Estimating the Contemporary Price Elasticity of Cigarettes in Canada

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Contents

1 Introduction

The taxation of cigarettes is a common tool for governments to generate revenue and reduce the consumption of tobacco products to improve the health of citizens. The extent to which cigarettes are taxed is a careful balancing act where the government aims to deter people from smoking by increasing prices while not making the taxes so excessive as to incentivize smuggling. A central determinant of what the optimal level of taxation should be is the price elasticity of demand for cigarettes. The more elastic demand is, the more raising taxes will reduce smoking. In this paper we build on Gruber et al.'s 2003 paper "Estimating price elasticities when there is smuggling: the sensitivity of smoking to price in Canada" using a similar model for estimating the price elasticity of cigarettes updated with recent data. We estimate the price elasticity of demand for legal cigarettes in the period 2003-2017 and investigate two problems with this estimation, including cigarette smuggling and price changes in electronic cigarettes, a substitute to conventional cigarettes. These phenomena present empirical challenges as an increase in taxes on tobacco may reduce smoking by less than estimated if individuals are do not cease or reduce their smoking but merely transition to smuggled cigarettes or e-cigarettes. Thus without controlling for both of these products, an estimate of cigarette price elasticity could be upwardly biased and in actuality the tobacco tax would be less effective at reducing smoking than estimated. To deal with this, we remove from our model provinces and years within our 2003-2017 range where smuggling is significant. With regards to e-cigarettes, we find that they likely do not have a biasing effect on our elasticity estimate. This is because we did not find that e-cigarette substitution by province is correlated with tax increases by province once we include time fixed effects. Instead e-cigarette substitution is likely driven by health considerations and societal trends more so than the price of cigarettes.

The second section of this paper provides some brief contextualizing data and a review of the literature regarding the prevalence of smuggling, estimates of the price elasticity of cigarettes by other authors, and the increase in the prevalence of e-cigarettes. The third section describes our model for classifying provinces where smuggling is significant. We find that most of the smuggling occured in Ontario after 2006 and briefly in Quebec, New Brunswick and Nova Scotia. The fourth section describes our data and empirical strategy for our legal cigarette sales model for the range 2003 – 2017. The legal cigarette sales model uses a difference-in-differences regression of legal sales on the price of cigarettes, instrumented by the taxes on cigarettes, and includes a host of economic and demographic controls. This regression estimates the price elasticity of cigarettes to be -0.73. We run our legal sales regression again, this time excluding the significant smuggling provinces and years. The new price elasticity estimate changes to -0.41, closer to what Gruber et al. (2003) estimated (-0.47). The fifth section deals with robustness tests for our model. In the sixth section we examine the self-reported reasons for why individuals smoke e-cigarettes to see if they are substituting due to increases in the price of cigarettes. We also run a difference-in-differences regression to see if there is a correlation between increases in cigarette prices and the adoption of e-cigarettes, using limited macrodata we do not find one. In the seventh and final section we propose some policy recommendations based on our findings.

2 Background

2.1 Trends in Smoking and Cigarette Prices

Using various data from the Canadian Community Health Survey and Statistics Canada we have produced two charts displaying trends in smoking and cigarette prices to provide additional background on the topic and contextualize our findings:[1]

[1] Note: the survey data was merged for the years 2007 and 2008, as well as 2015 and 2016. "Occasionally" was not defined and relies on how participants self-identify.

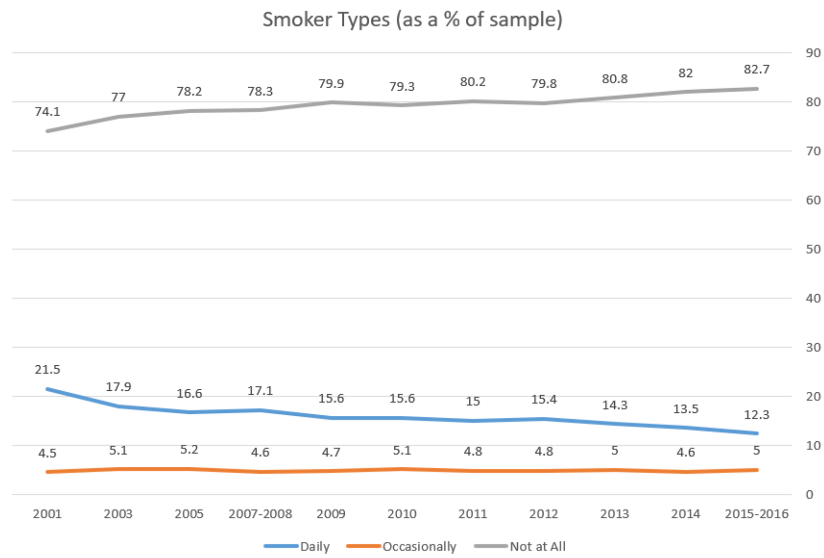

Figure 1: Based on data from the Canadian Community Health Survey.

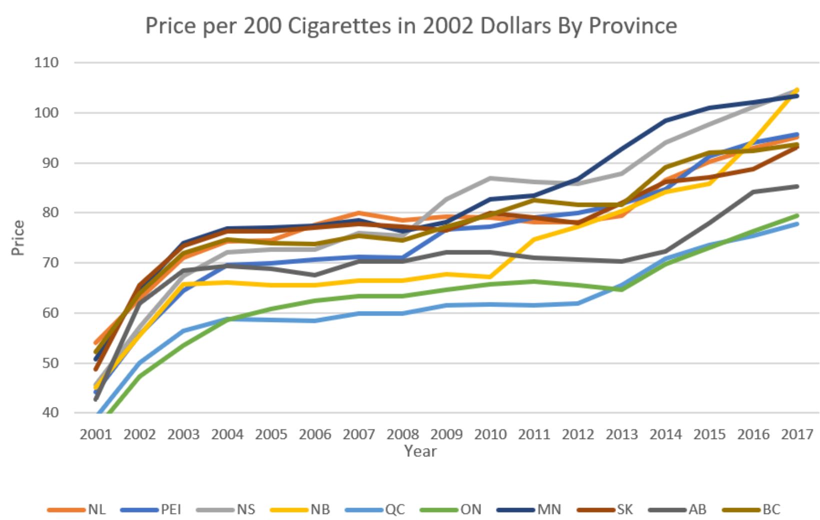

Figure 2: Prices Collected from Stats Canada and Standardized using CPI values

In figure 1, we observe a steady decrease in the proportion of daily smokers, while the proportion of occasional smokers remain steady. Figure 2 shows the price of cigarettes increasing at varying speeds across provinces. Additionally, for many provinces, the rate of change in prices picks up around 2013.

Descriptive statistics are reported in table 1. The mean price for cigarettes is $76.77, of which taxes make up $52.96. Per capita cigarette consumption was 8.7 cartons, or approximately 1745 cigarettes. An overview of the variance in tax levels by province over our time period is also reported below in figure 9 in section 6.

Variables	N	mean	sd	min	max
Price (2002 CAD)	135	76.77	11.08	53.56	104.6
Carton Sales	135	1.691e+07	1.776e+07	1.775e+06	7.898e+07
RGDP Per Capita (2002 CAD)	135	32,603	2,616	26,867	38,054
Total Weighted Tax	135	52.96	9.301	35.22	74.47
Population ≥ 15	135	3.121e+06	3.383e+06	432,006	1.182e+07
Cartons Per Capita (≥ 15 years)	135	5.809	1.045	3.388	8.188

Table 1: Descriptive Statistics for 2003 − 2017

2.2 Smuggling and Biasing the Price Elasticity of Legal Cigarettes

One of the primary problems with estimating the price elasticity of a good (and particularly addictive goods) are the illegal responses to price increases. Ideally, an increase in taxes on cigarettes will cause consumers to either substitute away from cigarettes or to quit consumption of cigarettes altogether. Both of these effects are measurable when looking at either data on smoking propensity or expenditures on legal cigarettes and the relevant substitutes. The problem arises in the case of illegal responses to price increases, such as cigarette smuggling. By looking at the data, a consumer who purchases smuggled cigarettes is virtually indistinguishable from a consumer who quits smoking altogether; in both cases, a reduction in the legal sales of cigarettes will be observed but in the first case, an individual may be consuming the same number of cigarettes as before, and thus aggregate cigarette consumption does not fall despite legal sales falling. As a result, there is a risk for estimates of the price elasticity (absolute value) of cigarettes to be biased upwards; an increase in price will appear to have a greater effect on the responding decrease in cigarette consumption than is actually the case. Mathematically, we can see this as follows: legal consumption of cigarettes is given by

$$Legal = Smoke - Smuggled \tag{1}$$

where $Smoke$ is the total number of cigarettes consumed, $Legal$ is the total number of legal cigarettes consumed, and $Smuggle$ is the total number of smuggled cigarettes consumed. The legal sales of cigarettes are equal to the aggregate consumption of cigarettes when $Smuggling = 0$. Our aim is to determine the elasticity of Smoke, but typically, only data on legal sales are directly observable.[2] Thus, we calculate the elasticity of $Legal$:

[2] Although data on consumption of cigarettes from the consumer's side may be available providing an estimate of aggregate cigarette consumption, there is a known problem in the economic literature of under reporting illegal consumption in consumer surveys, and this under reporting will have the same upwards biasing effect as in the case of legal sales of cigarettes.

$$\frac{\partial Legal}{\partial Price}\left(\frac{Price}{Legal}\right) = \left[\frac{\partial Legal}{\partial Smoke}\left(\frac{\partial Smoke}{\partial Price}\right) + \frac{\partial Legal}{\partial Smuggle}\left(\frac{\partial Smuggle}{\partial Price}\right)\right]\left(\frac{Price}{Legal}\right) \tag{2}$$

Simplifying by noting that $\frac{\partial Legal}{\partial Smoke} = 1$ and $\frac{\partial Legal}{\partial Smuggle} = -1$ and cancelling $\frac{Price}{Legal}$ for simplicity, we arrive at

$$\frac{\partial Legal}{\partial Price} = \frac{\partial Smoke}{\partial Price} - \frac{\partial Smuggle}{\partial Price} \tag{3}$$

The first term on the right hand side will be negative (since, all things being equal, as price of cigarettes increases, consumption of cigarettes decreases) and the second term on the right hand side will be positive (since, all things being equal, as the price of legal cigarettes increases, more consumers exit the legal market by substituting for the cheaper smuggled cigarettes). Thus, the absolute value of the elasticity of demand of legal cigarettes will be biased upwards; the effects of an increase in price on the reduction in the number of legal cigarettes consumed will be overstated. In order to successfully estimate the price elasticity of demand for cigarettes, smuggling must be accounted for in order to remove bias in the estimate of elasticity.

