

HUMBOLDT UNIVERSITY OF BERLIN

MASTER'S THESIS

**A Replication of Metcalf and Stock
(2020): The Macroeconomic Impact of
Europe's Carbon Taxes**

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for the degree of Master's of Economics and Management Science (M.Sc.)
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Declaration of Authorship

I, Jeffrey Giddens, declare that this thesis, titled A Replication of Metcalf and Stock (2020): The Macroeconomic Impact of Europe's Carbon Taxes and the work presented in it are my own. I confirm that:

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- Where I have consulted the published work of others, this is always clearly attributed.
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- I have acknowledged all main sources of help.
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Abstract

School of Business and Economics

Chair of Economic Theory II

Master's of Economics and Management Science (M.Sc.)

A Replication of Metcalf and Stock (2020): The Macroeconomic Impact of Europe's Carbon Taxes

by Jeffrey Giddens

Rationale and Objectives: The working paper Metcalf & Stock (2020c) is one of the first large scale empirical studies of the impacts of carbon taxes on macroeconomic variables. They find that estimating the Impulse Response of a moderate carbon tax on GDP or employment using data from European member states shows a neutral to modestly positive impact for both, as well as a modest reduction in emissions. This contradicts the predictions of traditional DSGE models. This thesis replicates the main results of Metcalf & Stock (2020c) and extends their analysis. Updating the data through 2020 has no significant impact on the results, while weighting the model by country population results in lower overall estimates of GDP and employment growth as well as larger estimates of emissions reductions.

Conclusion and Contributions: In support of Metcalf & Stock (2020c), I find no evidence of macroeconomic harm due to carbon taxes.

Keywords: Local Projections, Impulse Response Function, Carbon Tax, GDP, literature survey.

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List of Abbreviations

General Abbreviations

CIRF	Cumulative Impulse Response Function
CO ₂	Carbon Dioxide
DSGE	Dynamic Stochastic General Equilibrium
ETS	Emissions Trading System (European)
EU+	32 European countries in the study
GDP	Gross Domestic Product
IRF	Impulse Response Function
LP	Local Projections
OLS	Ordinary Least Squares
PPP	Purchasing Power Parity
SVAR	Structural Vector Autoregression

Chapter 1

Introduction

The concentration of carbon dioxide (CO₂) in the atmosphere over the last million years has varied between 170 and 280 parts per million (see [Figure 1.1](#)). Today the concentration of CO₂ is above 410 parts per million, the highest in human history, and continues to climb every year. It is clear that this abrupt increase over approximately the last 100 years is due to the burning of fossil fuels, as they release CO₂ and other gases as byproducts. Continuing research is also making clear that increased concentrations of CO₂ and other greenhouse gases, by trapping more solar radiation in the atmosphere, are leading to planetary temperature change, local climate changes and more frequent extreme weather phenomena.

The stable climate and weather patterns that exist now are ideal for life that has evolved to live on Earth. Sudden volatility and changes to ecosystems will threaten the survival of many of the species living today. By altering the makeup of our atmosphere and inducing climate change humanity runs the risk of endangering Earth's many ecosystems. Continuing down this path by adding more greenhouse gases (GHGs) to the atmosphere portends further warming, heat waves, droughts, floods, ocean acidification, sea level rise, ecosystem collapses, and much more (Hoegh-Guldberg et al. 2018).

Increasing the amount of carbon in the atmosphere will result in predominantly harmful consequences for humanity with the repercussions becoming more severe as sea levels continue to rise. The amount of carbon in the atmosphere must be minimized to mitigate the harmful effects to come.

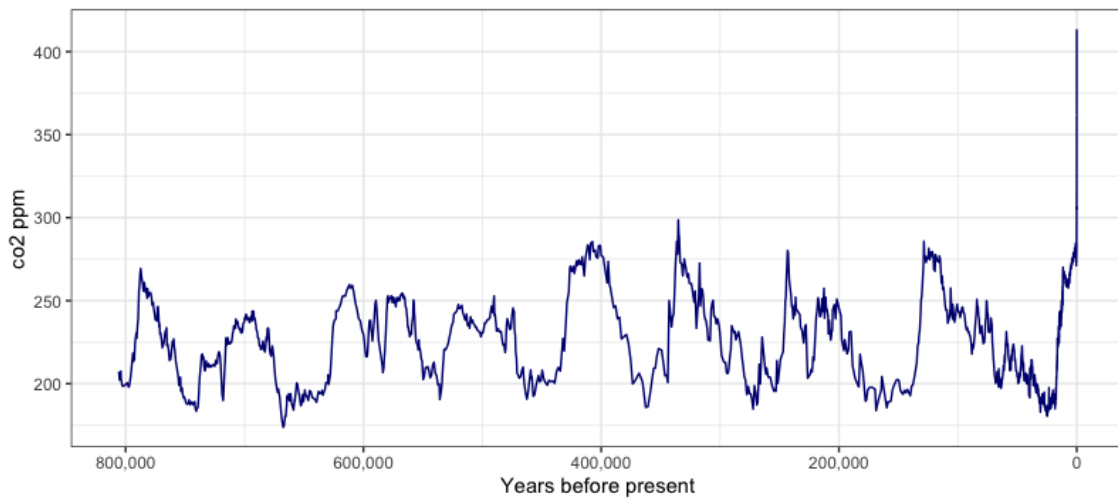


FIGURE 1.1: CO₂ concentrations over 800,000 years. Source: Bereiter et al. (2015)

There appears to be a tradeoff in reducing emissions. A high percentage of total emissions stem from the burning of fossil fuels for energy that powers much of the world's economy. Cutting emissions now would require a drastic reduction in energy use and therefore a reduction in economic activity, which could devastate millions if not billions of lives worldwide. Continuing to burn fossil fuels as we do now, however, will raise CO₂ levels by hundreds more parts per million. The consequences of this will be dire for the world economy and human welfare, if not civilization-destroying.

Without government intervention, fossil fuels will continue to deliver cheap and easy energy, and we will continue to use them at unacceptably high levels. Rapidly improving technology in renewable energy promises to be more cost effective than fossil fuels. In order to drive emissions down as quickly as possible, the use of fossil fuels also needs to be disincentivized.

Over 3500 economists signed the Climate Leadership Council's *Economists' Statement on Carbon Dividends* (2019) that calls carbon taxation "the most cost-effective lever to reduce carbon emissions at the scale and speed that is necessary." The goal of a carbon

tax is to internalize the hidden costs of air pollution to force those responsible to pay for the environmental damage. The increase in the relative price of fossil fuel energy would incentivize other forms of energy production and ideally reduce the total CO₂ emitted.

According to classical economics, a distortionary tax reduces market efficiency and shrinks the economy. Therefore, we should expect to see evidence of reductions in macroeconomic variables such as GDP and total employment when countries introduce carbon taxes. Surprisingly, however, Metcalf & Stock (2020c) find that implementing a carbon tax can not only reduce emissions, but also that there is no evidence of adverse effects on GDP growth or employment from doing so.

In this paper I replicate the main results from Metcalf & Stock (2020c) and extend the analysis to include more data and specifications. Metcalf & Stock's research is one of the first empirical studies on the macro impacts of carbon taxes. Therefore, their work is not the final word on this topic, and more research is needed to verify their findings. Though the findings of Metcalf & Stock (2020c) are encouraging, scientific rigor dictates that replication is a necessary step to ensure that their research can guide accurate policy suggestions.

Chapter 2 provides more background on Pigouvian taxation and the effects of carbon taxes. In Chapter 3 I briefly review the literature on the impacts of carbon taxes on emissions and the economy. Chapter 4 discusses the data used. Chapter 5 summarizes the econometric approach used to estimate the causal impact of carbon taxes. Chapter 6 presents the results. Chapter 7 discusses the validity and implications of these findings and Chapter 8 concludes.

Chapter 2

Background

Greenhouse gases in economic terms are a “public bad,” meaning that the costs of air pollution (warming, climate volatility, etc.) are not borne by those that pollute. This negative externality causes the market (in this case for GHGs and the benefits of burning fossil fuels, and pollution and other climate damages) to not work efficiently.

Pigouvian taxation, first described by Arthur Pigou in *The Economics of Welfare*, intends to correct the market by internalizing the externality with a tax. For greenhouse gases, CO₂ in particular, applying a tax at the mouth of the mine or anywhere along the production cycle would raise the price of using that resource, forcing those that benefit from it to pay for its resulting damages instead of passing on these costs.

The other method for pricing carbon is a cap and trade system. Whereas a carbon tax fixes the additional carbon price and lets the market determine the quantity used, a cap and trade fixes the quantity used and allows the market to determine the price. Metcalf (2019) discusses the advantages of a carbon tax over a cap and trade system. Price volatility with cap and trade reduces the ability to plan longer term projects and increases the risk of investing in new technologies. Cap and trade also necessitates the decision of how to distribute permits to pollute, which raises fairness considerations and the potential for fraud. Finally, cap and trade without a well designed cap trajectory will not drive emissions reductions, as a reduction in demand for emissions will lower their price and increase emissions from another polluter. Due to the shortcomings of cap and trade systems, carbon taxes are widely considered to be the more effective carbon pricing system

(*Economists' Statement on Carbon Dividends* 2019).

Metcalf (2019) discusses implementation of carbon taxes and their optimal price. Pigouvian theory suggests that the tax should be set equal to the marginal damage of one more ton of CO₂ emitted, and Metcalf (2019) estimates that in the United States, “a tax rate based on the social cost of carbon would be roughly \$50 a metric ton of CO₂ in 2020.” The paper also discusses distributional effects and shows that a carbon tax is regressive with respect to collection, meaning that those at lower incomes would pay proportionally more of their own wealth and earnings in tax than those with higher incomes. On the other hand, taxes generate revenue that can be redistributed with new spending, tax cuts, or cash grants. If distributed equally, these transfers can result in a net progressive tax.

