Carbon Taxes and CO₂ Emissions: Sweden as a Case Study

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Online Appendix

A Data Sources

- CO₂ emissions from transport. Measured in metric tons per capita. Source: The World Bank (2015) WDI Database. Available at: data.worldbank.org/indicator.
- GDP per capita (PPP, 2005 USD). Expenditure-side real GDP at chained PPPs, divided by population. Source: Feenstra, Inklaar, and Timmer (2013), "The Next Generation of the Penn World Table". Available at: www.ggdc.net/pwt.
- GDP per capita (2005 SEK). Expenditure-side real GDP, divided by population. Source: Statistics Sweden (2015) statistical databases. Available at: statistikdatabasen.scb.se.
- Motor Vehicles (per 1000 people). Source: Dargay, Gately, and Sommer (2007), "Vehicle Ownership and Income Growth, Worldwide: 1960-2030".
- Gasoline and Diesel consumption per capita. Measured in kg of oil equivalent. Source: The World Bank (2015) WDI Database. Available at: data.worldbank.org/indicator.
- Urban Population. Measured in percentage of total. Source: The World Bank (2015) WDI Database. Available at: data.worldbank.org/indicator.
- Unemployment rate in Sweden. Percentage of total labor force. Source: Statistics Sweden (2015), statistical databases. Available at: statistikdatabasen.scb.se.
- Unemployment rate in OECD countries. Percentage of total labor force. Source: AMECO (2018) database. Available at: ec.europa.eu/economy_finance/ameco/user/serie/SelectSerie.cfm.
- Gasoline prices and taxes in Sweden. Measured in 2005 Swedish Kronor. Sources: SPBI (2016), Statistics Sweden (2015), The Swedish Tax Agency (2018). Available
 - at: spbi.se/statistik/priser; statistikdatabasen.scb.se; skatteverket.se.

B Carbon Tax Rate

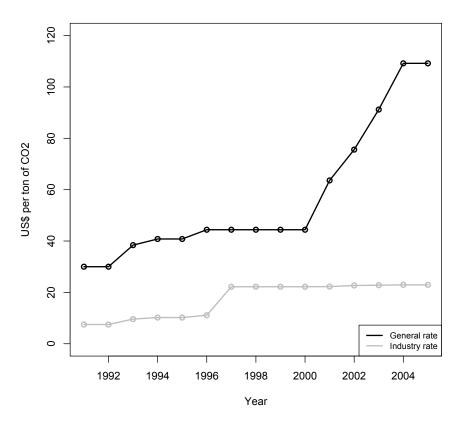


Figure 1: Carbon Tax Rate in Sweden 1991-2005

C Differences-in-differences

I use the differences-in-differences (DiD) method to estimate the following fixed-effects, panel data regression model:

$$Y_{it} = \delta_t + \lambda \mu_i + \alpha D_{it} + \epsilon_{it} \tag{1}$$

where *i* is country identifier and *t* is year. Y_{it} is per capita CO₂ emissions from transport, δ_t are (common) time fixed effects, μ_i are country fixed effects with a time-invariant parameter λ , D_{it} is the treatment indicator, taking the value of 1 for Sweden in the years after treatment and 0 otherwise, α measures the effect of the treatment and is thus our main coefficient of interest, and finally, ϵ_{it} are country-specific shocks with mean zero.

Table 1 presents the result from the DiD estimator. The estimated treatment effect from the implementation of VAT and a carbon tax is an emission reduction from the Swedish transport sector of 8.1 percent, or 0.214 metric tons of CO_2 per capita in an average year post-treatment.

Dependent variable	$\rm CO_2$ emissions from transport
Treatment	-0.214 (0.085)
Year fixed effects	Yes
Country fixed effects	Yes
Observations	690
R^2 (within)	0.806

Table 1: DiD Estimate of the Treatment Effect

Note: Robust standard errors in parenthesis (clustered by country).

D Details about the Synthetic Control Method

Formally, let J + 1 be the number of OECD countries in my sample, indexed by j, and let j = 1 denote Sweden, the "treated unit".¹ The units in the sample are observed for time periods t = 1, 2, ..., T. It is important to have data on a sufficient amount of time periods prior to treatment $1, 2, ..., T_0$ as well as post treatment $T_0 + 1, T_0 + 2, ..., T$ to be able to construct a synthetic Sweden and evaluate the effect of the treatment.

