (housing price, by increasing the value of the house) and independent variables (crimes, by making the property more attractive for criminals) but are difficult to observe and include in the model. That being said, the fact that the MLS Benchmark price has such characteristics ingrained in its calculation may complicate this mechanism in the context of this study, though exactly how is unclear.

The other two mechanisms lead to a negative bias of the estimators. One mechanism is that self-protection is expected to be greater in more affluent neighbourhoods. Individuals in wealthier neighbourhoods are more likely (and able) to invest in self-protection measures, such as a state-of-the-art alarm system, that will deter crimes. It seems reasonable to infer that this will impact both crime variables, though it will likely impact property crimes more. While superior self-protection may provide some level of protection from crimes involving intruding in one's home, it will not decrease one's chances of being a victim outside the home (as may be the case with assaults).

The other negative mechanism is due to the fact that lower-income individuals tend to reside in neighbourhoods with cheaper houses and that "income and propensity to commit crime are inversely related." Moreover, many criminals tend to commit crimes within their own neighbourhoods, which in this case are the ones with lower housing prices. This self-selection results in a higher number of crimes in neighbourhoods with lower property values. Figure 2 plots the MLS Benchmark price of all 22 neighbourhoods against the median income of that neighbourhood in 2005. There is a clear positive relationship, which suggests that this mechanism is quite present in Vancouver.

Source: Statistics Canada (2006) and Real Estate Board of Greater Vancouver (2015)

The overall impact of the endogeneity of crime on the results depends on which of the mechanisms described above dominates. It is therefore difficult to predict the direction of the bias. However, some of the previous studies that include both OLS and instrumented coefficients have found the IV-treated estimates to be *more negative* than the OLS ones, which suggests that the effects that lead to a positive bias tend to dominate (Ihlanfeldt and Mayock, 2010; Ceccato and Wilmhemsson, 2011; Pope and Pope, 2012).

4-7. An alternative way of grouping the crime variables: Factor Analysis

The method of grouping nine crime variables into the two broader categories of violent and property crime (as shown in Table 3) is consistent with previous studies. However, there is an alternative way of reducing the number of crime variables that does not appear to have been done in the literature on this topic: the method of factor analysis. As various types of crimes are highly collinear, having nine crime variables is impractical. Adding the four lags that were used in specification (IV) further increases the number of independent variables to 40. The data reduction power of the factor analysis method therefore seems highly practical in this case. Unfortunately, until the endogeneity issue is resolved, the results from the factor analysis are also unreliable. Nonetheless, the application of a factor analysis to this study is explored.

The corrections in the previous sections relating to nonstationary variables, lags, autocorrelation, heteroskedasticity, cross-sectional dependence and fixed effects are also applied in the factor analysis context. Thus, the final factor analysis model is presented by specification (V):

$$\Delta \boldsymbol{BP_{it}} = \boldsymbol{\alpha_i} + \boldsymbol{\gamma_t} + \sum_{j=0}^{4} \boldsymbol{\beta_j} \Delta \boldsymbol{F_{i,t-j}} + \boldsymbol{\varepsilon_{it}} \tag{V}$$

where F is the remaining factor with an eigenvalue greater than 1. It should be noted that only one factor met the Kaiser criterion of keeping only factors that have an eigenvalue equal to or greater than 1. Table 4 shows the coefficients obtained from running the regression of specification (V). The presence of endogeneity likely explains the positive coefficient for the change in the Factor in the current time period. However, the fact that the coefficients for the change in the crime factors in the t-3 and t-4 time periods are statistically significant and negative is promising.

TABLE 4: OLS Estimates for Factor Analysis ($) Dependent Variable: ΔMLS Benchmark Price	
Δ Factor (t)	197,671
	(2.19)
Δ Factor (t-1)	89,759
	(1.10)
Δ Factor (t-2)	-43,594
	(-0.62)
Δ Factor (t-3)	-266,100
	(-7.56)
Δ Factor (t-4)	-118195.9
	(-5.23)
Driscoll-Kraay SEs used?	Yes
Year and Region fixed effects?	Yes
R-squared	0.6552
F-statistic	602.89

The method of factor analysis is not without its shortcomings. The grouping of the nine crime variables into a single factor means that isolating the impact of individual crimes (or at least of violent and property crimes) on housing prices is not easy. This makes it difficult to offer policy recommendations regarding which type of crime should be most targeted by law enforcement.

5. CONCLUDING REMARKS

This study represents the first time that crime data from the VPD and housing price data from the REBGV have been made comparable and combined into a unique panel dataset using GIS software. Despite resolving many of the econometric problems, the presence of endogeneity makes it difficult to come up with any measured conclusion.

Nonetheless, this study provides important groundwork for using the crime-housing price relationship to measure the value of crime prevention for the City of Vancouver.

While dealing with the issue of endogeneity with violent and property crime as the independent variables can provide a good estimate of economic cost of crime for the City of Vancouver, this approach has limits on policy implications. In order to implement effective crime prevention measures, it is often necessary to have a specific goal in mind. In other words, attempting to prevent the "property crimes" may be more difficult than attempting to prevent, say, "breaking and entering," as the latter provides policy-makers with a focused target. Thus, once an appropriate instrumental variable is found, it would be interesting to apply it to a model that isolates the impacts of the more specific types of crime. This will allow policy-makers and law enforcement agencies to prioritize preventing the types of crime that are the most costly to society.