Raising the price of fossil fuels would make alternative energy sources comparably more attractive, hastening their adoption and potentially spurring innovation to further increase their utility over fossil fuels and increase the pace of adoption even more. Acemoglu et al. (2012) and Acemoglu et al. (2016) demonstrate that a temporary carbon tax environment can direct innovation and adoption of renewable energy, with the optimal policy including research subsidies and avoiding excessive carbon taxation.

A distorting tax reduces market efficiency and leads to declines in overall welfare. Without being able to empirically observe the social costs averted when applying the tax, the measurable negative impacts on the economy suggest that the tax would result in a net loss of welfare. Under this theory, the implementation of a carbon tax would prompt reductions in GDP and employment due to market distortions.

Chapter 3

Review of the Previous Literature

Metcalf & Stock (2020c) provide an overview of the literature related to the macroeconomic impacts of carbon taxes. In addition to the works they reference, more recent articles have been published that are also relevant to this topic. These works focus on one of three main themes within the broader topic of carbon taxation: theoretical models predicting carbon pricing outcomes, distributional impacts, and empirical studies similar to those of Metcalf & Stock.

3.1 Theoretical Models

Metcalf & Stock (2020c) cite the E3 model of Goulder & Hafstead (2017) as a middle estimate of DSGE models for the long-term reduction in GDP from a carbon tax—that the United States GDP would be about 1% less in 2035 with a \$40 per ton steadily growing carbon tax than without. Many estimates are even smaller or negligible. Yu et al. (2020) model China’s power industry for years 2020-2050 and find that a carbon tax at just 210 yuan today (\$32) rising to 910 (\$140) by 2050 would be sufficient to help China achieve peak emissions in the 2030s and fulfill its emissions reduction commitments. Looking at the consequences of worldwide carbon tax adoption, Hassler et al. (2020) find with their model that “the costs of underestimating climate change are roughly one order of magnitude larger than the costs of overestimating it.” They estimate an optimal tax for the entire world that would keep global warming to a 2.6°C increase in the far future. They also look at scenarios where all countries impose carbon taxes except either developing

countries (Africa and India) or China. When Africa and India are exempt from the tax, their relative welfare gains are less than 2% higher than when imposing the tax, while China would gain 15% in welfare without the tax. In the first scenario, under which Africa and India do not cut emissions, other countries would have to impose carbon taxes at 5.3 times the rate otherwise. Under the second, where China does not cut emissions, global carbon taxes would need to be 25 times higher. This emphasizes the importance of global acceptance of a price on carbon.

3.2 Distributional Impacts

Several studies focus on the distributional impacts of carbon taxation, meaning how different income groups will be affected. Kaenzig (2021) finds, along with temporary reductions in economic activity, that poorer households lower their consumption under a carbon tax due to the significant increase in energy prices, while richer households' behavior is unaffected. He thus advocates for redistribution of revenues. Brazil is currently considering a carbon tax, with Moz-Christofolletti (2021) finding that without compensation mechanisms the tax imposes welfare losses on the poor in an already regressive tax environment. Hsu (2021) discusses the political resistance to carbon taxes in the United States and their perception of regressivity and argues for their progressivity via revenue redistribution.

3.3 Empirical Studies

A number of studies assess the impact of carbon taxes on emissions. Andersson (2019) estimates a counterfactual reduction of emissions from transport in Sweden of 11%, primarily due to a carbon tax. Abrell et al. (2021) train a machine learning model on data

from the UK carbon levy that estimates a 6.2% reduction in emissions at an average price of €18 per ton without incurring significant costs. Best et al. (2020) perform an empirical study on 142 countries over two decades, finding that an additional euro per ton of CO₂ in carbon tax reduces annual emissions growth by 0.3% on average, and that emissions trajectories in countries with and without carbon taxes diverge over time.

Metcalf & Stock (2020c) is the first large scale empirical study of the impact of carbon taxation on macroeconomic variables. They discuss a number of empirical studies of British Columbia's carbon tax, including Metcalf (2019), and find no negative impact on GDP or total employment, but do find potential job shifts away from carbon intensive industries. Dussaux (2020) presents early evidence that the French carbon tax is not harming total employment. However, a simulated doubling of the tax shows "significant heterogeneity across sectors" in terms of jobs reallocated and emissions reductions.

Chapter 4

Data

The dataset used for Metcalf & Stock (2020a) is published as a data and code package (Metcalf & Stock (2020d)). This dataset comprises 32 countries over the years 1985 to 2018. This table includes series for GDP, employment, and real adjusted carbon tax rates. Metcalf and Stock Metcalf & Stock (2020c) use the same dataset, and so this data is used to replicate parts of their study.

The dataset used for this thesis¹ includes six main series: GDP, employment, two emissions series, and two carbon tax rate series, covering the same 32 countries and extending to 2020. All data is annual.

GDP data comes from the World Bank Group (2021) and matches the GDP series of Metcalf & Stock (2020d). The total employment series comes from Eurostat (2021) and also matches that of Metcalf & Stock (2020d). Both series extend to 2020. Emissions data comes from Eurostat (2021) and cover the years 1990 to 2019.

I use two different datasets for greenhouse gas emissions—the first is strictly CO₂ emissions from road transportation, a sector that is usually covered by the tax and not by the ETS. This is used to see if the adoption of carbon taxes has a direct impact on a specific sector. Road transportation is an appropriate sector to analyze because it is difficult to evade the tax by shifting road transportation operations to a lower tax country. The second dataset is of total greenhouse gas emissions, with other gases such as methane adjusted to their CO₂ equivalents. Though the carbon taxes do not cover all emissions,

¹Data and code are available at <https://github.com/jdgiddens/thesis>

a noticeable change in total emissions from the implementation of a carbon tax is still possible.

Data on carbon tax rates and the percentage of a country's emissions that they cover (coverage rates) come from the World Bank Carbon Pricing Dashboard (2021). Carbon tax prices are estimated and published in nominal US dollar equivalents. The real adjusted carbon tax series, hereafter referred to as the 2020 tax series, is calculated by dividing by the GDP deflator to get equivalent 2018 US dollars. This series differs systematically from that used by Metcalf & Stock (2020d), hereafter referred to as the 2018 tax series, and much of the difference over all countries in specific years will be captured by the year fixed effects (see Appendix A).

Chapter 5

Methods and Econometric Approach

The 32 European countries in the study sample are all subject to the same European Emissions Trading System (ETS) that covers the power sector, certain energy-intensive industries, and aviation. However, they differ considerably in implementation of further carbon taxes. Metcalf & Stock (2020c) summarize the various countries' taxes.

The study leverages the heterogeneity in carbon tax schemes between countries with otherwise similar political pressures to tease out the causal effect of solely the carbon tax on macroeconomic outcomes. I employ the same methods used by Metcalf & Stock (2020c). The regressions are estimated with the Jordà (2005) Local Projections method and the impulse responses are generated by the method described in Sims (1986) that “computes the sequence of shocks necessary to yield the specified counterfactual carbon tax increase” Metcalf & Stock (2020c).

I will use GDP as the variable in the description, as the setup is the same for employment and emissions. The regression is a two-way fixed effects panel model for each horizon level h :

$$100\Delta\ln(GDP_{it+h}) = \alpha_i + \Theta_{yh}\tau_{it} + \beta(L)\tau_{it-1} + \delta(L)\Delta\ln(GDP_{it-1}) + \gamma_t + e_{it} \quad (5.1)$$

Where τ_{it} is the real carbon tax rate, Θ_{yh} is the “effect of an unexpected change in the carbon tax rate”, α_i are country fixed effects, γ_t are year fixed effects, and $\beta(L)\tau_{it-1}$ and $\delta(L)\Delta\ln(GDP_{it-1})$ are the lags of the carbon tax and GDP series. Four lags are used throughout the study, determined by lowest AIC.

The IRF is derived by the multiplication of the estimates at each horizon h for Θ_{yh} , the rate of change of GDP for a unit change in the carbon tax rate, and the shock matrix, the sequence of shocks needed to produce the counterfactual tax increase considered. Specific calculations are available in the appendix of Metcalf & Stock (2020b), and I summarize my procedure in the code in Appendix C.

Country fixed effects address the possibility that countries with typically higher growth rates may be more likely to adopt carbon taxes, which would bias the results towards higher responses to GDP. Year fixed effects control for recessions, such as in 2009 and 2020, as well as for impacts from common pressures such as the ETS.

Table 3 of Metcalf & Stock (2020c) reports the results of the “panel Granger Causality test of the coefficients on GDP growth in a regression of the carbon tax rate on its lags and lagged GDP growth,” where the authors cannot reject that there is no feedback from shocks to GDP to tax rates. Therefore, the identifying assumption for their distributed lag method is not met, so we should treat carbon taxes as an endogenous variable while also using them as exogenous shocks. We can break the carbon tax down into two parts: the endogenous part, or predicted part, and the exogenous part, or the shock. Carbon tax rates are predicted using a similar regression, also at each horizon h :

$$\tau_{it} = \alpha_i + \beta(L)\tau_{it-1} + \delta(L)\Delta \ln(GDP_{it-1}) + \gamma_t + u_{it} \quad (5.2)$$

With the identifying assumption that the residuals u_{it} represent the exogenous policy variation and can be treated as shocks.

Metcalf & Stock (2020c) apply Structural Vector Autoregression (SVAR) alongside Local Projections as a robustness check. They find the same results using either method, as these results can differ in a finite sample but are the same in population, due to having the same identifying assumption and the same estimand (Plagborg-Møller & Wolf 2019). For this

study I do not replicate the SVAR results.

Another consideration taken by Metcalf & Stock (2020c) is the parallel path hypothesis. Most general equilibrium models construct long term growth rates based on economic fundamentals not affected by relative price fluctuations, implying that a carbon tax may impact GDP growth in the short term while it returns to the same growth rate in the long term. The temporary output loss puts a country on a slightly lower GDP trajectory but with the same GDP growth, yielding a parallel path. Table 2 of Metcalf & Stock (2020c) tests for long run growth rate changes and finds that long run growth rates are generally unaffected by imposition of a carbon tax. Consequently, the results for GDP, employment, or emissions using the restricted model (restricting long run GDP growth to zero) do not differ from those using the unrestricted model.