Next we define two potential outcomes: Y_{jt}^{I} refers to CO₂ emissions from transport when exposed to treatment for unit j at time t and Y_{jt}^{N} is CO₂ emissions without treatment. The goal of the analysis is to measure the post-treatment effect on emissions in Sweden, formalised as $\alpha_{1t} = Y_{1t}^{I} - Y_{1t}^{N} = Y_{1t} - Y_{1t}^{N}$. Since, however, we cannot observe Y_{1t}^{N} for $t > T_{0}$ we need to construct it using a synthetic control.

Synthetic Sweden is constructed as a weighted average of control countries $j = 2, \ldots, J+1$, and represented by a vector of weights $W = (w_2, \ldots, w_{J+1})'$ with $0 \le w_j \le 1$ and $w_2 + \cdots + w_{J+1} = 1$. Each choice of W gives a certain set of weights and hence characterises a possible synthetic control. We want the synthetic control to not only be able to reproduce the trajectory of CO₂ emissions but also to be similar to Sweden on a number of pre-treatment predictors of the outcome variable. Hence, let Z_j denote the vector of observed predictors for each unit in the sample. Now suppose that we find

¹The description here follows the structure in Abadie, Diamond, and Hainmueller (2010, 2011).

 $W = W^* = (w_2^*, \ldots, w_{J+1}^*)$ such that for the pre-treatment period $t \leq T_0$ we have that:

$$\sum_{j=2}^{J+1} w_j^* Y_{j1} = Y_{11}, \sum_{j=2}^{J+1} w_j^* Y_{j2} = Y_{12}, \cdots, \sum_{j=2}^{J+1} w_j^* Y_{jT_0} = Y_{1T_0}, \text{ and } \sum_{j=2}^{J+1} w_j^* Z_j = Z_1 \quad (2)$$

then, as proved in Abadie et al. (2010), for the post-treatment period T_0+1, T_0+2, \ldots, T we can use the following as an unbiased estimator of α_{1t} :

$$\hat{\alpha}_{1t} = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt}$$
(3)

To find W^* we need to define a measurable difference between Sweden and its control units which we then minimize. Let $X_1 = (Z'_1, Y_{11}, \ldots, Y_{1T_0})'$ denote an (kx1) vector of pre-treatment values for the key predictors of the outcome variable and the outcome variable itself for Sweden, and let the (kxJ) matrix X_0 contain similar variables for the control countries.² We then choose W^* so that the distance $||X_1 - X_0W||$ is minimized for the pre-treatment period, subject to the above (convexity) constraints on the weights. In this paper I solve for a W^* that minimizes:

$$||X_1 - X_0W|| v = \sqrt{(X_1 - X_0W)'V(X_1 - X_0W)}$$
(4)

where V here is the (kxk) symmetric and positive semidefinite matrix that minimizes the mean squared prediction error (MSPE) of the outcome variable over the entire pretreatment period.³

The purpose of introducing V is to weight the predictors and allow a larger weight being given to more important predictors of the outcome variable. Here, V is chosen through a data-driven procedure but other methods are possible, for instance, assigning weights based on empirical findings in the literature on the main drivers of CO_2 emissions, or cross-validation methods (Abadie, Diamond, and Hainmueller, 2015).

 $^{^{2}}$ Note that the main analysis does not use all pre-treatment values for the outcome variable, only three distinct years.

³To find V(which here is diagonal) and W^* I used a statistical package for R called Synth (Abadie et al., 2011).

E Full-Sample Test

Variables	Sweden	Synth Sweden	OECD Sample
GDP per capita	20121.5	20116.7	18466.1
Motor vehicles (per 1000 people)	405.6	405.5	379.7
Gasoline consumption per capita	456.2	401.7	386.5
Urban population	83.1	83.1	72.4
$\rm CO_2$ from transport per capita 1989	2.5	2.5	2.3
$\rm CO_2$ from transport per capita 1980	2.0	2.0	1.9
$\rm CO_2$ from transport per capita 1970	1.7	1.7	1.4

Table 2: CO₂ Emissions from Transport Predictor Means before Tax Reform

Note: All variables except lagged CO_2 are averaged for the period 1980-89. GDP per capita is Purchasing Power Parity (PPP)-adjusted and measured in 2005 U.S. dollars. Gasoline consumption is measured in kg of oil equivalent. Urban population is measured as percentage of total population. CO_2 emissions are measured in metric tons. The values for the 24 countries in the OECD sample are simple averages.