2.3 Review of Gruber et al. (2003)

In their paper, Gruber et al. (2003) investigate the relationship between tobacco taxes and smoking behaviour, particularly examining the problem of cigarette smuggling in relation to estimating the price elasticity of legal cigarettes. This problem exists in the Canadian context and was especially a problem in the period analyzed by Gruber et al. (2003): 1981 to 1999. As the authors note, in the face of rising taxes during the early 1990s, cigarette smuggling increased dramatically. The primary mechanism through which cigarette smuggling occurred was via legal export to the United States, and then illegal re-import back into Canada, typically through First Nations Reserves which straddle the US/Canadian border. As a result, estimating the sales of smuggled cigarettes in Canada during the early 1990s usually involves tracking increases in cigarette exports relative to their levels prior to the 1990s. Measuring exports of cigarettes from Canada as a proportion of legal cigarette sales within Canada, exports sharply rose from a pre-1990 average of slightly less than 1.5% of legal sales to approximately 50% of legal sales in 1993, returning to around 2% of legal sales in 1994. This trend in cigarette exports corresponds to the sharp increases and declines in federal and provincial taxes on cigarettes in the early 1990s and 1994 respectively, as well as the fall of legal sales of cigarettes during the period of high exports, strongly suggesting a period of large-scale smuggling according to Gruber et al. (2003). The data also shows that cigarette smuggling was more concentrated in five eastern provinces (Ontario, Quebec, New Brunswick, Nova Scotia, and Prince Edward Island), particularly from 1990-1994, whereas the western provinces (British Columbia, Alberta, Saskatchewan, and Manitoba) and Newfoundland had a less severe smuggling problem.

The main goal of Gruber et al. (2003) is to estimate cigarette demand models for Canada while correcting for the smuggling problem. They perform this correction in two ways. First, they used legal sales data and excluded the regions and years where smuggling was the worst: the eastern provinces during 1990-1994. Then, they created a second model using microdata on consumer cigarette expenditure to capture both legal and illegal cigarette consumption. For both the legal sales and the consumer expenditure models, Gruber et al. (2003) use a difference-in-differences estimation, regressing legal sales and consumer expenditure (both in USD) on the price of cigarettes and several controls such as province fixed effects, year fixed effects, a linear time trend, and demographic and business cycle controls. Because prices may be endogenous since both price and quantity are jointly determined by the interaction between demand and supply as tobacco companies may adjust prices in response to shocks to tastes for smoking at the province level, there is likely simultaneity bias. Therefore, they use changes in federal and provincial taxes on cigarettes as a source of exogenous variation in cigarette prices, using these taxes as instruments for price resolves the simultaneity problem.

When the worst smuggling years and provinces are excluded, the elasticity estimated by the legal sales model and the one based on consumption become similar in the range of -0.45 to -0.47. This is consistent with expectations based on the US' elasticity which is less than -0.5 in absolute value (Gruber et al., 2003). Without the smuggling provinces excluded, the legal sales regression estimates elasticity to be -0.72. According to Gruber et al. (2003), this is most likely because smuggling is biasing the estimate upwards as people do not actually consume so many fewer cigarettes, but just switch to illegal cigarettes. To then examine the tax's effect on smoking cessation, the authors find the effect of price changes on a dummy variable for whether a person has smoked that year or not. The value on the coefficient for change in price is very low, while it is much higher when the dependent variable is instead the total amount spent on cigarettes that year. This suggests that few people are quitting smoking due to changes in prices, rather the effect of the price change is mostly felt as a reduction in individual consumption (Gruber et al., 2003).

2.4 The Literature on Cigarette Smuggling in Canada

Given the empirical problem posed by cigarette smuggling to the estimation of the price elasticity of legal cigarettes, it is crucial to examine the current trends surrounding cigarette smuggling in Canada if the current price elasticity of legal cigarettes is to be estimated. Our strategy for accounting for smuggling is adopted from Gruber et al. (2003): we first identify the provinces in which there is substantial degree of cigarette smuggling, and then we run our model excluding those provinces. Assuming that we have excluded the correct provinces during the correct time periods, the resulting estimate of the elasticity of cigarettes will be unbiased.

In Canada, contraband cigarettes are typically sold on First Nations Reserves or through criminal networks operating off-reserves. In either case, federal and provincial taxes are not collected on these cigarettes, and since taxes can contribute up to 70% of the price of a carton of cigarettes depending upon the province in which the carton is sold, these smuggled cigarettes can sell at a price substantially lower than non-smuggled cigarettes. For example, Luk et al. (2007) find that illegal cigarettes in Ontario are sold at less than a third of the price of legal, taxed cigarettes. A very large proportion of these smuggled cigarettes are believed to originate either from the Akwesasne/Saint

Regis Reservations, which border Ontario and Quebec and the state of New York, or from the Six Nations Reserve in southwestern Ontario (Haché T, 2009). As a result, the majority of smuggled cigarettes are distributed to the eastern provinces, with particular offenders including Ontario, Quebec, Nova Scotia, and New Brunswick.

Unfortunately, unlike in the time period that Gruber et al. (2003) address (1980 – 1996) where there is general consensus about which provinces had a significant degree of smuggling during which years, there is a clear division in the 2003 – 2017 range between years where there is consensus over which provinces have a substantial degree of smuggling and years where there is considerable disagreement. For instance, there is near consensus that across Canada, cigarette smuggling appears to occur to a fairly minimal degree from 1996 until around 2005, after which Ontario, Quebec, and Nova Scotia experience substantial smuggling from 2006 – 2007 (Ontario and Quebec) and 2006 – 2008 (Nova Scotia), as well as 2014 – 2017 for both Ontario and New Brunswick. The Ontario Convenience Stores Association (OCSA), for instance, estimate that nearly 37.2% of cigarettes consumed in Ontario are illegal, an estimate which they arrive at by collecting and analyzing 18,816 cigarette butts found in 135 public smoking areas across Ontario in 2017 (OCSA, 2017). Similar studies conducted by the OCSA in 2015 and 2016 show an increasing trend, with 24.6% and 32.8% respectively of all cigarettes consumed in Ontario being illegal. The Ontario Tobacco Research Unit also confirms this result. Similar to Guindon et al. (2016) (see page 8), they estimate the trends in cigarette smuggling in Ontario by examining the number of smokers who purchase cigarettes from a First Nations Reserve, noting an increase in the number of smokers from 12 million in 2015 to 18 million in 2017 (OTRU, 2018).

Unfortunately, given their smaller size and the more recent time periods involved, there is a lack of peer reviewed studies concerning cigarette smuggling in both Nova Scotia and New Brunswick. Nevertheless, these provinces both have had historical problems with cigarette smuggling, particularly during 1990 – 1995, and cigarette seizure statistics from the RCMP generally confirm trends in cigarette smuggling in Nova Scotia from 2006 – 2008 and 2014 – 2017 in New Brunswick. In addition, for Nova Scotia, Stoklosa (2018) uses data from the Provincial Tax Commission to track the number of illegal cigarettes seized in Nova Scotia, and argues that smuggling has decreased from high levels in 2006 to 2008 to much lower ones by 2009 until 2017. Service Nova Scotia agrees with these estimates, predicting that the amount of illegal tobacco in the province has decreased from 30% of all tobacco consumed in 2006/2007 to less than 10% in 2017 (Service Nova Scotia, 2017).

Finally, for New Brunswick, a study conducted by the Atlantic Convenience Stores Association (ACSA) in partnership with Montreal research firm NIRIC collected cigarette butts from 27 sites across the province in 2015, with 24% of the cigarettes collected in their sample being determined to be smuggled cigarettes, with previous studies conducted by ACSA showing an increasing trend of smuggled cigarette use since 2014 (Pre-Budget Submission, 2016). These results are confirmed by several RCMP reports detailing the seizure statistics of illegal cigarettes from 2014 to 2017, that show the illegal cigarette market has grown substantially (CEU, 2017).

In contrast to these periods of general consensus, there is debate about the nature of smuggling in both Ontario and Quebec from 2007 – 2014. Guindon et al. (2017) examine data from 1999 to 2013 with a particular focus on Ontario and Quebec in order to determine the more recent trends in cigarette smuggling. Their paper employs two approaches. First, they contrast estimates of legal sales of cigarettes (as reported by manufacturers to Health Canada) with consumption estimates based on survey data from two large national surveys, the Canadian Community Health Survey (CCHS) and the Canadian Tobacco Use Monitoring Survey (CTUMS). Second, Guindon et al. (2017) examine micro-data concerning smokers' purchasing and use behaviours to estimate the number of purchased illegal or smuggled cigarettes. Through these two approaches, Guindon et al. (2017) construct 95% confidence intervals for each year from 1999 until 2013 to estimate the ratio of self-reported cigarette consumption to legal cigarette sales in Ontario, Quebec, and Canada more broadly.[3] Similar trends emerge among these confidence intervals among Ontario, Quebec, and Canada, showing a clear upwards trend in illegal cigarette consumption, followed by a decreasing trend from 2008 and onwards, with substantial smuggling in Ontario and Quebec occurring from 2006 – 2011 and 2006 – 2010 respectively. In addition, the authors examine the percentage of consumers who purchase cigarettes on a First Nations Reserve (or in general any cigarettes which may have been smuggled in the past 6 months). The trend that emerges matches the trends of the 95% confidence intervals over time, with the peak occurring in 2008 with approximately 30% of Ontario and 22% of Quebec smokers report having purchased cigarettes on a First Nations Reserve or having purchased cigarettes which may have been smuggled in the past 6 months.