In this paper I will use the unrestricted model for two reasons. First, the results will differ very little if long run growth change is estimated to be close to zero regardless. Second, restricting change in long term GDP growth to zero quiets any potential *positive* impacts on the economy due to the tax. For example, relative price changes can spur innovation and investment that would lead to a stronger GDP growth path than would have occurred without the tax. In the longer term with more nations involved, climate damages avoided solely by applying the tax could result in permanently better GDP outcomes.

The experiment used in Metcalf & Stock (2020c) and this paper is the increase of a carbon tax rate by \$40 on 30% of a country's emissions and remaining at that level. In the data, many of the carbon taxes are higher than this while others are lower, so the carbon tax data that exists is similar to the counterfactual. This is also similar to levels proposed and used elsewhere in the world (*Carbon Pricing Dashboard* 2021). For example, Brown (2019) estimates that "a \$10/tCO₂ tax rising to \$27/tCO₂ in 2040 (in \$2013) would achieve the U.S. electric sector's carbon budget" by reducing emissions by 20%, so a \$40 per ton tax

would go far in achieving emissions reduction goals.

The model used in this paper is linear, meaning that proportional changes in the inputs cause proportional changes in the results. For example, changing the counterfactual tax rate to \$80 just doubles the estimates for the IRFs. This model is likely to be misspecified at this rate, as the data for countries operating with this tax rate is sparse. Metcalf & Stock (2020c) attempts to address if much higher tax rates have different outcomes on GDP by using a subset of countries with the highest tax rates, but the empirical analysis is limited by the data available.

Many countries' tax rate paths grow steadily over time, as do many proposals worldwide. In this model, changing the counterfactual tax rate hike to a growing path simply affects the results in a linear fashion, with years in the past affecting the future.

To perform this analysis, I use the data and code from Metcalf & Stock (2020d) and translate their Stata code into R with R Studio. GDP, employment, and emissions variables appear as percentage annual changes, calculated by taking differences in logs. A country's coverage rate is multiplied by the tax rate to yield the final tax series used in levels. The underlying assumption of this multiplication is that the magnitude of the effect of a carbon tax on GDP will be proportional to how much of the total emissions that are covered. For example, if Sweden's carbon tax covers 20% of their emissions and causes a 1% increase in GDP, then the model would predict a 2% GDP for a coverage rate of 40%. For the emissions IRFs, since taxed sectors such as transportation are more difficult to decarbonize than sectors such as power, the reduction effect could be more pronounced in practice if the tax covered larger percentages of total CO₂ and other greenhouse gasses.

With these specifications, I run the model with changes in data, including subsamples of countries and with weighting of the regressions by country population. A handful of other considerations are covered in Appendix C.

Chapter 6

Results

I will present the results in order of GDP, employment, CO₂ emissions from land transportation, and finally total greenhouse gas emissions. All impulse response functions were obtained using the local projections method with the unrestricted model and four lags of the variables. Standard errors are robust to heteroskedasticity. For direct replications, I use the Metcalf & Stock (2020d) tax rate, tax coverage share, GDP, and employment series. When applying the model to new data, I use the real adjusted tax rate series, coverage share, GDP, employment, and emissions series provided by Eurostat (2021) and the World Bank (2021). The impulse response function graphs display the estimated impact of a counterfactual \$40 carbon tax increase on 30% of emissions that remains in place for six years. The red line displays the point estimates, the estimated percentage change in growth of the variable in that year, and the bands display 67% and 95% confidence intervals. When zero is still within the confidence band, then the model cannot predict a statistically significant impact of the carbon tax increase on that variable in that year.

6.1 GDP

Metcalf & Stock (2020c) find no evidence of GDP loss in any of their formulations. This result holds whether using either LP or SVAR methods, a restricted or unrestricted model, or an alternative tax series. When applying the model to subsets of the data such as revenue recycling countries, non-revenue recycling countries, high carbon tax countries, Scandinavian countries or non-Scandinavian countries, they still find no evidence of GDP

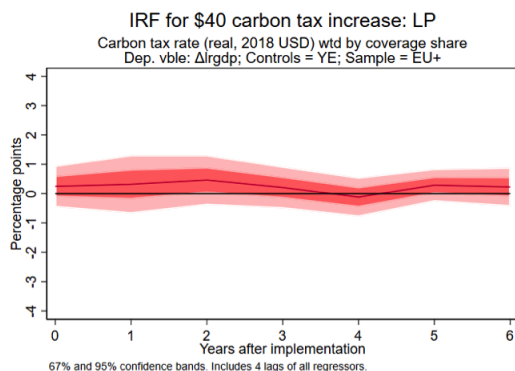


FIGURE 6.1: Metcalf & Stock (2020c) Figure 3a

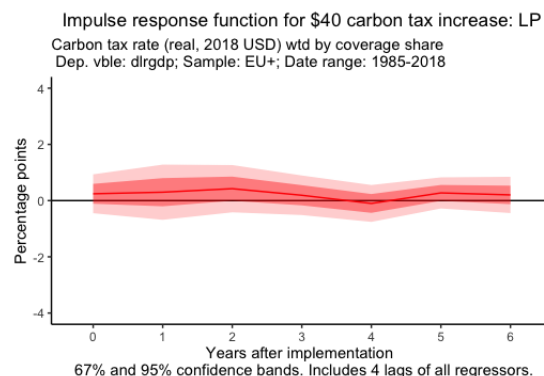


FIGURE 6.2: Replication of Figure 6.1

loss. I present a direct replication of the full sample LP unrestricted IRF and a series of new IRF estimations. Further additional IRFs are included in Appendix C.

Figures 6.1 and 6.2 show Metcalf and Stock's GDP IRF alongside the direct replication. Point estimates are slightly positive aside from year four but never significantly different from zero.

Figures 6.3, 6.4, and 6.5 show the same IRF – impulse of carbon tax on GDP – but with slightly different specifications. Figure 6.3 extends the dataset through 2020 by using the 2020 tax series. Even with the narrower error bands, the point estimate is only significantly different from zero in year two, and hovers around zero otherwise.

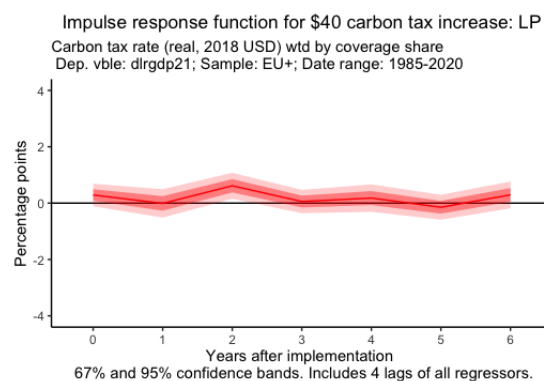


FIGURE 6.3: GDP IRF with 2020 tax series

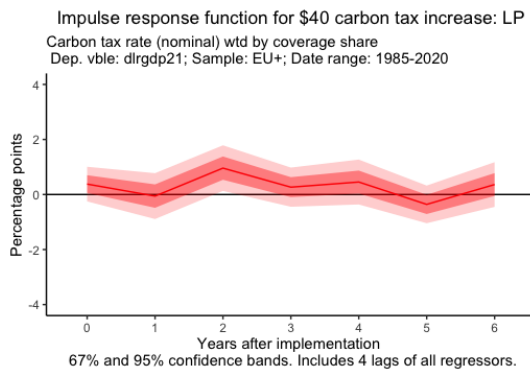


FIGURE 6.4: GDP IRF
with nominal tax series

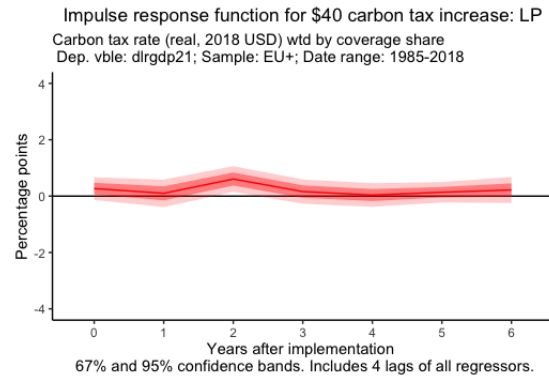


FIGURE 6.5: GDP IRF
with 2020 tax series
through 2018

Figure 6.4 uses the unadjusted nominal tax series as reported by the World Bank. The trajectories displayed in Figures 6.3 and 6.4 are the same, with larger standard errors in the nominal tax series version. Figure 6.5 uses the 2020 tax series but only with data through 2018. Figure 6.5 has narrow error bands like 6.3, confirming that the 2020 tax series is responsible for IRFs with lower standard errors than when using the 2018 tax series or nominal tax series.

In equation 5.2, when the tax series is regressed on its own lags, as well as the other factors, the 2020 tax series likely produces smaller residuals, meaning that the 2020 tax series is generally more predictable. Therefore, in the 2020 tax series the endogenous portion of the tax rates is higher, so the exogenous parts of the tax rate (the shocks) are generally smaller.

Figures 6.6 and 6.7 display the weighted OLS versions of Figures 6.2 and 6.3, the standard GDP IRF from Metcalf & Stock (2020c) and the IRF using the 2020 tax rates. The regressions are weighed by a country's population in 2018. Though the trajectories are similar to the unweighted versions, point estimates are consistently lower. This suggests that larger countries have a generally worse GDP response to applying carbon taxes than smaller ones.