Country	Weight	Country	Weight	Country	Weight
Australia	0.001	Greece	0.003	Norway	0.002
Austria	0.002	Iceland	0.001	Poland	0.003
Belgium	0.097	Ireland	0.002	Portugal	0.002
Canada	0.001	Italy	0.002	Spain	0.002
Denmark	0.479	Japan	0.002	Switzerland	0.012
Finland	0.004	Luxembourg	0.012	Turkey	0.003
France	0.002	Netherlands	0.002	United Kingdom	0.128
Germany	0.002	New Zealand	0.172	United States	0.065

Table 3: Country Weights in Synthetic Sweden

Note: All weights are between $0 \le w_j \le 1$ and $\sum w_j = 1$.

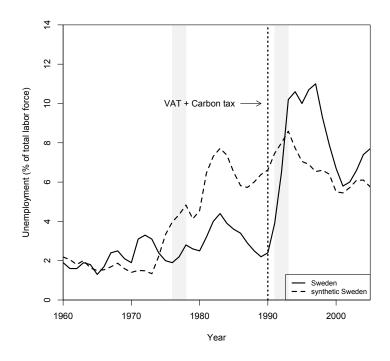


Figure 2: Path Plot of Unemployment during 1960-2005: Sweden vs. Synthetic Sweden Note: Unemployment is measured as percentage of total labor force. The shaded areas highlights the two major recessions during the sample period.

F Further Analysis of Possible Confounders

Section 3.D in the main article analyses changes to GDP per capita as a potential driver of emissions reductions in the post-treatment period. But what about another possible confounder: the unemployment rate?

Figure 2 shows that the unemployment series for Sweden and synthetic Sweden are not as closely aligned as those for GDP per capita (see Figure 11 in the main article). Although the two series move in tandem the magnitudes of the movements are different: synthetic Sweden has comparatively larger swings in the pre-treatment period and Sweden has larger swings post-treatment. Nevertheless, extending this figure out into 2017 (Figure 3), we find that the two series are aligned at the start and end: in both "countries", unemployment is around 2 percent in the 1960s, and 5-8 percent from 2000 to 2017. However, during the thirty years in-between – when unemployment transitions to a higher level – the two series follow different paths.

If we compare and contrast the unemployment rate and GDP in their ability to predict long-run levels of emissions, we find that GDP is considerably more accurate.⁴ GDP per capita is highly correlated with CO_2 emissions per capita from the transport sector in the pre-treatment period (r=0.99), whereas the correlation is weaker (and positive)

 $^{^{4}}$ The literature has also focused on, and established, a clear link between GDP and CO₂ emissions. There is however, to my knowledge, no literature that analyses a similar connection between unemployment and emissions.

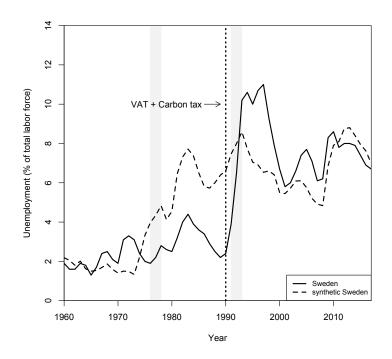


Figure 3: Path Plot of Unemployment during 1960-2017: Sweden vs. Synthetic Sweden Note: Unemployment is measured as percentage of total labor force. The shaded areas highlights the two major recessions during the sample period.

for unemployment (r=0.61). From 1976 to 1989, unemployment increases from 2 to 6 percent in synthetic Sweden but remains around 2 percent in Sweden. At the same time, CO_2 emissions in both "countries" track each other closely. Thus, compared to GDP, unemployment is not an accurate macro-predictor of the long-run level of CO_2 emissions from transport in the pre-treatment period. If unemployment was a good predictor we would find that in 1989, compared to 1960, relative transport emissions would be significantly higher in Sweden, and this we do not find.

Although unemployment is not an accurate predictor of the long-run level of emissions, it might still affect relative emissions in the short-run. Figure 4 is a gap plot with the gap in emissions between Sweden and its synthetic counterpart on the left y-axis and the gap in unemployment rates on the right y-axis. If we focus on the two recessions, we find that relative unemployment is unchanged in 1976-78 but increases with 5.2 percentage points in Sweden in 1991-93. Looking at relative emissions, we find that they increase slightly during 1976-78, and decrease quite a bit during 1991-93, -0.113 tonnes per capita. So, changes to the unemployment rate may, similar to the drop in relative GDP, be a possible explanation for the emission reductions during the recession in the early 1990s.