In another study, Sen (2017) estimates the degree of smuggling in Ontario and Quebec from 2006 – 2014 by running a regression model to predict legal cigarette sales per capita of population aged 15 and over. The model is constructed using data for years and provinces where it is generally agreed that smuggling does not occur to a significant degree, including Alberta, Manitoba and Saskatchewan for 1996 — 2014 and Ontario and Quebec for 1996 – 2005. The estimation results from this model for years when smuggling was not at significant levels yields estimates which are used by Sen to predict the sales of legal cigarettes that should have occurred for years in which the levels of smuggled cigarettes may have been high; namely Ontario and Quebec from 2006 – 2014. By subtracting the actual legal sales of cigarettes per capita for these years and in these provinces from the estimates of this regression model, the results yield a prediction of the amount of smuggled cigarettes in Ontario and Quebec from 2006 — 2017. As with Guindon et al. (2016), Sen (2017) predicts that Ontario and Quebec have periods of substantial smuggling from 2006 – 2007. However, in contrast to Guindon et al. (2016), Sen (2017) predicts that Ontario and Quebec have periods of substantial smuggling from 2007 - 2014 and 2007 – 2009 respectively, with an increasing trend for smuggling in Ontario in contrast with Guindon et al.'s (2016) predicted decreasing trend.

As a third and final comparison, Zhang et al. (2015) similarly examine this time period for Ontario and Quebec. Looking at both consumption surveys such as the CTUMS (as with Guindon

[3] A rising ratio would indicate either an increasing share of illegal cigarette sales or else a decrease in the under-reporting of self-reported cigarette consumption.

et al. (2016)) as well as seizures of illegal cigarettes by the RCMP. Once again, Zhang et al. (2015) agree with Guindon et al. (2016) and Sen (2017) in predicting at Ontario and Quebec have a substantial degree of smuggling from 2006 – 2007, but disagree for years after 2007, predicting periods of substantial smuggling for Ontario and Quebec for 2006 – 2012 and 2006 – 2010 respectively, with a slightly decreasing trend for Ontario (Zhang, et al., 2015).

The following two tables provide a general summary of findings for this section.

Province	Ontario	Quebec	Nova Scotia	New Brunswick
Years	2006 – 2007 2014 – 2017	2006 – 2007	2006 – 2008	2015 – 2017

Table 2: Periods of Substantial Smuggling (Consensus)

Authors	Anindya Sen (2017)	Guindon et al. (2016)	Zhang et al. (2015)
Ontario	2007 – 2014	2007 – 2011	2008 – 2012
Quebec	2007 – 2009	2007 – 2010	2006 – 2010
Trend	Increasing trend for Ontario	Decrease trend for Ontario	Slightly decrease trend for Ontario

Table 3: Differing Predictions of Years of Substantial Smuggling

Since our methodology of accounting for the upwards biasing of elasticity that cigarette smuggling causes is to exclude provinces that have substantial smuggling, the upshot of this section is that, if we are unable to identify the time periods where Ontario and Quebec experience substantial smuggling from 2007 until the present, we will be unable to derive an unbiased estimate of elasticity for cigarettes. In section 3, we develop a way of predicting the degree of smuggling in these provinces from 2007 until 2017, the results of which are used in section 4.4 to give an unbiased estimate of elasticity.

2.5 Price Elasticity of Cigarettes

Recent studies have expanded their analyses of own-price elasticities of demand for cigarettes by allowing for heterogeneous responses to changes in cigarette prices. Hansen et al. (2015) use a difference-in-differences approach to estimate the semi-elasticity of demand for cigarettes among youth in the United States. They use state and national-level observational data from the Youth Risk Behaviour Survey between 2007 and 2013. Their regression specification is largely similar to that employed by Gruber et al. (2003), however instead of instrumenting price with the tax rate, they put the excise tax rate of cigarettes in their model directly. Hansen et al. (2015) find that elasticities of demand for cigarettes have weakened over time. Between 1991 – 2005, an increase in excise tax on cigarettes of USD $1 is associated with a 3.0 percentage point decrease in smoking. When they expand their sample to 2013, the elasticity falls by 50%.

Tauras et al. (2016) employ a slightly more complex design. They use aggregate data at the state level during the period between 1991 and 2012 in the United States and employ a two-way fixed effects Generalized Linear Model to estimate a set of cigarette demand equations. They find that price elasticity monotonically increases with price and that price elasticity is considerably higher at higher prices than at lower prices. At a price of USD $2 per pack of cigarettes, they estimate that the average price elasticity of demand is -0.34. At a price of USD $10 per pack, they estimate the average price elasticity of demand is -1.70 (Tauras et al. 2016). This represents a significant increase over the price elasticity of demand of cigarettes at a lower price point.

Azagba and Sharaf (2011) employ a similar empirical strategy as Gruber et al. (2003) for estimating the price elasticity of demand for cigarettes in Canada. They use data from the National Population Health Survey for the period between 1998 and 2009 and employ a difference-in-differences approach, although they estimate elasticity using a probit regression instead of OLS. They find that the elasticity of demand for cigarettes in Canada is -0.227 for the entire population.

2.6 Overview of E-Cigarettes

An additional problem with estimating the price elasticity of legal cigarettes is the rising popularity of e-cigarettes, often among cigarette smokers. Shiplo et al. (2015) conducted a survey of e-cigarette use among 1095 Canadians, that confirmed this. According to their results, 18% of cigarette smokers aged 16 – 24 and 10% of smokers aged 25 years and older regularly used e-cigarettes. It is not just a matter of smokers picking up e-cigarettes in addition to smoking. E-cigarettes are often being adopted as a substitute to regular cigarettes, leading to a decrease in consumption of the latter. This gives rise to the issue of parsing out the effect of tobacco taxation on smoking from the confounding effect of e-cigarette prices. The goal of estimating the price elasticity of legal cigarettes is to determine the impact of a change in price on the consumption of cigarettes, all things being equal. If smokers consider e-cigarettes as a substitute for legal cigarettes, and more importantly the relative price of cigarettes is what drives this substitution (as opposed to health or social reasons), a decrease (or increase) in the price of e-cigarettes would result in a decrease (or increase) in the consumption of cigarettes among smokers. Thus, as with the problem of smuggling, the price of e-cigarettes can affect an estimate of the price elasticity of cigarettes. Though it should be noted that our difference-in-differences model will control for such a substitution trend if it is uniform across provinces, which we will investigate in later sections.

A study by Grace, et al. (2014) provides confirmation that e-cigarettes are considered among smokers as "partial substitutes" for legal cigarettes on the basis of their relative prices. Using a sample of New Zealand smokers, they find a cross-price elasticity for cigarettes and e-cigarettes to be 0.16 and statistically significant. A study by Huang et al. (2014) using store scanner data compiled by the Nielsen Company estimates the elasticity of e-cigarettes. Using controls for year, quarter, market, and store, they estimate the elasticity of both disposable and reusable e-cigarettes. But they found "no consistent relationships between cigarette tax/price and e-cigarette sales" with the sign flipping, and the coefficient losing or gaining significance in different variations of the model. Stoklosa et al. (2016) estimate very high cross-price elasticities, as high as 4.55. But they caution that this is the result of the comparatively smaller size of the e-cigarette market. For example, a 10% increase in the price of cigarettes, even if it causes only a slight substitution into e-cigarettes, because of the comparatively small market of the latter, will disproportionately increase the percent of e-cigarette sales. This phenomenon can easily play out in other studies and encourages adopting a very cautious interpretation of the meaningfulness of cross-price elasticity of these two goods as it says little regarding what proportion of conventional smokers will shift into e-cigarettes as the price of cigarettes goes up.

As is intuitively expected, the literature suggests that e-cigarettes are being used as substitutes for conventional cigarettes. But whether this is driven by their relative prices and to what extent is more unclear, with Huang et al. (2014) having failed to find a statistically significant relationship between cigarette tax/price and e-cigarette sales, and Grace et al. (2014) finding a small positive cross-price elasticity of 0.16. Lastly, even if the price of cigarettes is a significant factor in e-cigarette consumption, it will not necessarily bias our model if the increases in e-cigarette consumption and the increases in cigarette price by province are not correlated once we add year fixed effects, which we will examine in detail in section 6.

3 Classifying Smuggling Provinces

In table 3 of section 2.4, we note that there is considerable debate on the degree of smuggling that has occurred in Ontario and Quebec from 2007 — 2014. Since our methodology for estimating the elasticity of cigarettes requires that we successfully identify the provinces and years in which substantial smuggling occurs, we use machine learning techniques to classify the degree of smuggling in Ontario and Quebec from 2007 — 2014.

3.1 Data and Selecting Independent Variables

The data that we use to build and test our classifier consists of 234 observations, where each observation is a particular province (British Columbia, Alberta, Manitoba, Saskatchewan, Ontario, Quebec, Nova Scotia, or New Brunswick) at a particular year (1989 — 2017). Since our goal is to predict whether Ontario and Quebec have substantial cigarette smuggling from 2007 — 2014, these observations are not included in the 234 observations used to build and test our classifier. We save these 14 observations for the prediction stage and use only those data points for which there is no controversy with regards to smuggling status. The dependent variable that we use is a binary variable which is 1 if the observation is a province which does have a substantial degree of smuggling at a given year and 0 otherwise. In this case, we use only those provinces and years where there is consensus on the degree of smuggling in the province at a given year, as determined in section 2.4.

Having defined our dependent variable, we then select a set of independent variables where our selection criteria is based on economic theory and the variable's predictive power of both smoking propensity and illegal activities in general. Our independent variables (in addition to province dummies as well as a linear time trend) include the consumer price index (CPI) of cigarettes in each province, the proportion of individuals (15 years or older for all population measures) under the Low Income Cut Off (LICO) point in each province, the proportion of current smokers in each province, the number of cartons of cigarettes per capita of legal sales in each province, the unemployment rate in each province, the number of police officers per capita in each province, the number of criminal code offences per officer in each province, and finally, the RGDP per capita in 2012 CAD for each province.

The CPI of cigarettes per province (sourced from Statistics Canada) is our general measure of the changes in price of cigarettes, and we expect that higher cigarette prices are generally correlated with greater amounts of cigarette smuggling. The proportion of individuals under the LICO point (sourced from Statistics Canada) is our metric of the proportion of low-income individuals in each province which is typically correlated with smoking propensity (Widome, et al. 2015, Peretti-Watel et al. 2009). This supplements our use of the unemployment rate in each province and RGDP per capita as a measure of average income as well as a proxy for business cycles across provinces. We include both the number of cartons of cigarettes per capita of legal sales and the proportion of current smokers in each province (where a smoker is defined as an individual who reports that they are either a regular or occasional smoker), sourcing the former from Health Canada and the latter from consumer surveys including the CCHS and CTUMS. Comparing this expenditure and propensity data will help our classifier to detect decreases in legal sales that may be related to cigarette smuggling (for instance, if legal sales decrease per capita decrease at a much faster rate than smoking propensity, this may be an indication of an increase in cigarette smuggling). Finally, the number of police officers per capita in each province and the number of criminal code offences per officer in each province are included to proxy police resources and crime rates respectively, both of which are generally correlated with illegal activities, including smuggling of cigarettes (von Lampe, 2005, van Duyne, 2003).