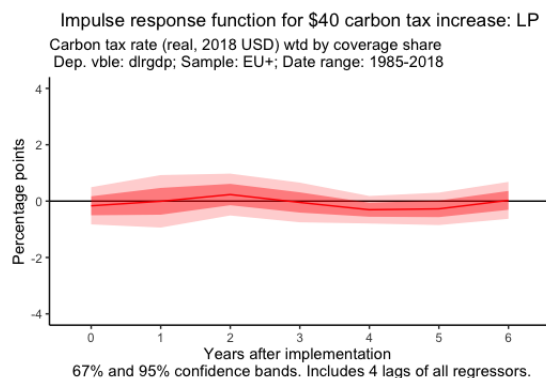


FIGURE 6.6: Weighted
IRF with 2018 tax series

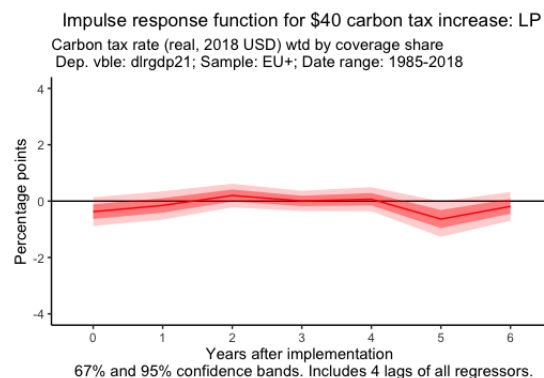


FIGURE 6.7: Weighted
IRF with 2020 tax series

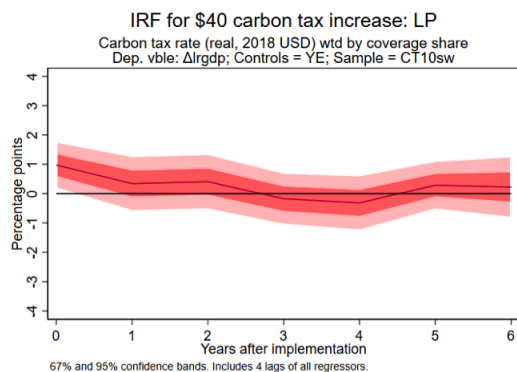


FIGURE 6.8: Metcalf &
Stock (2020c) Figure 12a

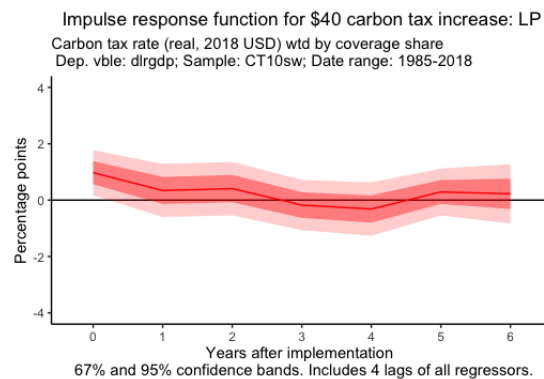


FIGURE 6.9: Replication
of Figure 6.8

Figure 6.8 is Figure 12a of Metcalf & Stock (2020c) and Figure 6.9 show the replication. The IRFs use only countries with coverage-rate-adjusted carbon taxes of \$20 or higher in any year. Under the classical theory that a tax will introduce economic distortions, we might expect to see a more damaging effect of the tax on GDP in countries with larger carbon taxes. However, as with other specifications, estimates are not significantly different from zero. Figure 6.9 applies this high tax country filter to the data through 2020, but this subset now includes ten countries instead of seven, and with more data the estimates move closer to zero with smaller standard errors. In these specifications, despite lower point estimates when weighting by country population, I still find no evidence of GDP reduction due to the introduction of carbon taxes in Europe.

6.2 Employment

Figures 6.10 and 6.11 are Figure 6a of Metcalf & Stock (2020c) and the replication. Point estimates for total employment run slightly positive for the first two years after implementation of the tax, then drop close to zero.

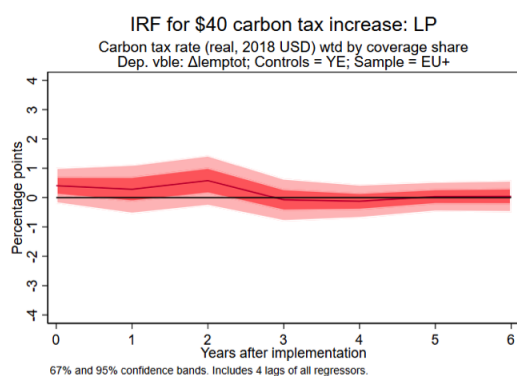


FIGURE 6.10: Metcalf & Stock (2020c) Figure 6a

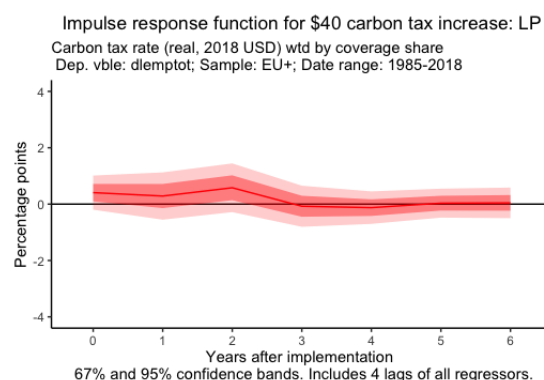


FIGURE 6.11: Replication of Figure 6.10

Figure 6.12 applies the specification to data through 2020, and the trajectory is similar, with the narrower standard error bands presumably due to the 2020 tax series.

Figures 6.13 and 6.14 are the weighted OLS specifications of Figures 6.11 and 6.12, the standard total employment IRFs using the 2018 and 2020 tax series.

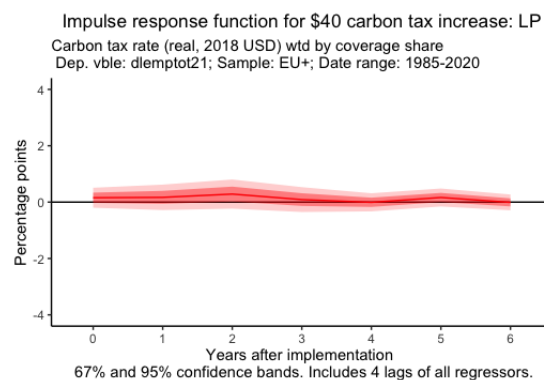


FIGURE 6.12: Employment IRF with 2020 tax series

Weighting the impact on total employment by population has a similar effect that it did on GDP—to lower the point estimates. It again suggests that for larger countries the positive macroeconomic impacts of a carbon tax are not as pronounced as they are in smaller countries, or that the impact is neutral or slightly negative. As with GDP, despite lower

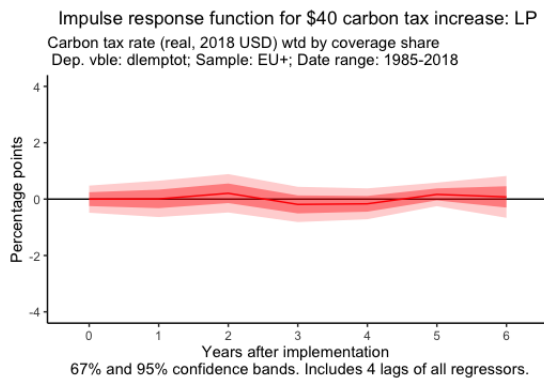


FIGURE 6.13: Weighted
IRF with 2018 tax series

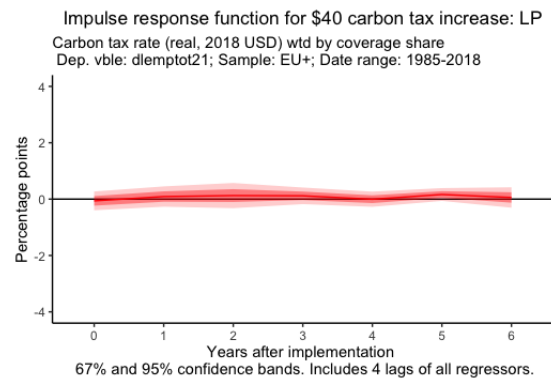


FIGURE 6.14: Weighted
IRF with 2020 tax series

estimates in the weighted models, I still find no evidence of total employment reduction due to the introduction of carbon taxes.

6.3 CO₂ Emissions from Land Transportation

I use two emissions series from Eurostat (2021). The first series measures CO₂ emissions strictly from land transportation, a sector typically covered by the various carbon taxes. This choice of emissions series is intended to closely reflect the emissions results of Metcalf & Stock (2020c). The second emissions series is of total greenhouse gas emissions in CO₂ equivalents from all sources, and is intended to reflect an impact on the final goal of reducing total emissions.

Figures 6.15, 6.16, 6.17, and 6.18 show the IRFs and CIRFs for CO₂ emissions from land transportation, using the 2018 and 2020 tax series. A large increase followed by a large decrease in emissions is a surprising result. The most likely explanation here is that many of the countries' emissions series start in 2009, and some countries have no data, so the dataset is sparse and not large enough to give accurate or precise estimations.