If we analyze time periods outside of the recessions, however, we find similarly large changes to relative unemployment which are not matched with the expected changes in emissions. For example, the large relative reduction in unemployment of 6 percentage points from 1973 to 1989 is matched with nearly unchanged relative emissions. Similarly,

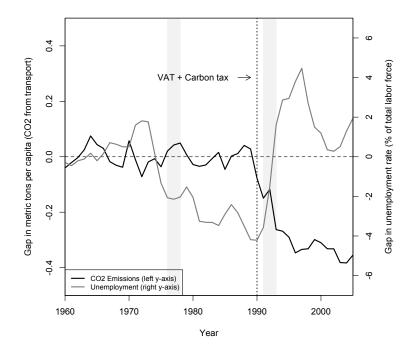


Figure 4: Gap in Unemployment Rate and per capita CO_2 Emissions from Transport between Sweden and Synthetic Sweden

Note: The variables are computed as the gap between Sweden and synthetic Sweden. Unemployment is measured as percentage of total labor force. CO_2 emissions are measured in metric tons. The shaded areas highlights the two major recessions during the sample period.

from 1997 to 2001-03, relative unemployment drops with 4.1 percentage points in Sweden, but relative emissions are again almost unchanged. We noticed the same non-existent "bounce back" in emissions from the catch-up in growth of GDP per capita from 1993 and onwards. If the unemployment rate is driving relative emission reductions we would expect a large increase in emissions from 1973 to 1989 and again from 1997 to 2001-03, but instead we see very small changes in both time periods.

In summary, prior to the environmental tax reform in the early 1990s, large changes to the unemployment rate had no discernible impact on CO_2 emissions from transport. In the post-treatment period the connection goes both ways; the large increase in unemployment from 1991 to 1993 is accompanied by a decrease in emissions, but the large *decrease* in unemployment from 1997 to 2001-03 is also accompanied with a decrease in emissions.

If neither GDP nor unemployment is the main driver of changes to CO_2 emissions in the transport sector, what is? The variable that consistently explains all relative changes in emissions during 1960-2005, I argue, is the real fuel tax rate.

In Figure 5, changes to the real total tax rate for gasoline is computed against the pre-treatment (1960-1989) average in Sweden. The figure shows clearly the (negative) correlation between changes to fuel tax rates and changes to CO_2 emissions from transport.

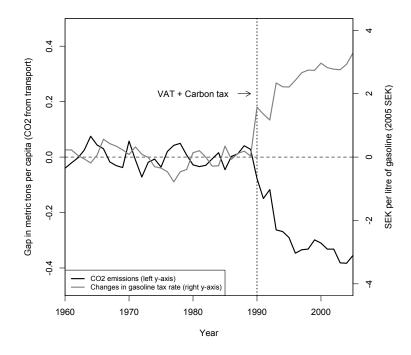


Figure 5: Gap in Gasoline Tax Rate and per capita CO_2 Emissions from Transport Note: Changes to the real gasoline tax rate is computed against the pre-treatment average (1960-1989) in Sweden, and measured in 2005 Swedish kronor. The gap in CO_2 emissions from transport is computed as the gap between Sweden and synthetic Sweden, and measured in metric tons.

Finally, in addition to descriptive evidence of the relationship between changes to emissions and changes to GDP, unemployment and fuel tax rates, I ran a regression model to determine the effect and significance of each of the independent variables. The dependent variable in all specifications is the gap in per capita CO_2 emissions from transport. All variables, except the gasoline tax rate, are computed as the gap between Sweden and synthetic Sweden. Table 4 presents the output from the OLS regressions.