3.2 Building the Classifier

Using this data, we build an ensemble classifier to compute the probability that Ontario and Quebec have a substantial degree of smuggling in each year from 2007 — 2014. This classifier uses a weighted combination of two algorithms: random forests and LASSO regression, two classifier algorithms which are well suited to this particular problem. First, random forests is a decision tree based classifier that is particularly useful at identifying underlying patterns (this algorithm, for instance, is very commonly used in cases of fraud detection). A decision tree works in a similar way to a flowchart: the decision tree begins by splitting the data into two subsets based on the first variable chosen by the decision tree, and then continues to split the data into further groups based on the additional variables. At the very bottom of the tree, a decision is made corresponding to the values of the dependent variable. Figure 3 gives a simple example of a decision tree, where the dependent variable is whether or not an applicant receives a loan, and where the independent variables are the income of the applicant, the number of years the applicant has worked in their present job, and the criminal record of the applicant.[4]

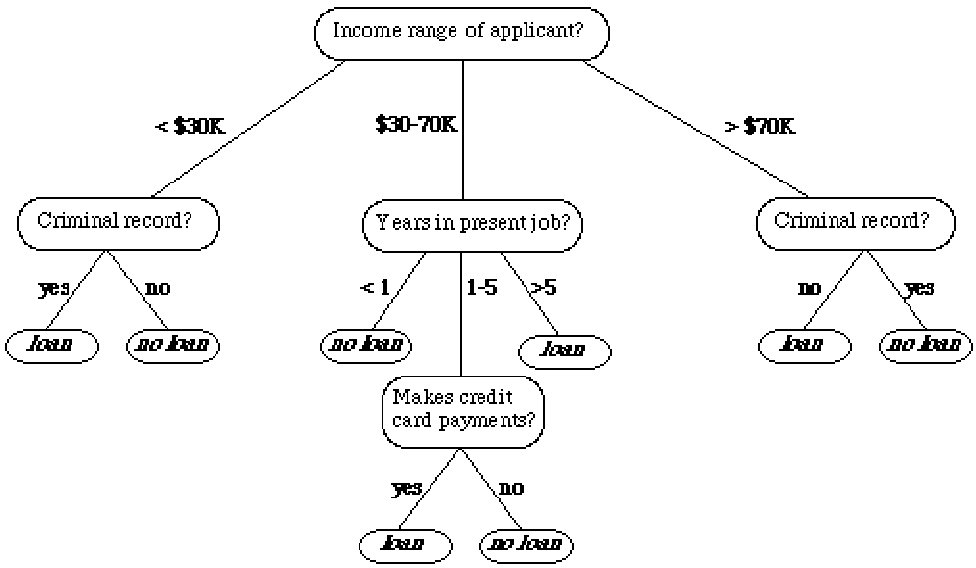

Figure 3: Example of a Simple Decision Tree

To make predictions, then, every new observation begins at the top of the tree and moves along the branches until it reaches a leaf node where no further branching out is possible. At this point, a decision has been reached for the observation. The particular values that determine how the data is split into subgroups is determined by minimizing the risk of misclassification (see page 14 for more details).

Random forests takes decision trees a step further: rather than simply using one decision tree, random forests uses a bagging method, whereby a certain number of randomly drawn subsets of the training data are fitted via a decision tree. The resulting trees are then aggregated and averaged to produce a single model. The upshot is that random forests is able to make stable predictions using a number of potentially weakly predictive decision trees.

Second, LASSO regression is a type of linear regression that imposes a penalty term equal to the absolute value of the coefficients. This penalty term is imposed when deriving the least squares estimates of the coefficients on the independent variables that we use as part of our classifier. Thus, we define the coefficients to be the solution to the following minimization problem:

[4]Image taken from Chapter 4 of *Deep Math Machine Learning.ai by Madhu Sanjeevi*

$$\hat{\boldsymbol{\beta}}_{LASSO} = \text{argmin}_{\beta_0,\beta}\left\{\sum_{i=1}^{N}(y_i - \boldsymbol{\beta_0} - \boldsymbol{x_i^T}\boldsymbol{\beta})^2\right\} \text{ subject to } \sum_{j=1}^{k}|\beta_j| \leq \lambda \tag{4}$$

Where y_i is the actual classification of whether a province is a smuggling province or not, $\boldsymbol{\beta_0}$ is a $k \times 1$ vector of the intercept term β_0 repeated k times, $\boldsymbol{x_i}$ is a $k \times 1$ vector of values for the ith observation, and $\boldsymbol{\beta}$ is a $k \times 1$ vector of coefficients for each of the k independent variables. Finally, λ is a free parameter that determines the penalty applied to the coefficients. Note that although the only difference between ordinary least squares and LASSO regression is the penalty term, unlike ordinary least squares, there is generally no closed form solution for $\hat{\boldsymbol{\beta}}_{LASSO}$. Instead, $\hat{\boldsymbol{\beta}}_{LASSO}$ is computed using a numerical solver, such as gradient descent, the details of which are unimportant for the purposes of this section.

Ultimately, this type of regularization introduces sparsity into the regression, where some coefficients on the independent variables may be reduced close to 0, primarily to control multicollinearity between independent variables and to remove independent variables which explain little variation in the data. This penalty additionally helps to prevent the data from overfitting the model, which is a serious concern with smaller data sets such as ours. It is important to note that this penalty term is indeed adding bias into the model; while the coefficients for ordinary least squares are unbiased estimators, this is not the case for LASSO regression. In predictive modeling, however, it is well known that there is a tradeoff between bias and variance. This is to say, models that have a lower bias in the parameters have a higher variance of the parameter estimates across different samples, and vice versa. Since our data set is small, and since we do not care about the interpretation of the coefficients, we introduce a small amount of bias for a decrease in the variance of our parameter estimates, and thus a decrease in the variance of our predictions of smuggling provinces over different samples.

Our ensemble classifier determines the weight of each algorithm by minimizing the risk, which in this case, is the mathematical cost associated with misclassifying an observation. For a non-negative real-valued loss function $L(\hat{y}, y)$ which measures how different a prediction $\hat{y}$ is from the actual value y, the risk associated with a classifier $c(\boldsymbol{X})$ (where $\boldsymbol{X}$ is a matrix of independent variables) is defined as the expectation of the loss function:

$$R(c) = E[L(c(\boldsymbol{X}), y)] = \int\int L(c(\boldsymbol{X}), y)p(x, y)dydx \tag{5}$$

Since, however, we in general do not know the joint probability distribution of our independent and dependent variables, we minimize the empirical risk:

$$\widehat{R(c)} = \frac{1}{N}\sum_{i=1}^{N} L(h(x_i), y_i) \tag{6}$$

Where N is the sample size of our data set. In this particular situation, we use a 0-1 loss function $L(\hat{y}, y) = I(\hat{y} \neq y)$ where $I(\hat{y} \neq y)$ is an indicator function and is 1 when the predicted classification of smuggling $\hat{y}$ is not equal to the actual classification of smuggling y and 0 otherwise.

Our ensemble classifier c searches for a weighted combination of random forests and LASSO regression that minimizes the empirical risk $\widehat{R(c)}$ To do this, we randomly split our data of 234 observations into a training set and a test set, with our training set comprising 75% of the observations and the test set 25%. We then build our model using this training set. Table 4 shows the weights for each algorithm, corresponding to the minimized risk that each algorithm contributes:

	Risk	**Weight**
Random Forests	0.06864890	0.7717984
LASSO Regression	0.07650352	0.2282016

Table 4: Risks and Weights for Classifier

3.3 Assessing Performance and Making Predictions

In order to assess the performance of our classifier, we refer to table 5, which shows the confusion matrix for our test data. The columns represent the actual classification of the province at a given year and the rows represent the predictions made by our classifier on the test data. In this case, we choose a probability threshold of 0.38 such that if the probability that a province has substantial smuggling in a given year is greater than 0.38, that province is classified as a smuggling province in that year (we choose this probability threshold based on maximizing the true positive and true negative rate, placing more weight on the true positive rate, since we consider incorrectly classifying a province as non-smuggling when it is in fact a smuggling province to be worse, given our goal of calculating an unbiased estimate of elasticity by excluding smuggling provinces).

	Actual Non-Smuggling	**Actual Smuggling**
Predicted Non-Smuggling	52 (True Negative: TN)	1 (False Negative: FN)
Predicted Smuggling	2 (False Positive: FP)	5 (True Positive: TP)

Table 5: Confusion Matrix

Using this table, we compute three important metrics for our classifier. First is the true positive rate, which is the number of provinces which are correctly classified as smuggling provinces out of the total actual number of smuggling provinces. In our case, the true positive rate is $TP/(TP + FN) = 5/(5 + 1) = 83\%$. Second, the true negative rate is the number of provinces which are correctly classified as non-smuggling provinces out of the total number of actual non-smuggling provinces. In our case, the true negative rate is $TN/(TN + FP) = 52/(52 + 2) = 96.3\%$. Third, we compute the accuracy, which is the correct classification rate, and in our case is $(TP+TN)/total = (52+5)/60 = 95\%$. These metrics are very high for this type of predictive modelling.

Given that our model is performing very well on the data, we finally use this classifier to predict whether Ontario or Quebec have substantial smuggling from 2007 – 2014. Our classifier predicts with a high probability that Ontario has a substantial degree of smuggling from 2007 – 2014, while Quebec has a substantial degree of smuggling from 2007 – 2009. The table below summarizes the provinces and time periods of substantial smuggling, sourced both from the periods in which there is general consensus as reported in section 2.4 and from the classification performed in this section.