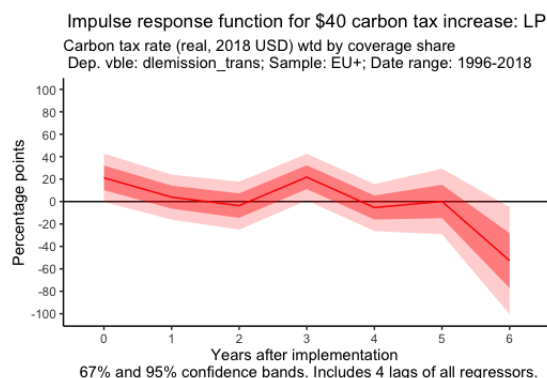


FIGURE 6.15: Emissions
from land transportation
IRF

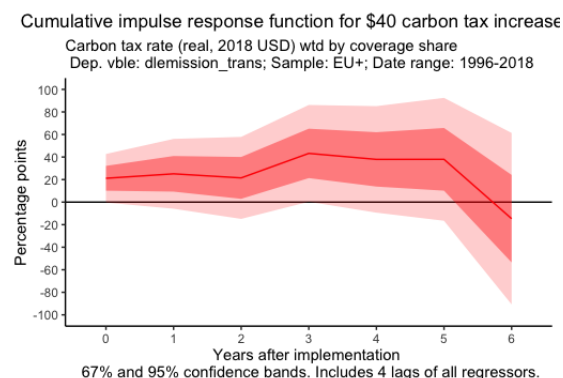


FIGURE 6.16: Emissions
from land transportation
CIRF

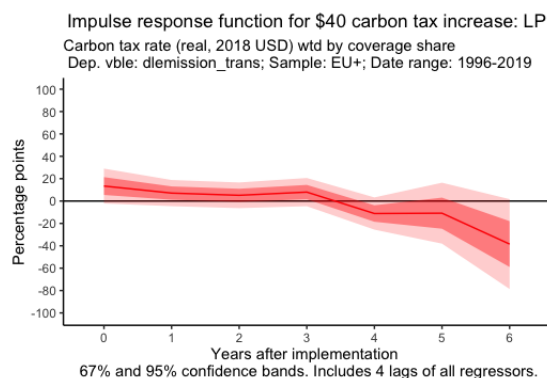


FIGURE 6.17: Emissions
IRF using the 2020 tax se-
ries

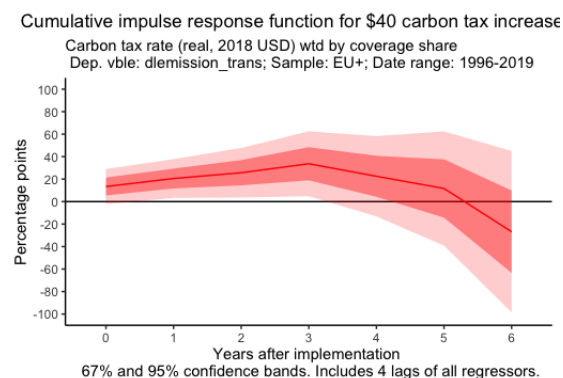


FIGURE 6.18: Emissions
CIRF using the 2020 tax
series

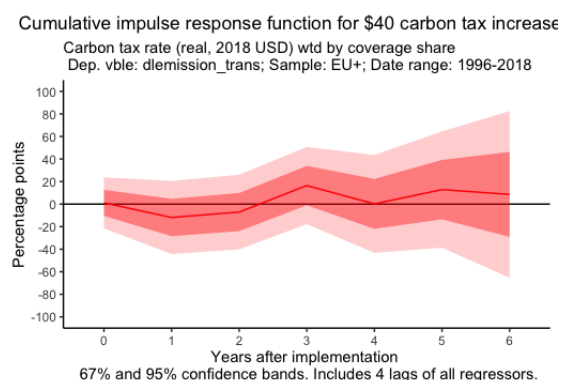


FIGURE 6.19: Weighted
CIRF using the 2018 tax
series

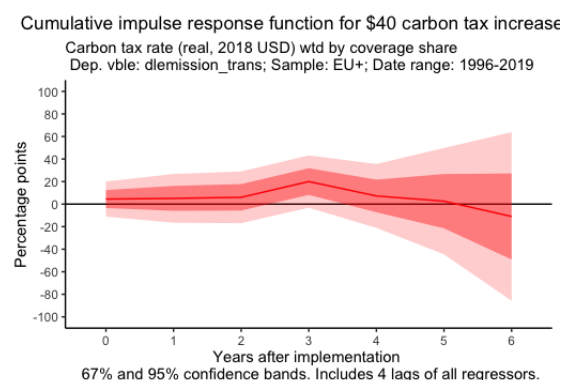


FIGURE 6.20: Weighted
CIRF using the 2020 tax
series

Figures 6.19 and 6.20 show the weighted model for the 2018 and 2020 tax series, respectively. Point estimates are slightly higher than in Figures 6.15 and 6.16. In all specifications, the estimates do not differ significantly from zero.

6.4 Total Emissions

The total greenhouse gas emissions series has more data than the land transportation series, as well as very different results. Figures 6.21 to 6.28 show the IRFs, CIRFs, and weighted IRFs and CIRFs for the 2018 and 2020 tax series. These figures suggest a different story than the land transportation series: in most specifications, point estimates are negative and increasingly so at further horizons. The four cumulative IRFs suggest a 9-13% decrease in total emissions by year six from the deployment of a 40\$ per ton carbon tax in year zero. Some of the point estimates at year six are significantly different from zero, suggesting that a \$40 increase in a country's carbon tax would significantly reduce its emissions.

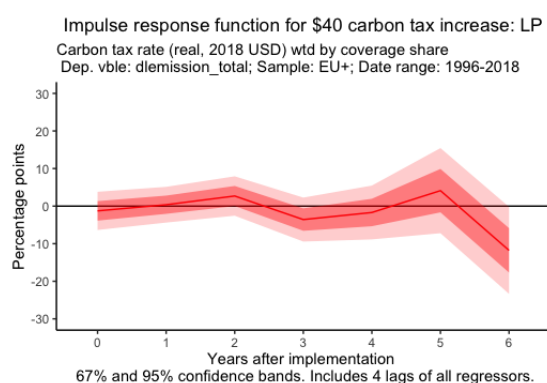


FIGURE 6.21: Total emissions IRF using the 2018 tax series

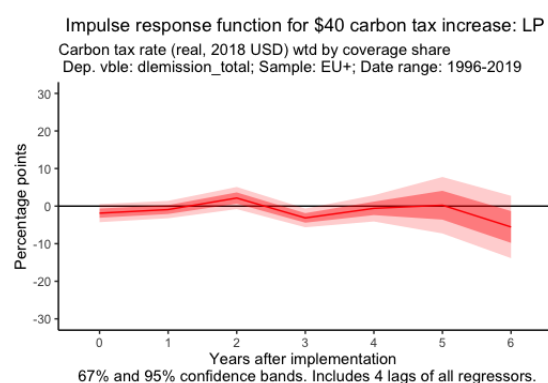


FIGURE 6.22: Total emissions IRF using the 2020 tax series

Cumulative impulse response function for \$40 carbon tax increase
Carbon tax rate (real, 2018 USD) wtd by coverage share
Dep. vble: dlemission_total; Sample: EU+; Date range: 1996-2018

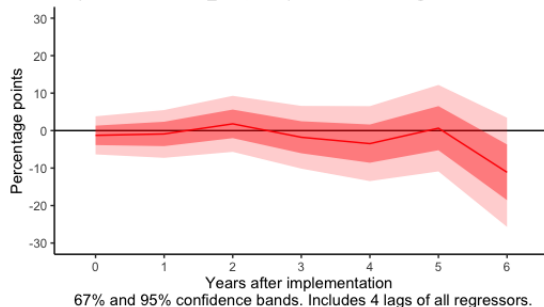


FIGURE 6.23: Total emissions CIRF using the 2018 tax series

Cumulative impulse response function for \$40 carbon tax increase
Carbon tax rate (real, 2018 USD) wtd by coverage share
Dep. vble: dlemission_total; Sample: EU+; Date range: 1996-2019

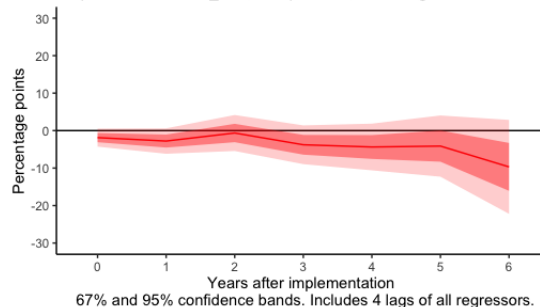


FIGURE 6.24: Total emissions CIRF using the 2020 tax series

Impulse response function for \$40 carbon tax increase: LP
Carbon tax rate (real, 2018 USD) wtd by coverage share
Dep. vble: dlemission_total; Sample: EU+; Date range: 1996-2018

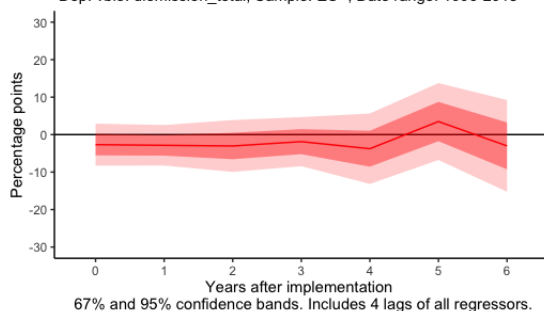


FIGURE 6.25: Weighted IRF using the 2018 tax series

Impulse response function for \$40 carbon tax increase: LP
Carbon tax rate (real, 2018 USD) wtd by coverage share
Dep. vble: dlemission_total; Sample: EU+; Date range: 1996-2019

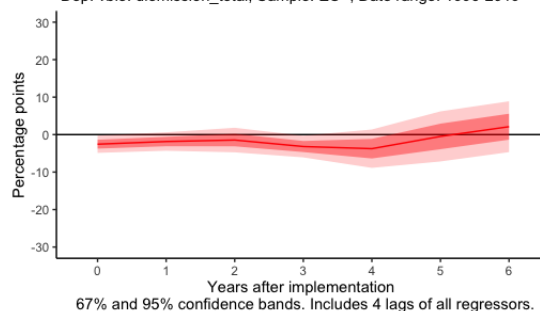


FIGURE 6.26: Weighted IRF using the 2020 tax series

Cumulative impulse response function for \$40 carbon tax increase
Carbon tax rate (real, 2018 USD) wtd by coverage share
Dep. vble: dlemission_total; Sample: EU+; Date range: 1996-2018

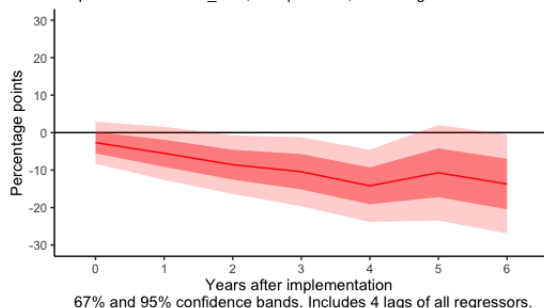


FIGURE 6.27: Weighted CIRF using the 2018 tax series

Cumulative impulse response function for \$40 carbon tax increase
Carbon tax rate (real, 2018 USD) wtd by coverage share
Dep. vble: dlemission_total; Sample: EU+; Date range: 1996-2019

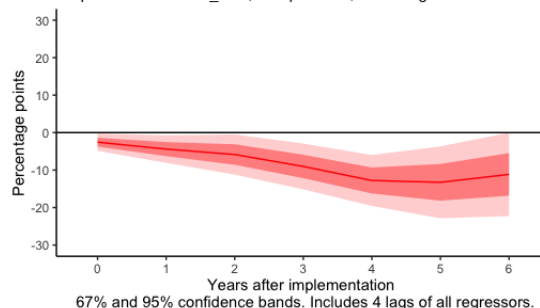


FIGURE 6.28: Weighted CIRF using the 2020 tax series

Chapter 7

Discussion

7.1 Model Validity

Metcalf & Stock (2020c) find no evidence of negative outcomes on GDP or employment due to carbon taxes. The data used for the study are publicly available and constructed by credible sources. I was able to replicate the GDP and employment series exactly, the carbon tax rates very closely, and the emissions series approximately. Their model and cleaned dataset from an earlier version of the paper is published (Metcalf & Stock (2020d)), while the final publication of the paper in a scientific journal and the release of the data and code are forthcoming. The Stata code available now is reproducible in any common statistical software package as all the regressions are solved using simple ordinary least squares—I was able to obtain the same results using R.