That being said, even it is not immediately possible to break down the costs of crime into specific offences, the results can still have important implications. Property crimes may be easier to prevent than violent crimes, and the private and public sector can work towards achieving this goal together. For instance, a tax credit could be offered for households that purchase a good that contributes to their self-protection, such as an alarm system. In order to determine the amount of this tax credit, the coefficients obtained in a study of this nature could provide guidance, as it would measure the economic value of preventing property crimes. Of course, the amount of this tax credit would also be based on a number of other factors, amongst which the effectiveness of the specific crime-preventing product. Determining which crime prevention measures are most effective for the City of Vancouver is a task that is left to criminologists and other experts in the field.

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7. APPENDICES

7-1. Appendix A – Control variables used in the MLS Benchmark Price calculation

Parking access
Tangible or intangible benefits that increase attractiveness or value
Property is serviced by municipal aqueduct
Property is near a shopping mall
Method of heating
Source of energy for heating
Flooring type
Foundation material
Property is equipped with a fireplace
Garage has two parking spaces
Property is equipped with geothermal energy
Property building is semi-detached
Land size in square feet
Property siding material
Property has undergone major renovations
Only a part of Property is renovated
Property is equipped with a roughed-in fireplace
Basement is finished
Parking lot has a shelter or carport
Garage is located below main floor
Roofing material
Property has a crawlspace
Property has a view of water
Property has a panoramic view
Number of bathrooms
Number of half-bathrooms
Property is in proximity to an elementary school or a high school
Hydro line neighbours Property lot
Property has a view of power lines
Property is in proximity to a train station
Property is in proximity to a church
Property is in proximity to an airport
Property is in proximity to a boulevard
Property is adjacent to a boulevard
Property in proximity to a sports center
Property is in proximity to a railroad
Property is in proximity to a hospital
Property is in proximity to a police station
Property is in proximity to a prison
Property is in proximity to a golf course
Property is in proximity to a park

Property is adjacent to a park
Basement living area in square feet
Time dummy variable month and year
Number of rooms above basement level
Main living area in square feet
Number of rooms at basement level
Age of property

Source: *Multiple Listing Service, 2014, pp. 18-19*

7-2. Appendix B – Neighbourhood weights

VPD Nhood (i) (Map 1)	REBGV Nhood (k) (Map 2)	Weight (w)
Arbutus-Ridge	Arbutus	38.79%
Arbutus-Ridge	Quilchena	36.06%
Arbutus-Ridge	MacKenzie Heights	12.93%
Arbutus-Ridge	Kerrisdale	12.23%
Downtown	Downtown West	46.01%
Downtown	Yaletown	22.25%
Downtown	Coal Harbour	17.82%
Downtown	Downtown East	9.53%
Downtown	Mount Pleasant East	4.38%
Dunbar-Southlands	Dunbar	44.57%
Dunbar-Southlands	Southlands	21.82%
Dunbar-Southlands	University	20.46%
Dunbar-Southlands	Mackenzie Heights	8.87%
Dunbar-Southlands	Kerrisdale	2.98%
Dunbar-Southlands	Arbutus	1.31%
Fairview	Fairview	67.93%
Fairview	False Creek	32.07%
Grandview-Woodland	Grandview	54.24%
Grandview-Woodland	Hastings	45.76%
Hastings-Sunrise	Renfrew	62.77%
Hastings-Sunrise	Hastings East	37.23%
Kensington-Cedar Cottage	Knight	30.29%
Kensington-Cedar Cottage	Victoria	29.01%
Kensington-Cedar Cottage	Fraser	20.35%
Kensington-Cedar Cottage	Grandview	20.35%
Kerrisdale	Southlands	35.02%
Kerrisdale	Kerrisdale	29.44%
Kerrisdale	South Granville	18.88%
Kerrisdale	S.W. Marine	16.67%
Killarney	Killarney	40.56%
Killarney	Champlain Heights	37.52%
Killarney	Fraserview	21.92%
Kitsilano	Kitsilano	99.19%
Kitsilano	Point Grey	0.81%
Marpole	Marpole	74.62%
Marpole	South Granville	12.93%
Marpole	South Cambie	6.88%

Marpole	S.W. Marine	5.58%
Mount Pleasant	Mount Pleasant East	65.97%
Mount Pleasant	Mount Pleasant West	19.63%
Mount Pleasant	False Creek	14.40%
Oakridge	South Granville	34.72%
Oakridge	Oakridge	33.25%
Oakridge	South Cambie	32.03%
Renfrew-Collingwood	Renfrew Heights	43.16%
Renfrew-Collingwood	Collingwood	42.81%
Renfrew-Collingwood	Renfrew	14.03%
Riley Park	Cambie	42.25%
Riley Park	Main	32.13%
Riley Park	Fraser	25.62%
Shaughnessy	Shaughnessy	90.31%
Shaughnessy	Quilchena	6.97%
Shaughnessy	Kerrisdale	2.73%
South Cambie	Cambie	100.00%
Strathcona	Mount Pleasant East	70.40%
Strathcona	Hastings	29.60%
Sunset	South Vancouver	72.55%
Sunset	Fraser	13.56%
Sunset	Main	8.06%
Sunset	Knight	5.83%
Victoria-Fraserview	Fraserview	47.92%
Victoria-Fraserview	Killarney	41.77%
Victoria-Fraserview	Knight	10.31%
West End	West End	100.00%
West Point Grey	Point Grey	100.00%