Province	**Ontario**	**Quebec**	**Nova Scotia**	**New Brunswick**
Years (Consensus)	2006 – 2007 2014 – 2017	2006 – 2007	2006 – 2008	2015 – 2017
Years (Predicted)	2007 – 2009	2007 – 2009	(.)	(.)

Table 6: Periods of Substantial Smuggling (Consensus and Predicted)

4 Data and Empirical Strategy

4.1 Data

We collected all of our data for nine provinces (excluding PEI, because of inconsistent reporting) for the years 2003 – 2017. We obtained changes in provincial and federal excise and sales taxes from a report by the Canadian Cancer Society, which also provided the current level of excise tax in 2017. We used that as a baseline, using changes in excise taxes to determine the excise tax rate in every other period of time prior to the publication of the report. We applied a similar technique to determine the sales tax rate in each province in the years that preceded the Canadian Cancer Society's report, using changes in the sales tax rate to determine the sales tax rates in all the other periods.

However, given that excise taxes are calculated as a constant dollar amount per carton, we had to adjust excise taxes for inflation. We therefore converted excise taxes into 2002 dollars by deflating them using the CPI. We then added the sales tax that would have been assessed on that carton of cigarettes based on the price of cigarettes in each province in each year. In order to get a final dollar amount of total tax per province, per year, we used a system of weighting based on when the tax change was implemented. If a tax change occurred during the year, we weighted the tax faced by consumers pre-change by the percentage of the year that had elapsed before the change. We then added it to the tax rate faced by consumers after the change, which was weighted by the percentage of the year remaining. This became our measure of the *average* yearly tax rate. In this way, we ensured that our tax rate would be calculated in the same way as the CPI for cigarettes, which was collected monthly and averaged to create a yearly measure.

There is no comprehensive database of cigarette prices in each province for all the years we are interested in. To get around this, we obtained the average price per pack of cigarettes in each province in 2006 from the Non-Smokers Rights Association, and we used the cigarette-specific province-level CPI from Statistics Canada to extrapolate from that year to all the rest of the years in the study. We also obtained yearly legal sales data from Statistics Canada. All Canadian tobacco manufacturers and importers are required by law to report the number of packs of cigarettes that they sell in each province every month to Health Canada. Data on cigarette sales disaggregated by month was not available publicly, however we were able to obtain the yearly aggregate number of cigarettes sold to wholesalers in each province. We divided that number by the mid-year population in each province to obtain per-capita cigarette sales per province.

We tried to complement our aggregate-data analysis using microdata on expenditures on cigarettes from the Survey of Household Spending, which was the successor to the Survey of Family Expenditure (FAMEX) which Gruber et al. (2003) used in their analysis. However, public use microdata files released by Statistics Canada for the Survey of Household Spending were only available until 2009, and cigarette expenditure was not reported on its own until 2004. Prior to 2004, expenditures on cigarettes were only reported aggregated with spending on tobacco products in general, leaving us with microdata between 2004 and 2009. We briefly discuss the challenges of this approach in 4.3.

4.2 Empirical Strategy

Borrowing from the methodology used by Gruber et al. (2003), we use a difference-in-differences approach to estimate the consumption response to a change in the price of cigarettes. Our basic regression equation is as follows:

$$\ln Sales = \alpha + \beta(\ln Price) + \delta + \tau + \delta(Time) + \boldsymbol{x}^T\boldsymbol{\lambda} + \epsilon \tag{7}$$

where $Sales$ is legal sales data; $Price$ is the price of cigarettes in each province in a given year; $\boldsymbol{x}^T$ is a vector of controls composed of unemployment and per capita RGDP. We also add year fixed effects represented by τ to control for any unobserved variation common across all provinces in a year, and province fixed effects represented by δ to control for unobserved variation between provinces. Finally, we add province-specific linear time trends to account for the fact that smoking behaviour may be evolving differently across provinces independently of changes in price.

We use provincial per capita RGDP and unemployment rates to control for business cycle changes at the province level. Previous research has shown that involuntary job loss, financial stress, and unemployment are associated with increased smoking, reduced likelihood of quitting, and increased probability of relapsing following quitting (McClure et al. 2012; Kendzor et al. 2010; Siahpush and Carlin 2006; Falba et al. 2005). Changes in income may impact how many cigarettes are consumed. We therefore include province-level RGDP and unemployment to control for business cycle changes in each province that would not be captured by the year or province fixed effects.

However, this simplified approach suffers from a significant flaw. We suspect that cigarette prices and quantities consumed are endogenous, and may actually be functions of supply and demand forces that jointly determine price and quantity consumed. In this case, simultaneity bias is a concern. To address this issue, we use the tax rate on cigarettes as an instrument for the price of cigarettes and re-run our regression. Cigarette taxes represent a significant portion of the price of cigarettes, averaging 69.1% of the total price of cigarettes in our sample. Furthermore, changes in the tax rate should be exogenous, being determined by political factors that are not (at least directly) related to supply and demand conditions. We specify our first-stage equation as:

$$\ln Price = \alpha + \beta(\ln Tax) + \delta + \tau + \delta(Time) + \boldsymbol{x}^T\boldsymbol{\lambda} + \epsilon \tag{8}$$

where Tax is the average tax rate applied to cigarettes in that year in that province, and weighted by the time that the tax was implemented according to the process described earlier.

For this to be a valid approach, it must satisfy four assumptions. First, the instrument must be correlated with the endogenous variable. We can test this first assumption empirically. The F-statistic on our first-stage is 611.24, indicating that the instrument is highly correlated with the endogenous variable and that a weak instrument is unlikely to be a concern. Monotonicity is satisfied almost by definition since an increase in taxes is very unlikely to lower the overall price of legal cigarettes. The exclusion restriction is also likely to be satisfied. There are few plausible pathways through which cigarette taxes could affect consumption of cigarettes except through their effect on its price. While it's possible that increases in excise taxes on cigarette taxes may signal to consumers that consumption of cigarettes is undesirable, given packaging laws it is unlikely that this would signal information that consumers did not already know.

The most serious concern comes from the independence assumption. It is plausible that changes in tax are correlated with the consumption of cigarettes. Provinces view excise taxes as a way to generate revenue in addition to discouraging smoking. Provinces therefore have an interest in setting prices in such as way that revenue is maximized at a given level of smoking, and may adjust tax rates in response to shifts in smuggling. If they reduce the tax rate in response to an increase in smuggling, it may make it appear as if a reduction in the tax rate is correlated with a reduction in smoking when in reality the tax change is responding to the substitution of legal cigarettes with smuggled cigarettes. The opposite could also be true if provinces increase taxes because the difficulty in obtaining smuggled cigarettes increases.

However, tracking smuggling is difficult and it is unlikely that provinces have sufficiently granular data to adjust tax rates in response to moderate shifts in smuggling. Furthermore, it should not be a concern for our empirical strategy once we drop provinces where smuggling was an issue. We therefore conclude that taxes are a valid instrument for cigarette prices. We estimate our equation instrumenting yearly provincial cigarette prices with the level of total weighted tax on cigarettes in each province. We use RGDP and unemployment to control for business cycles, province and year fixed effects, and a province-specific linear time trend. We report the results later in table 7.

4.3 Regression Results

By running our regression (see table 7), we find that our price elasticity estimate is -0.73, which is very similar to the estimate found by Gruber et al. (2003) of -0.72. This is very encouraging and suggests that in general consumers behave roughly the same in the post-2000 era as they did in the 80s and 90s. We have not here accounted for smuggling, so the estimate is likewise probably quite biased upwards, and the true elasticity without the presence of smuggled cigarettes is lower.

	Coefficient	**Standard Error**	**P-Value**	**Confidence Interval**
ln $Price$	-0.7376567	0.2182823	0.001	[-1.165482, -0.3098313]
RGDP	0.0000726	0.0000159	0.000	[0.0000414, 0.0001037]
Unemployment	-0.0080643	0.0096593	0.404	[-0.0269962, 0.0108677]
2004	-0.0103049	0.0275478	0.708	[-0.0642976, 0.0436878]
2005	-0.0839905	0.0317697	0.008	[-0.146258, -0.0217229]
2006	-0.1973338	0.0403743	0.000	[-0.2764659, -0.1182017]
2007	-0.2969474	0.0553156	0.000	[-0.4053639, -0.1885308]
2008	-0.3687766	0.0649448	0.000	[-0.4960661, -0.2414871]
2009	-0.3181342	0.0787003	0.000	[-0.4723839, -0.1638845]
2010	-0.2973452	0.0893254	0.001	[-0.4724197, -0.1222707]
2011	-0.3471363	0.0924743	0.000	[-0.5283825, -0.16589]
2012	-0.3805701	0.0963104	0.000	[-0.5693351, -.1918052]
2013	-0.4195563	0.1048538	0.000	[-0.625066, -0.2140466]
2014	-0.4640996	0.1130816	0.000	[-0.6857354, -0.2424638]
2015	-0.4861013	0.1229261	0.000	[-0.727032, -0.2451705]
2016	-0.4853703	0.1273859	0.000	[-0.7350422, -0.2356985]
2017	-0.5795235	0.1361704	0.000	[-0.8464125, -0.3126345]

Table 7: IV Estimates of Price Elasticity using Legal Sales Data

The coefficient for RGDP turns out to be positive and significant which is as expected. If a province in a given year has a higher GDP then they will experience higher sales because people have more money to spend, and some of it will be spent on cigarettes. Our year dummies' coefficients are very satisfying as well. Almost all are very significant, and become progressively more negative as the years move on. It is a very clear and continuous trend, which gives good evidence for a decrease in sales (per capita) over time. This mirrors our societal intuition that smoking has been decreasing steadily over time. Due to public awareness campaigns about the negative health effects of smoking, the reduction of positive portrayals of smoking in the media, and the general attitude in society that smoking is a harmful and undesirable behavior, we would assume that smoking has been decreasing over time. The year dummies excellently portray that constant decline. Our unemployment coefficient had a p-value over 0.4 so we are unable to draw useful correlational information from it.

After removing Ontario from 2006 to 2017, Quebec from 2006 to 2009, New Brunswick from 2015 to 2017, and Nova Scotia from 2006 to 2008, we run our same regression equation again. We excluded the years and provinces that we classified in section 3 as suffering from a large amount of smuggling.