The methodology of local projections is an effective strategy for estimating the causal impact of a policy variable on economic variables, and the procedure to obtain the impulse response functions using all data points available at each horizon is statistically sound. Using robust standard errors allows for more confidence that claims of significance account for heteroskedasticity or autocorrelation. In sum, the data and methodology are technically sound.

7.2 Strength of Results

The empirical evidence presented by Metcalf & Stock (2020c) and this replication stand largely in contrast to the expected theoretical outcomes. To attempt to bolster this result and empirically test for possible explanations, Metcalf & Stock (2020c) perform a series of robustness checks by generating IRFs of various specifications. To check that the local projections formulation functions as expected, they repeat all their analyses with SVAR and both yield the same results. To check if effects of larger tax rates differ from those of smaller ones, they use a subset of larger tax rate countries and still find no significant effect. To attempt to answer if revenue recycling countries experience a different impact on their economies from carbon taxes, they run the model with countries that state that they recycle revenue as well as with countries that do not report revenue recycling. The results are consistent with both groups. In their appendix, they also ask a politically contentious question: will employment in manufacturing be affected by carbon taxes? They find no significant impacts for this sector either.

This thesis supplies two more major robustness checks: a new set of data and a weighted model. With different data, the results are largely the same as those from Metcalf & Stock (2020c). Weighting the model by a country's population checks that the estimations are not driven disproportionately by impacts in small countries and potentially reveals differences between large and small countries in their GDP, employment, and emissions responses to carbon taxes. The weighted model returns lower responses to GDP and employment, suggesting that larger countries do not experience as much of a boost to the economy from carbon taxes as smaller countries. The weighted model also estimates larger emission reductions than the unweighted. This suggests that an equivalent carbon tax can have a proportionally larger reduction effect on a larger country.

There are many reasons why the empirical evidence found in this study might prevail over

the classical theoretical predictions. The first and most likely scenario is that the revenues collected are being put to productive use. This study uses a single number per country per year for the carbon tax rates. This simplicity obscures considerable heterogeneity among these taxation schemes. It is possible, however, that on balance the collected revenues are leading to GDP and employment growth through investment in green technology, lowering distortionary taxes, or increasing aggregate demand via redistribution.

There are other limitations in the data that pose a challenge to empirically estimating causality. From the example above, obtaining reliable data about how various countries are using their carbon tax revenue is challenging: because a country cannot credibly commit to a stated action, and because it can be difficult to draw a direct connection between two items in a fiscal budget, such as lowering income tax rates while raising carbon prices.

Also, some countries might serve as poor counterfactuals. Germany has no carbon tax but has other policies in place that could behave like one. Comparing a carbon tax country to Germany and finding no difference would not be significant if the two countries have similar overall effective policies. More generally, a quick look at the map of which countries do and do not have taxes shows that most carbon tax free countries lie in central and eastern Europe, so there is the possibility of other confounding factors and omitted variables beyond the country fixed effects.

Another potential issue comes from the EU ETS. The countries all operate with the same clearing prices for the power sector and other sectors covered, but a group of countries experiencing tax rate shocks at the same time as ETS rate shocks might bias the results. For example, the ETS clearing prices have risen to over \$60 per ton in 2021, well above rates in any previous year, and this could impact countries unevenly. Germany, implementing a new carbon tax in 2021, might see a larger impact to its GDP, employment, and emissions than its carbon price of \$29 might suggest. The standard errors only reflect uncertainty

in the model, not uncertainty in the data, so this should be considered when evaluating an empirical analysis such as this one.

While empirical analysis has data limitations, theoretical modeling has limitations in assumptions. Moyer et al. (2014) points out that the estimations for the social cost of carbon—the damage to welfare including non-financial concepts—vary wildly just by changing the model assumptions. Other models’ estimations continue to vary wildly for every question we have about our highly uncertain planetary system and economy. The models that predict effects on GDP from carbon taxes often assume that long run economic growth will be unchanged by anything but fundamentals, which leads to the parallel path hypothesis, and that carbon taxes will create distortions that will affect the economy. Previous notions of elasticities of substitution away from carbonized goods may need to be updated, as renewable energy technology rapidly advances, allowing for a more seamless transition to taxing carbon and shifting output and jobs to non-polluting companies. Even as the models stand, they do not predict drastic consequences of carbon taxes, often fractions of a percent of GDP loss over decades (Goulder et al. 2019), and so the empirical result of zero impact should not be too surprising.

7.3 Application to Policy

Sims (1986) discusses the applicability of using forecasting models for policy analysis, suggesting that “identification becomes more difficult and controversial,” “the more remote is the action we contemplate taking from any historically observable event.” In this case, when applying results from 32 European countries in the sample to policy options for other countries worldwide, there are potential differences that raise questions about identification. For example, the majority of the European countries are very small on the world scale, and the applicability of the study to larger nations elsewhere in the world is

less convincing if the data from Europe suggest differences in response to carbon taxes based on country size.

The estimated impulse responses weighted by population still show no evidence of harm to the economy, implying that the larger countries do not suffer economic consequences from carbon taxes. This is an important finding if it does apply to the rest of the world—decisions are overwhelmingly made selfishly, and so very little can be changed if it portends worse economic outcomes. If it can be shown that the tax actually does not harm economies, adoption will be much more palatable for governments and voters, the majority of whom are not likely to be direct beneficiaries of fossil fuel industry profits.

With respect to national economies, there is no inherent urgency to implementing a carbon tax, but on a world scale, we need to make emissions reduction decisions before being absolutely certain of their impacts. The data that is available today suggests that the economic downsides to carbon taxes at the macro level are minor to non-existent in comparison to the future economic and climate damages from not reducing carbon emissions. Therefore, results such as these supplement a strong body of evidence in support of carbon taxes worldwide.

Chapter 8

Conclusion

Metcalf & Stock (2020c) is the first large-scale study of the empirical impacts of carbon taxes on GDP and employment. This paper was able to replicate the original results for GDP and employment series exactly, and find similar results for emissions reductions. As more countries and jurisdictions institute carbon taxes every year, including Germany, the Netherlands, and Luxembourg in 2021, a worldwide study of impacts of carbon taxes will become possible. Currently the data are too sparse and recent to yield any significant results.

The data and results will improve over time, but governments need to be making emissions reduction decisions now. Weitzman (2009) discusses the implications of fat-tailed thinking with respect to climate change, referring to the non-zero probability of extreme consequences. The need to minimize the odds of extreme planetary consequences strengthens the argument for carbon taxes that reduce emissions.

The cost/benefit analysis of implementing carbon taxes is improving rapidly. Well articulated data and studies on carbon taxation, successful examples of carbon tax policies in many countries, and rapidly improving technology to replace sources of pollution will inspire jurisdictions around the world to establish their own carbon taxation policies. This shift towards the mass adoption of carbon taxation will be an important step in halting the rise of CO₂ concentrations and stabilizing the climate for the generations to come.

Appendix A

Data - Finer Details

This section details the minor adjustments made to the data.

GDP data from Metcalf & Stock (2020d) differ from my own series only in years 2017 and 2018, and I suspect this is due to revisions in the data that have been made since Metcalf and Stock accessed it in 2019¹. For Ireland, GNI is used in place of GDP because its status as a tax haven generates non-representative figures (such as 25% growth in 2015). The data – table N2025 gathered using the R package ‘csodata’ – starts in 1996 and matches Metcalf closely, so I use Metcalf and Stock’s series before 1996. Norway keeps offshore and onshore accounts. I use Metcalf and Stock’s GDP series of Norway’s onshore GDP, adding the published .9 and -.08 percent growth for 2019 and 2020, respectively.

Employment data, similarly to GDP data, differ from Metcalf and Stock in years 2017 and 2018, most likely due to revisions made since 2019. Data before 2016 is identical, except for Greece, which tends to report higher employment numbers in my series. It is worth noting that Spain and Portugal introduced carbon taxes in the mid 2010s, shortly after they and other Mediterranean nations suffered high unemployment rates during the European debt crisis. This apparent boost in employment from the introduction of a carbon tax would not be picked up by the country or year effects, and is one example of the limitations of the study design.

¹I contacted the World Bank (2021) as well as Professors Gilbert Metcalf and James Stock to investigate these discrepancies. The World Bank did not reply, and the authors will release a data and code file with the forthcoming publication of Metcalf & Stock (2020c) in a scientific journal

The Metcalf & Stock (2020d) carbon tax series (the 2018 tax series) is designed to account for inflation and purchasing power parity differences (PPP) to represent the same “impact to the economy” of a \$40 per ton increase in each nation. I use inflation adjusted rates without adjusting for purchasing power parity. Attempting to adjust for PPP creates carbon tax rates further away from those of Metcalf and Stock Metcalf & Stock (2020d). When a country reports multiple tax rates, the highest one is used (which is often the rate on gasoline and diesel). Figure A.1 shows the discrepancies between Metcalf & Stock (2020d)’s rates and my own—in years 1999-2003 their rates are consistently higher, while in the early 2010s theirs are consistently lower.