Changes to the real total tax rate on gasoline has the largest predictive power out of the three explanatory variables: an \mathbb{R}^2 value of 0.93 compared with <0.01 for GDP and 0.37 for the unemployment rate. The coefficients on the three variables have the expected signs, but GDP per capita is not significant. Running the full model, including all three predictors of emissions, we find that the unemployment coefficient decreases with more than one order of magnitude in size and is no longer significant compared to estimation (3) and (5), where the gasoline tax rate is excluded from the model. GDP per capita is significant at the 5 percent level in the full model, but the coefficient indicates a fairly small impact on emissions: a \$1000 change in relative GDP per capita changes CO_2 emissions by only 0.018 metric tons per capita. The coefficient for the gasoline tax rate is however highly significant and similar in size in all models where it is included. An increase in the tax rate of 3 SEK, corresponding roughly to the total increase in the post-treatment period from 1990 to 2005, reduces CO_2 emissions by -0.342 metric tons per capita.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Gasoline tax rate	-0.116 (0.006)			-0.117 (0.005)		-0.111 (0.008)	-0.114 (0.008)
GDP per capita		$0.003 \\ (0.048)$		$\begin{array}{c} 0.021 \\ (0.007) \end{array}$	-0.022 (0.026)		$0.018 \\ (0.009)$
Unemployment			-0.041 (0.012)		-0.042 (0.008)	-0.005 (0.005)	-0.003 (0.004)
$\frac{\text{Observations}}{R^2}$	$\begin{array}{c} 46 \\ 0.929 \end{array}$	$\begin{array}{c} 46 \\ 0.000 \end{array}$	$\begin{array}{c} 46 \\ 0.365 \end{array}$	$\begin{array}{c} 46 \\ 0.937 \end{array}$	$\begin{array}{c} 46 \\ 0.374 \end{array}$	$\begin{array}{c} 46 \\ 0.932 \end{array}$	$\begin{array}{c} 46 \\ 0.938 \end{array}$

Table 4: Estimation Results from Gap in CO₂ Emissions Regressions

Note: The dependent variable is the gap in per capita CO_2 emissions from transport. All variables, except the real gasoline tax rate, are computed as the gap between Sweden and Synthetic Sweden. Changes to the real gasoline tax rate is compared to the pre-treatment average (1960-1989) in Sweden, and measured in 2005 Swedish kronor. Real GDP per capita is Purchasing Power Parity (PPP)-adjusted and measured in 2005 U.S. dollars (thousands). Unemployment is measured as percentage of total labor force. Newey-West standard errors in parentheses; heteroscedasticity and autocorrelation robust. Standard errors are calculated using 16 lags, chosen with the Newey West (1994) method. The constant is omitted from the output.

G Carbon Tax Salience

The evidence from Sweden indicates that there is a significantly larger behavioural response to changes to the carbon tax rate than to equivalent gasoline price changes. This finding is in line with previous empirical evidence, where changes to gasoline and carbon tax rates have been found to create two and a half to four times larger demand responses (Davis and Kilian, 2011; Li, Linn, and Muehlegger, 2014; Rivers and Schaufele, 2015; Antweiler and Gulati, 2016), a difference observed to persist over the long run (Li et al., 2014). Multiple explanations – that are not necessarily mutually exclusive – have been given to account for this finding. Davis and Kilian (2011) and Li et al. (2014) discuss "salience", the fact that tax changes often are accompanied by media coverage, thereby notifying consumers about the change in price; and "persistence", the fact that tax changes are more long-lasting (and upwards-trending (Hammar, Löfgren, and Sterner, 2004) than oil-induced changes to the price of transport fuel. Li et al. (2014) analyses gasoline tax changes in the US and finds that "a \$0.01 tax change is associated with an order of magnitude greater increase in media coverage, as compared to a \$0.01 change in the tax-exclusive price" (p. 327). Antweiler and Gulati (2016), on the other hand, suggests that the explanation lies in the difference between making buying decisions under certainty versus uncertainty – the tax part of the gasoline price being stable and certain compared to the volatile and uncertain part driven by fluctuations in crude oil prices. Lastly, Rivers and Schaufele (2015) refer to other-regarding preferences and a resentment

of free-riding – the carbon tax eliminates the opportunity to free-ride on an environmental public good provision – to explain the larger behavioural response that the carbon tax produces.

If carbon tax elasticities are indeed larger than price elasticities of demand for some goods, this has implications for public policies as well as economic theory. When conducting policy analysis of the impact of price changes on the demand for a certain good or service, it would be important to consider the source of the price variation (Li et al., 2014). The salience finding also has implications for calibrations of optimal tax rates (combining Pigouvian and Ramsey taxation). When numerically calculating the optimal gasoline tax for the UK and the US, Parry and Small (2005) use estimates of the price elasticity of demand for gasoline in each country. If, however, the absolute value of the tax elasticity will result in a lower optimal tax rate. Finally, a central assumption in public economics is that agents fully optimize when it comes to tax policies and thus react in a similar way to tax changes as to equivalent price changes. Chetty, Looney, and Kroft (2009) points out that canonical results in the analyses of tax incidence, efficiency costs and optimal income taxation all rely on this assumption.

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