Variables	Model 1: All Provinces	Model 2: Smuggling Provinces Removed
$\ln Price$	-0.738***	-0.414**
	(0.218)	(0.211)
RGDP (2002 CAD)	7.26e-05***	5.03e-05***
	(1.59e-05)	(1.26e-05)
Unemployment	-0.00806	-0.00689
	(0.00966)	(0.00889)
Observations	135	113

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 8: Regression Results of Models with All Provinces and without Smuggling Provinces

In this second regression we find that our price elasticity estimate is -0.41, which is in the neighbourhood of -0.47, which is what Gruber et al. (2003) obtain after removing smuggling provinces. The lack of a dramatic difference between the estimates makes us feel generally satisfied with our results. It's reasonable that our elasticity estimate is lower than that found for pre-2000 consumers because it may be that smokers simply have become less elastic. Given the continuously declining rate of smoking, it is possible that the consumers who are still in the market are just less prone to quit. It could increasingly be the case that people who continue to smoke despite having an awareness of its health risks are unwilling or unable to quit. This would manifest itself as a lower elasticity in the post 2000 era, because consumers are less responsive to changes in cigarette prices.

We likewise find in this case that as the years increase, the number of cigarette sales per capita decrease, confirming our preconceived belief about smoking decline. Similarly, we again find that real GDP contributes positively to cigarette sales. If people have more money to spend in general, then they will spend some of it on cigarettes.

4.4 Estimating Price-Elasticity using Microdata

Finally, we complement our analysis using microdata from from the Survey of Household Spending. Expenditure microdata offers two key advantages over aggregate legal sales. First, we know that our elasticity estimates based on legal sales data will be biased in provinces in which smuggling is high as legal sales will not capture the portion of cigarettes consumed that were sold illegally. Expenditure data is potentially less biased as individuals themselves report their expenditure on cigarettes.

While they may conceivably still under-report if they purchase illegal cigarettes, there is little incentive to lie given that SHS does not distinguish between legal and illegal cigarettes. Nevertheless, even if SHS perfectly captured expenditure on cigarettes, we should still expect our coefficients to be biased because smuggled cigarettes are significantly less expensive than non-smuggled cigarettes. It is estimated that the price per carton of smuggled cigarettes is between CAD $6 and $20, meaning that substituting legal cigarettes for smuggled cigarettes would look like a substantial decrease in cigarette-related expenditure even if the total number of cigarettes remained constant (NSRA 2009).

Microdata also allows us to control for a richer set of covariates. We expect that the price elasticities of cigarettes will differ based on household income, and possibly also on characteristics such as the level of education a person obtained, their age, or whether or not they live in an urban area. Microdata could allow us to estimate the differential effects of a rise in cigarette prices on subsequent purchasing behaviour. Despite these two advantages, we were unable to supplement our primary analysis with evidence from microdata because of limitations on the availability of publicly-accessible data. While the Survey of Household Spending continues on today, public use microdata files are only available until 2009, while our measure of interest – expenditure on cigarettes – was only available starting in 2004. The period between 2004 and 2009 is characterized by a notable stability of both taxes and the price of cigarettes. Because of this, we were unable to precisely estimate an elasticity for cigarettes and we believe that our results are not reliable.

5 Robustness Test

To see if our results depend on the particular regression specification employed, we re-run our regressions from table 9 without business cycle controls and linear-time trends (1 and 4), and then with a linear time trend but without business cycle controls (2 and 5). Model 3 and 6 are the same as those reported earlier. We find that our regressions – both for all provinces and excluding provinces with smuggling – are sensitive to omitting controls and the linear time trend. However, as discussed earlier there are strong theoretical reasons to expect that the these controls belong in our model. Failing to include them may lead to omitted variable bias, which is what we pick up in our robustness tests.

Variables	Model (1) All Provinces	Model (2) All Provinces	Model (3) All Provinces	Model (4) Non-Smuggling	Model (5) Non-Smuggling	Model (6) Non-Smuggling
ln *Price*	-0.584**	-0.973***	-0.738***	-0.581*	-0.642***	-0.415**
	(0.271)	(0.230)	(0.218)	(0.301)	(0.201)	(0.211)
RGDP (2002 CAD)	(.)	(.)	7.26e-05***	(.)	(.)	5.03e-05***
	(.)	(.)	(1.59e-05)	(.)	(.)	(1.27e-05)
Unemployment	(.)	(.)	-0.00807	(.)	(.)	-0.00686
	(.)	(.)	(0.00966)	(.)	(.)	(0.00889)
Constant	4.443***	39.53***	13.91	4.390***	37.42***	18.81**
	(1.127)	(10.38)	(10.03)	(1.253)	(7.600)	(7.639)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Linear Time Trend	No	Yes	Yes	No	Yes	Yes
Observations	135	135	135	113	113	113
R-squared	0.668	0.892	0.917	0.714	0.942	0.956

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Robustness Test with 6 Models

6 E-Cigarettes

A potential concern relating to our findings is that the price-elasticity of demand for cigarettes may in fact be lower if the increasing popularity of e-cigarettes were "biasing" our estimates upward. Substitution of cigarettes for e-cigarettes could affect our estimate for elasticity in a similar way as smuggling. As the prices of cigarettes increases, some individuals may switch to using e-cigarettes instead of quitting smoking altogether. In this way, the impact of tobacco taxes on smoking cessation would appear more powerful than it actually is, hence the upwards bias. Note that the price-elasticity of cigarette is not itself biased, since people are truly buying fewer cigarettes as the price increases. However, for the purpose of this paper we consider the elasticity estimates to be "biased" because we are not just interested in consumption of cigarettes specifically, but smoking of nicotine-based cigarette products in general since they are all harmful to a degree. Thus the rise of e-cigarettes can be thought of as having a "biasing" effect because it could cause our model to *overstate* the impact of tobacco taxes on smoking cessation.

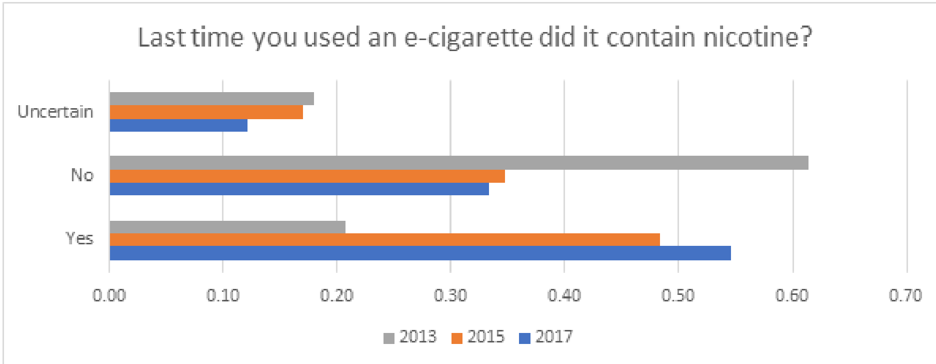

Figure 4: Canadian Tobacco, Alcohol and Drugs Survey from Statistics Canada (CTADS)

Cognisant of the potential for bias, we decided to investigate the effect of e-cigarettes on our estimates. We first wanted to investigate the theory that individuals are not substituting e-cigarettes for regular cigarettes based on the relative price of cigarettes, but instead because of personal and social factors, namely the desire to reduce consumption of cigarettes for health reasons. Due to the lack of microdata on individual-level e-cigarette expenditure and the limited amount of aggregate data available, we turned to data on people's stated reasons for consuming e-cigarettes. We also ran a regression using aggregate data, which we describe later in the paper. For our e-cigarette investigation we relied on the Canadian Tobacco, Alcohol and Drugs Survey (CTADS) from Statistics Canada which was conducted in 2013, 2015 and 2017.

Used e-cigarette as smoking cessation aid - 2 years	Yes	No	Total	N=
Used e-cigarette - 30 days				
Yes	57.0	43.0	100.0	242
No	46.5	53.5	100.0	714
Total	49.2	50.8	100.0	956

Figure 5: CTADS 2013, Sample: Individuals who have ever Smoked an E-Cigarette.

Used e-cigarette as smoking cessation aid - 2 years	Yes	No	Total	N=
Frequency of use - e-cigarette - current				
Every day	79.7	20.3	100.0	79
Occasionally	66.1	33.9	100.0	254
Not at all	39.9	60.1	100.0	807
Total	48.5	51.5	100.0	1,140

Figure 6: CTADS 2015, Sample: Individuals who have ever Smoked an E-Cigarette.

The data from 2013 and 2015, displayed in figures 4 and 5[5] show that, in 2013 among those who used an e-cigarette in the previous 30 days, 57% had used it for smoking cessation, while among every day e-cigarette smokers in 2015, the proportion was 79.7%. In the 2017 survey, new questions regarding the reasons for using e-cigarettes were introduced. Respondents were asked to answer yes to any of the reasons that applied to them (questions and distributions in figure 7). Though 15% cited the affordability of e-cigarettes, many other reasons were selected with far greater frequency. This includes several related to the perceived lower-level of negative health effects and their ability to help people quit smoking.

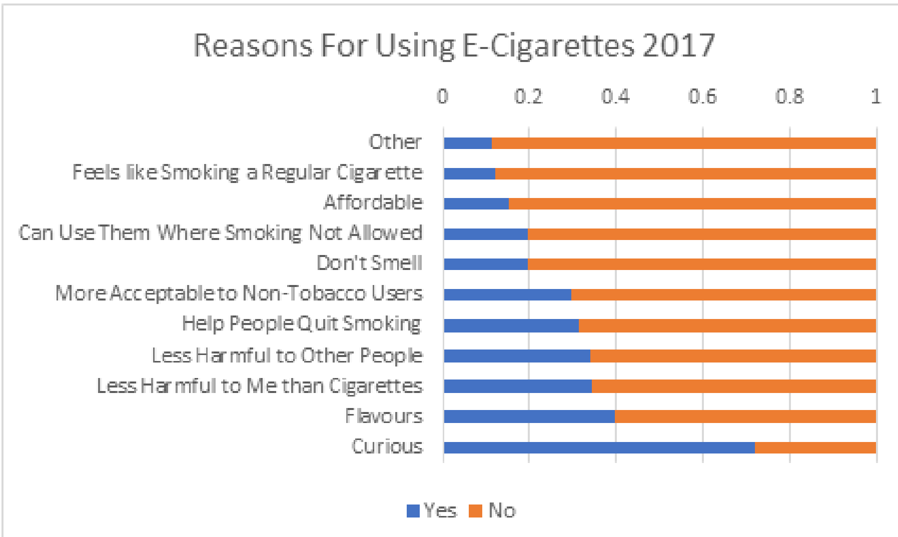

Figure 7: CTADS 2017, Sample: Individuals who have ever Smoked and E-Cigarette.