FIGURE A.1: Ratio of carbon tax rate from Metcalf & Stock (2020d) to my own. Pink shades are greater than one and blue shades are less than one.

Some rates were not reported in 2020, but again reported in 2021. With no evidence that the tax was halted for the year, I interpolated their 2020 rates from the surrounding two years. France reported a very low rate for 2020, so this value was also replaced by

interpolation².

Table A.1 displays carbon tax coverage rates from the World Bank Carbon Pricing Dashboard differ from those used by Metcalf and stock for these countries. In some cases, Metcalf & Stock (2020d) report higher tax rates in countries where the coverage rate is lower, which balances out the final rate used. In the case of Latvia, both my carbon tax rates and coverage rates are much lower than in Metcalf & Stock (2020d).

TABLE A.1: Coverage rate discrepancies between 2019 and 2021

Country	2019	2021	Average tax rate adjustment
Denmark	.40	.35	
Estonia	.03	.06	- (minimizes coverage rate change)
Iceland	.29	.55	
Latvia	.15	.03	+ (amplifies coverage rate change)
Norway	.62	.66	
Slovenia	.24	.5	- (minimizes coverage rate change)

Finally, population data, used to weight the counties in the weighted specifications, and GDP deflator data, come from the World Bank Group (2021).

Starting in 2021, Germany, Luxembourg, and The Netherlands have introduced new carbon taxes, at \$29.36, \$40.12 (diesel)/\$23.49(other), and \$35.24, respectively, bringing the number of EU+ countries with a carbon tax to 18 (of 32). The UK, as of 2021, has set up its own ETS that will have a slightly lower cap level than under the EU ETS, which would indicate higher clearing prices. Differences in macroeconomic variables could then come from differences in ETS prices or from differences in carbon tax prices, and so the UK, like other nations, will not fit into the EU+ only study going forward.

Any regressions using 31 countries instead of 32 are omitting Liechtenstein, as it functions largely as a part of Switzerland (under the same carbon tax rates).

²France has halted its carbon tax rate increase, but not lowered it (Savolainen 2020)

Appendix B

Event Studies

This section contains event study plots for each of the five data series, and Table B.1, which details the 32 European countries' carbon tax status.

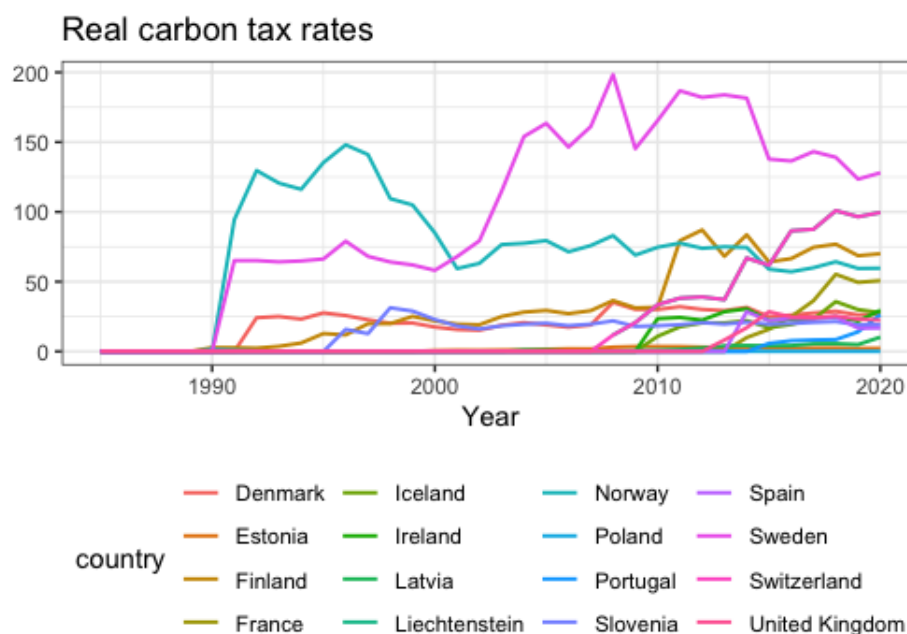


FIGURE B.1: Real carbon tax rates over time

Figure B.1 displays the 2020 tax series for each of the 16 nations that have implemented them thus far. Norway had a higher carbon tax rate in the 1990s than today, but countries have otherwise left tax rates constant or continued to raise them. As of 2020, Sweden has the highest carbon tax rate, followed by Switzerland and Finland.

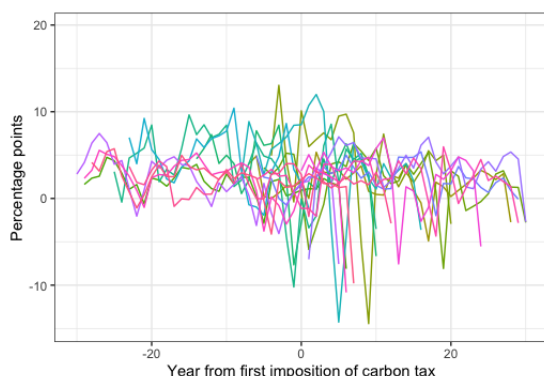


FIGURE B.2: GDP growth rates

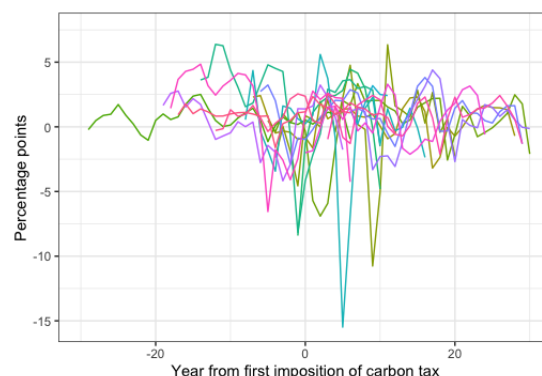


FIGURE B.3: Total employment growth rates

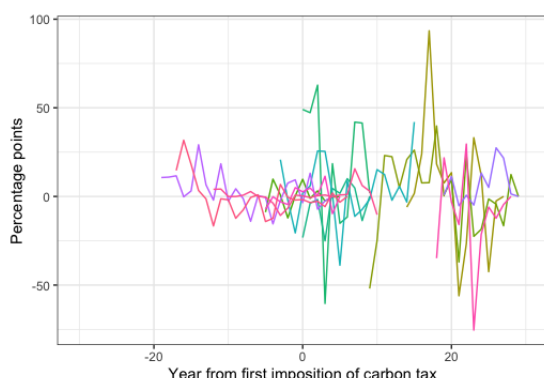


FIGURE B.4: CO₂ emissions from land transportation growth rates

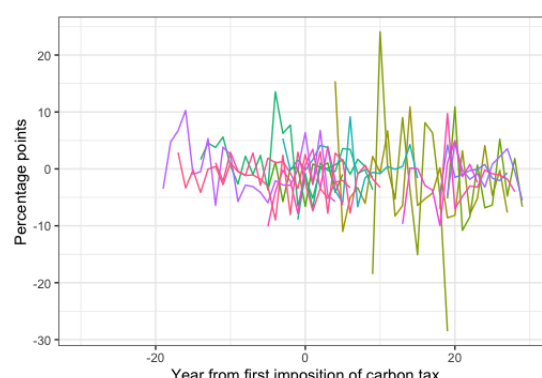


FIGURE B.5: Total greenhouse emissions (CO₂ equivalent) growth rates

Figures B.2 through B.5 display percentage annual growth of the GDP, employment, and emissions data by aligning the countries by the year they first instituted a carbon tax. Figure B.2 displays GDP growth. The years surrounding the imposition of a carbon tax appear more volatile, but this is likely spurious. Figure B.3 displays employment growth. The large negative years belong to the 2009 recession and to austerity measures taken in Greece, Portugal, Spain and Italy in the early 2010s. Figure B.4 displays emissions growth from land transportation. This makes clear the sparsity of this dataset, as well as the volatility, with some years experiencing well over 50% positive or negative change. Figure B.5 displays total emissions from greenhouse gases in CO₂ equivalents. This dataset is more robust - the volatile country in olive green is Estonia.

Table B.1 displays the countries in the study, and their most recent carbon tax and coverage rates.

TABLE B.1: EU+ carbon taxes

Country	Year of Enactment	2020 Tax Rate (2018 USD)	Share of GHG Emissions Covered by Tax
Austria		0	0
Belgium		0	0
Bulgaria		0	0
Croatia		0	0
Cyprus		0	0
Czech Rep		0	0
Denmark	1992	26.87	35
Estonia	2000	2.24	6
Finland	1990	70	36
France	2014	50.75	35
Germany		0	0
Greece		0	0
Hungary		0	0
Iceland	2010	27.76	55
Ireland	2010	29.51	49
Italy		0	0
Latvia	2004	10.24	3
Liechtenstein	2008	99.57	26
Lithuania		0	0
Luxembourg		0	0
Malta		0	0
Netherlands		0	0
Norway	1991	59.63	66
Poland	1990	0.07	4
Portugal	2015	26.42	29
Romania		0	0
Slovakia		0	0
Slovenia	1996	19.2	50
Spain	2014	16.82	3
Sweden	1991	128.01	40
Switzerland	2008	99.57	33
United Kingdom	2013	22.43	23

Appendix C

R Code Summary

This section summarizes the R script used to process the data and generate the IRFs.

After a tax series, economic variable, and other specifications are selected, lag, lead, and dummy variables are created to be used as factors in the regressions. For each horizon h , which for this study is the years 0 through 6, three regressions are calculated.