There are some caveats to the interpretation of this data. Even for those that cited affordability, it is unclear to what extent this is related to changes in the price of cigarettes over this period (2013 – 2017). The e-cigarette market is marked by a wide spread in costs, both fixed (e.g. vaporizer pens) and variable (e.g "vape juice"). Individuals could pursue "premium" consumption and spending habits which could make e-cigarettes a more expensive habit than regular cigarettes. But the range in prices also allows them to pursue a "budget" consumption habit which would make their e-cigarette consumption a cheaper alternative to regular cigarettes. A US study by the CDC (Wang et al.) tracking the price of various e-cigarette products between 2012 and the start of 2017 shows that even though the price of these products has been convergning, there remains a significant range with e-liquids averaging around $7.50 and Prefilled cartridges at around $12.50, a 66% difference. (Though the prices of all these products is expected to be higher in Canada, we find no reason for the difference between them not to scale proportionally, meaning the argument holds).[6]

[5] Tables generated from Odesi

[6] In an attempt to standardize the nature of these different products, prices were calculated by "using only items sold in the most common package size for each product. For example, only prefilled cartridges that were sold in a pack of 5 were included in price calculations for prefilled cartridges."

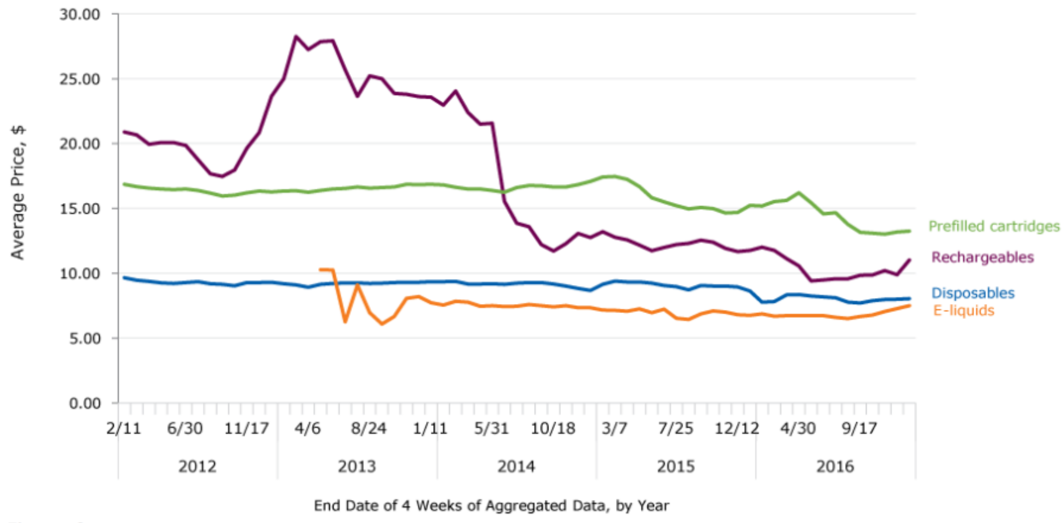

Figure 8: Average Prices of E-Cigarettes by Product Type and by 4-Week Periods, United States 2012–2016

Furthermore, a 30mL bottle of e-liquid can last a "pack-a-day smoker" one or two months and can cost between \$10 and \$20, resulting in a daily cost of less than \$2 (Ripton, 2013) (Canada Vapes) (Ligaya, 2013), much cheaper than the cost of buying a pack a day ever was in the 2013 – 2017 range. Thus, even for those who switched for affordability reasons, it could be because as a type of good e-cigarettes can be more affordable than cigarettes, independent of the marginal increases in cigarettes taxes 2013 to 2017. We are not suggesting that the increases in tobacco taxes did not contribute to some individuals' shift to e-cigarettes; we suspect they do given findings of positive cross-price elasticity between the two goods in the literature. We are merely suggesting that it should not be interpreted that all or even most of the 15% who cited affordability are people who switched because of the increased relative costs of cigarettes due to rising taxes in this period. On another cautionary note, it is also possible the individuals are underestimating the extent to which they are influenced by price. One may conceptualize their decision to switch as based on health reasons, but they may not have taken that decision if the price difference between cigarettes and e-cigarettes was smaller, or if e-cigarettes were always more expensive. Understanding the pitfalls in the interpretation of these self-reported reasons combined with the weak or mixed findings in the literature, we are merely asserting that there is good reason to doubt that the substitution of e-cigarettes for conventional cigarettes is primarily driven by the rising price of cigarettes due to taxes. Conversely, there is reason to believe that social and health reasons are mainly driving this change. These health and social factors we assert are causally independent from changes in price and tax.

Even if rising cigarette prices do not have a significant causal effect on the substitution of e-cigarettes, upward bias may nonetheless exist in our model. If the provinces where e-cigarettes are being adopted at a high rate (causing legal sales of cigarettes to decline) are also those where tobacco taxes are rising faster than the rest, such a correlation could bias our estimate of the price elasticity of cigarettes because e-cigarettes are making the negative effect of tobacco taxes on cigarette sales seem amplified. Thus we wish to test the correlation between the level of cigarette tax in a province and the adoption of e-cigarettes in that province.

The shift away from cigarettes due to taxes for a given consumer does not realistically happen on the margin. Most consumers will not change their behavior if the tax they face happens to increase slightly. Taken on an aggregate level however, consumers are being faced with many different incentives to quit smoking. Many of them would like to quit but have too little motivation to do so. For some consumers, increases in cigarette taxes may act as the "straw that broke the camel's back" and cause them to quit or to substitute into e-cigarettes.

If there existed a price effect pushing people towards e-cigarettes we would expect to see a positive correlation between cigarette taxes and e-cigarette usage. Using data collected by the Canadian Tobacco and Drugs Survey collected in 2013, 2015, and 2017, we are able to obtain data on the percentage of the population of each Canadian province that used an e-cigarette in the past 30 days. We use this is a proxy for someone who is an "active" e-cigarette user.

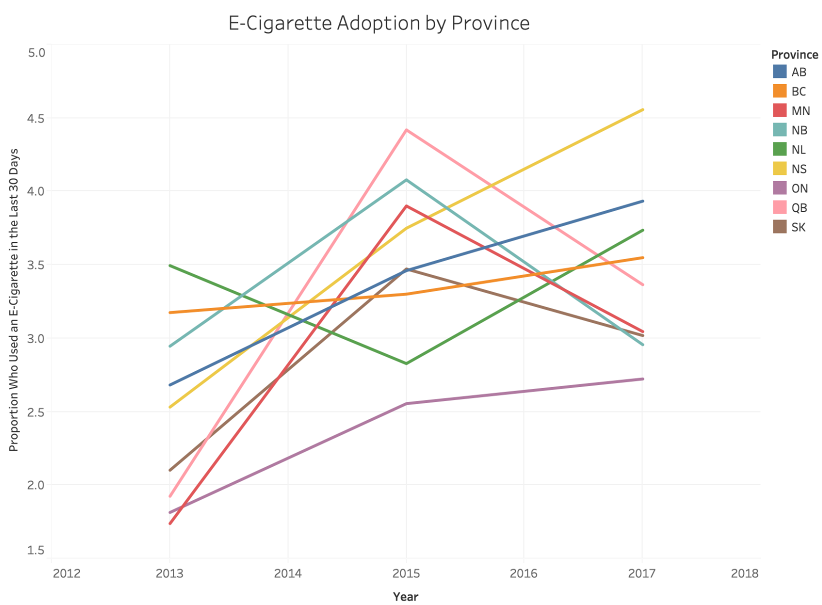

Figure 9: Rates of E-Cigarette Adoption Among Provinces

By regressing the proportion of the population in a province that is an active e-cigarette user on the amount of total tax, with appropriate controls as in our original regression, we test whether we can find evidence of a correlation.

In table 10, the coefficient on the price of cigarettes (which is instrumented by the total tax on cigarettes) is very close to zero, and the standard error is much larger, making the confidence interval spill over roughly evenly on both sides of zero. Given the extremely high p-value of 0.962 we cannot

	Coefficient	Standard Error	P-Value	Confidence Interval
ln *Price*	-0.0000331	0.0007041	0.962	[-0.0014132. 0.001347]
RGDP	-0.0000365	7.08e-06	0.000	[-0.0000504, -0.0000226]
Unemployment	-0.0038933	0.0022694	0.086	[-0.0083411, 0.0005546]
Cartons Per Capita $\geq$ 15	0.026298	0.0093901	0.005	[0.0078937, 0.0447023]
LICO	0.0006786	0.0013818	0.623	[-0.0020297, .0033868]

Table 10: Testing the Effect of Cigarette Price on E-Cigarette Usage

reject that the effect cigarette prices on e-cigarette adoption may in fact be zero. Considering the confidence interval above, the effect of taxes/cigarette prices on e-cigarette usage seems to be anyone's guess, and may well be somewhere around zero. This leads us to believe that the potential elasticity estimate bias caused by smokers substituting into e-cigarettes is probably very small, and we cannot determine whether it is positive, or negative. We proceed under the assumption that e-cigarettes do not significantly bias our cigarette elasticity estimate.

We used dummies for the years we had survey data on, which resulted in estimates of 0.031 for 2015 and 0.044 for 2017. Compared to the base year of 2013 the passage of time is associated with a significant increase in the proportion of people who use e-cigarettes, an estimated 3.1% more of the population consuming them in 2015 and then an additional 1.3% by 2017. This is to be expected, as e-cigarettes were really only gaining prominence in society by the early 2010s. We therefore expect that the usage of e-cigarettes would increase over time. These effects are very significant, with a p-value of 0.000. Because we only had three years of data on nine provinces we only had 27 data points in total to work with. This being said, we are simply providing some cursory evidence to suggest that if a substitution effect exists, it is probably small. We will analyze our results with that in mind.

Regarding the limited data, most reports concerned with smoking and smoker health that deal with the issue and prevalence of e-cigarettes unfortunately get their primary data from the Canadian Tobacco and Drugs Survey. This means that this survey is the only real source of primary data from which to answer questions about e-cigarette usage. Bodies like the Heart Stroke foundation and the *Tobacco Use in Canada* report published annually by the University of Waterloo use the CTADS as a source for their summary statistics, in addition to other research about cigarettes' and e-cigarettes' health effects. Because this is currently the only adequate source of primary e-cigarette data usage available, we are forced to use it.

We also test whether the elasticity of conventional cigarettes is different before and after 2013, to see if the adoption of e-cigarettes affects estimates of conventional cigarette price-elasticity. We chose the year 2013 as a benchmark for when e-cigarette usage really picks up, since it is also the start of data collection by Statistics Canada on this topic. We run the same regression as our original legal sales one, but for the first variation we exclude years after 2012 and for the second exclude years before 2013.

	Coefficient	Standard Error	P-Value	Confidence Interval
$\ln Price_{<2013}$	-0.2766471	0.3682618	0.453	[-0.998427, 0.4451328]
$\ln Price_{\geq 2013}$	-0.7458306	0.82717	0.000	[-0.9058322, -0.5815874]

Table 11: Comparing the Main Model Split into Before and After 2013 Parts

The coefficient for the pre-2013 regression is -0.27 but has a p-value of 0.453. There was relatively little variance in the level of taxation during these years so we are unable to obtain a significant result. We cannot draw conclusions from the unexpectedly low coefficient pre-2013.

Figure 10 confirms the claim that the variance in taxes across provinces in Canada was much lower in the pre-2009 era compared to post-2011. This could be the reason why our post-2012 model is significant and why its elasticity estimate (-0.74) also aligns more closely with what we estimate it to be overall for the 2003-2017 range, and what Gruber et al. (2003) estimate as well.

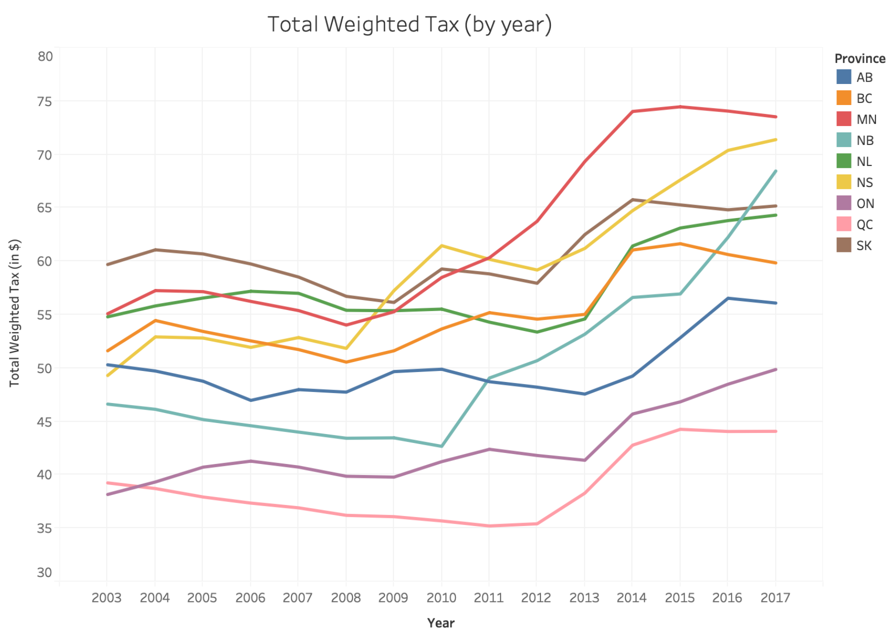

Figure 10: Total Weighted Tax from 2003 – 2017

We also run a combined model, where we include dummies for *post-2013* and *pre-2013*. We interact these dummies with the price of cigarettes, RGDP, and unemployment to test whether these new interaction terms are significant.

	Coefficient	**Standard Error**	**P-Value**	**Confidence Interval**
$\ln Price_{g1}$	-0.2704677	0.3067928	0.378	[-0.8717704, 0.3308351]
$\ln Price_{g2}$	-0.7479082	0.5146539	0.146	[-1.756611, 0.260795]
RGDP_{g1}	0.0000325	0.0000211	0.378	[-0.8717704, 0.3308351]
RGDP_{g2}	0.000027	0.000082	0.742	[-0.0001338, 0.0001878]
Unemployment_{g1}	-0.029485	0.0137077	0.031	[-0.0563517, -0.0026184]
Unemployment_{g2}	-0.0070616	0.0299522	0.814	[-0.0657669, 0.0516436]

Table 12: Combined Model with Coefficient for Variables pre-2013 and post-2013

In table 12, we see the combined model, with $g1$ as the pre-2013 dummy and $g2$ as the post-2013 dummy. We notice that the $\ln Price_{g1}$ and $\ln Price_{g2}$ coefficients are very similar to their split model values, namely -0.27 and -0.74. This indicates that the effect on cigarette sales of the explanatory variables for which we have created interaction terms are likely the same after 2013 as they are throughout the 2003-2017 range. We now explicitly test whether the coefficients on the pre-2013 versions of the explanatory variables are the same as the post-2013 versions.

	Model 1	**Model 2**	**Model 3**
	$\ln Price_{g1} = \ln Price_{g2}$	$\ln Price_{g1} = \ln Price_{g2}$ $\ln \text{RGDP}_{g1} = \ln \text{RGDP}_{g2}$	$\ln Price_{g1} = \ln Price_{g2}$ $\ln \text{RGDP}_{g1} = \ln \text{RGDP}_{g2}$ $\ln \text{Unemployment}_{g1} = \ln \text{Unemployment}_{g2}$
χ^2	0.63	0.68	1.07
P-Value	0.4270	0.7118	0.7851

Table 13: Testing the Joint Model to see if pre-2013 and post-2013 coefficients are the same

We obtain a high p-value of over 0.7 for all three pairs of coefficients (pre-2013 RGDP, Unemployment, and Price, each paired with their post-2013 variant). From our chi-squared test, we fail to reject that the coefficients pre- and post-2013 are the same, so we have no reason to believe that there is a fundamentally different price elasticity of cigarettes before and after 2013. It is important to note that this *does not* prove that the coefficients are the same. Rather, we note that testing whether the coefficients are the same has *failed* to prove that they are different. As was discussed above, there are different amounts of variation in price before and after 2013 leading to insignificance for the pre-2013 variables. We do not claim that this is definitive proof against e-cigarettes creating bias in our main model, we simply offer this as evidence that if the adoption of e-cigarettes has an effect on the estimate of the price-elasticity of conventional cigarettes in our difference-in-differences model it is not a strong one.

7 Conclusion and Policy Recommendations

7.1 Conclusion and Limitations

In this paper we have constructed a difference-in-differences approach to try to estimate the price elasticity of cigarettes for the purpose of determining the effectiveness of tobacco taxes on cigarette consumption. By controlling for demographic, regional, and temporal factors, we obtain a preliminary estimate of this elasticity. Using a review of relevant literature on smuggling prevalence in Canada, and additionally by constructing a predictive model of smuggling, we obtained a list of provinces and years in which we believe a significant amount of smuggling occured. We omit these provinces for these years from our regression and obtain a lower estimate of elasticity, one that we believe is much closer to the actual price elasticity of cigarettes. We then discuss the robustness concerns associated with our functional form. Finally, we address concerns about the possible "biasing" effect of e-cigarettes, and argue that the substitution of e-cigarettes is not primarily driven by the increases in taxes on conventional cigarettes that have occured since since e-cigarettes emerged (2013 – 2017). Instead, evidence suggests substitution is driven by health concerns and social trends during this period. In addition to e-cigarette substitution not being causally driven by cigarette prices, we found that cigarette tax increases are not correlated with e-cigarette usage increases once we added time fixed effects to our model.

In terms of limitations, we note that our methodology to produce an unbiased estimate of the price elasticity of cigarettes required that we correctly identify the provinces that have substantial smuggling. Since there is no consensus concerning the nature of smuggling in Ontario and Quebec from 2007 – 2014, we estimated the degree of smuggling using machine learning techniques (particularly building an ensemble classifier). Despite having a very good predictive performance on our test data, our data set used to build and assess the machine learning algorithm is fairly small, which often results in the data overfitting the model; a peril in predictive modelling. Although we have attempted to correct for this the best that we could (particularly in using LASSO regression which helps to penalize overfitting and reduce the variance of our predictions across samples), better predictions would be made with a greater availability of data. Monthly data, for instance, would have been better suited for this model, but unfortunately, we were unable to obtain such data from Statistics Canada.

7.2 Policy Recommendations

After controlling for smuggling, our legal sales model indicates that the price elasticity of cigarettes is lower than it was in previous decades. This indicates that consumers are quite inelastic with respect to taxes on cigarettes. While tobacco taxes can remain an effective source of income for the government, they have increasingly little effect on smoker behaviour. It seems that societal forces and a concern for health are the primary factors driving the reduction in smoking, as is shown by our year effects.

We have discussed the prevalence of e-cigarettes and the reasons why people may choose to substitute e-cigarettes for conventional cigarettes. We have argued that these reasons may not be led by increases in the price of cigarettes, but due to health and social reasons. Even if the government considers it desirable for conventional smokers to switch to less harmful e-cigarettes, it has room to implement and increase taxes on e-cigarettes without severely impairing the health-driven substitution trend. This is because the trend is not primarily driven by the comparative affordability of e-cigarettes and the cross-price elasticity is estimated to be weak. Even regarding individuals who are substituting for affordability reasons, given the significant cost difference between daily conventional smoking and the average cost of daily e-cigarette smoking, there is still room for the government to implement taxes on e-cigarette products and still have e-cigarettes be less costly than cigarettes.

Additional studies should be done to examine the price elasticity of e-cigarettes. As e-cigarettes become more prevalent and more data becomes available on their usage, it would be valuable to test to see how responsive e-cigarette users are to price. Data on individuals' yearly spending on e-cigarettes is also lacking, resulting in inadequate data on e-cigarette costs and spending habits. Perhaps e-cigarette users will in fact be more elastic than regular cigarette users and taxes on e-cigarettes will be quite effective in reducing their use. This resurgence in smoking behavior accompanied by a new societal acceptability could be stymied by such an effective tax.

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