The first is the model:

$$100\Delta\ln(GDP_{it+h}) = \alpha_i + \Theta_{yh}\tau_{it} + \beta(L)\tau_{it-1} + \delta(L)\Delta\ln(GDP_{it-1}) + \gamma_t + e_{it} \quad (C.1)$$

The coefficient for the response of the economic variable to a unit change in the policy variable, Θ_{yh} , is stored as

$$b99 = \begin{bmatrix} \Theta_{y1} & \Theta_{y2} & \dots & \Theta_{yh} \end{bmatrix},$$

The second regression is the prediction equation for policy variable:

$$\tau_{it} = \alpha_i + \beta(L)\tau_{it-1} + \delta(L)\Delta\ln(GDP_{it-1}) + \gamma_t + u_{it} \quad (C.2)$$

For each h , the residuals from equations C.1 and C.2 are used to generate zz_h . This result is then used in the formulation of $v99$, the variance covariance matrix of the local projections:

$$v99 = \begin{bmatrix} cov(zz_0, zz_0) & \dots & cov(zz_0, zz_h) \\ \vdots & & \vdots \\ cov(zz_h, zz_0) & \dots & cov(zz_h, zz_h) \end{bmatrix} \quad \text{where} \quad zz_h = \frac{n}{n-1} * \frac{e_{it} * u_{it}}{\sigma_{e_{it}}^2 \sqrt{n-k}}$$

The third regression at each h is the local projection of the future tax rate h steps ahead:

$$\tau_{it+h} = \alpha_i + \Theta_{xh} \tau_{it} + \beta(L) \tau_{it-1} + \delta(L) \Delta \ln(GDP_{it-1}) + \gamma_i + v_{it} \quad (C.3)$$

Θ_{xh} , the predicted effect of a unit increase in the tax rate on the future tax rate, are stored as `theta11`:

$$\text{theta11} = \begin{bmatrix} \Theta_{x1} & \Theta_{x2} & \dots & \Theta_{xh} \end{bmatrix},$$

Calculating the IRF:

B is the diagonalized `theta11`. The diagonalization applies the effect for the number of years forward to the correct columns. The ones on the diagonal are the effect of the current tax rate on the current tax rate, which is itself, while Θ_h is only applied once - to the current rate for the furthest horizon.

$$B = \begin{bmatrix} 1 & 0 & \dots & 0 \\ \Theta_{x1} & 1 & 0 & 0 \\ \vdots & \dots & \ddots & \dots \\ \Theta_{xh} & \Theta_{xh-1} & \dots & 1 \end{bmatrix}$$

For a \$40 increase on 30% of emissions,

$$\text{xpath} = \begin{bmatrix} 12 & 12 & \dots & 12 \end{bmatrix}$$

To get the counterfactual tax increase, the `xpath`, we multiply the required shocks, `epsx` by B , the carbon tax path. Or more specifically, since we know `xpath`, we solve for `epsx`:

$$xpath = B * epsx$$

$$epsx = B^{-1} * xpath$$

Shockmat is the diagonalization of epsx, which is set up similarly to B to apply the effects to the appropriate columns:

$$\text{shockmat} = \begin{bmatrix} epsx_0 & 0 & \dots & 0 \\ epsx_1 & epsx_0 & 0 & 0 \\ \vdots & \dots & \ddots & \vdots \\ epsx_h & epsx_{h-1} & \dots & epsx_0 \end{bmatrix}$$

Finally, we compute the impulse response function by multiplying the estimates for the change in the economic variable by the shock matrix:

$$IRF = \text{shockmat} * b99$$

with the variances of the IRF on the diagonal of VIRF:

$$VIRF = \text{shockmat} * v99 * \text{shockmat}'$$

Appendix D

Continued Results

D.1 GDP

Figure D.1 shows an IRF for an increasing carbon tax path, in this case starting at \$40 and increasing by \$10 per year to \$100 in year six. Because the local projections model is linear, doubling the counterfactual rate in year zero would simply double the GDP response for that year, along with doubling the standard error. A change in

the counterfactual tax increase affects the response in subsequent years as well, while of course changes in the counterfactual rate in later years do not affect the past. So raising the rate as time passes just amplifies the estimates (either positively or negatively) in subsequent years. With Figure 6.1 having generally positive estimates for GDP response, increasing the tax rate simply increases the height of the estimates.

Figures D.2 and D.3 are Figure 5a of Metcalf & Stock (2020c) and the replication - the cumulative IRF (CIRF) of Figures 6.1 and 6.2. I calculate the CIRF by adding the point estimates and variances sequentially. Standard error bands appear slightly smaller for the CIRF from Metcalf & Stock (2020c) – this could be due to a different variance calculation,

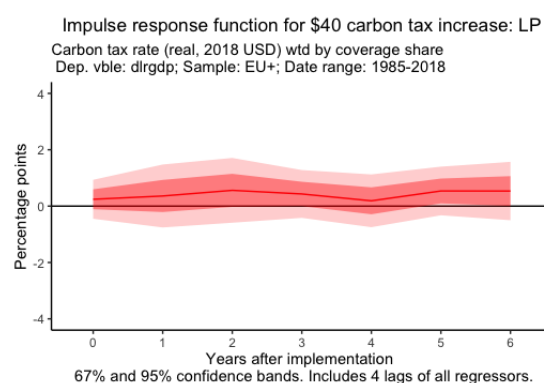


FIGURE D.1: IRF for increasing tax rate

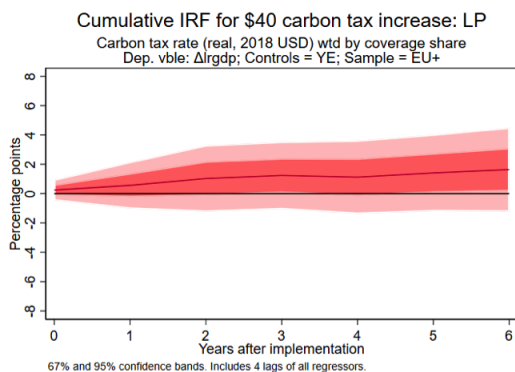


FIGURE D.2: Metcalf & Stock (2020c) Figure 5a

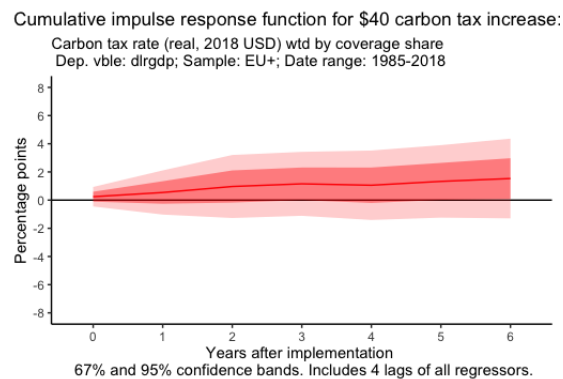


FIGURE D.3: Replication of Figure D.2

or simply to what confidence level is represented. CIRFs of the other model specifications are not displayed here.

D.2 Employment

Figure D.4 shows the response of employment for large carbon tax countries, and the effect is not considerably different than in the full sample. Figures D.5 and D.6 are Figure 7a of Metcalf & Stock (2020c) and the replication, the CIRF for total employment.

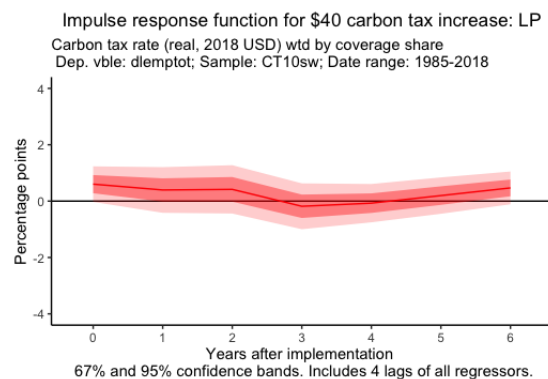


FIGURE D.4: Employment IRF high carbon tax countries

D.3 Lags

One final consideration for the study design is the number of lags used in the model. Four lags is used by Metcalf & Stock (2020c), while the earlier version (Metcalf & Stock

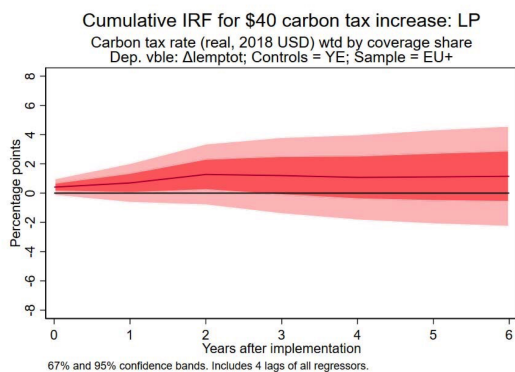


FIGURE D.5: Metcalf &
Stock (2020c) Figure 7a

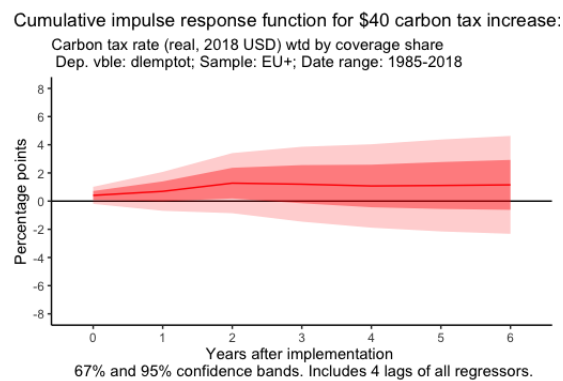


FIGURE D.6: Replication
of Figure D.5

(2020b) uses two. In a test of the standard GDP IRF, using different numbers of lags, increasing the number of lags steadily decreases the model AIC, and steadily drags the point estimates closer to zero until six lags where they converge near zero. At seven lags the standard errors explode, as the number of data points available gets very small. For the emissions series, since there is less data available, a test of two lags instead of four would be a better model fit yielded neutral results - both specifications result in the same IRF.

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