CARBON TAX FORECASTS: VARs & CONTROL VARIABLES

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Boston University
February, 2019

School of Economics & Management,
Far Eastern Federal University (Vladivostok, Russia)
December 2017

Findings:

- *Carbon taxes make Natural Gas the last big fossil fuel*. A very modest Carbon Tax ($20 per metric ton) causes a large drop in Coal and a small drop in Oil consumption. Natural gas is stable, however, for a slight reduction in the trend of CO_2.

- *Vector Auto-Regressions (VARs),* a standard tool in Finance, are a *useful but under-utilized method* to gauge short-term energy and environmental impact.

- *Constrained VARs* are particularly useful for gauging the effects of Quantity vs. Price Controls; i.e., a policy of *Pollution Permits vs. Carbon Taxes*.

Taxes per unit of Fuel

	<u>COAL</u>	<u>OIL</u>	<u>GAS</u>
Unit of Fuel (UF)_	Short ton	Barrel	Mcf
Aggregate UF_	(1,000 tons)	(1,000 barrels)	(1,000 Mcf)
Tp/Tc_	3	4.5	0.5
Tp/(Tp+Tc)_	0.75	0.8182	0.333
*CO_2 Tonne/UF*_	*2.101*	*0.4102*	*0.0544*
Tax per Tonne *CO_2*_	$20	$20	$20
Tax per UF_	$42.02	$8.20	$1.09
-P*_	$31.62	$6.71	$0.37
+P*_	$10.40	$1.49	$0.72

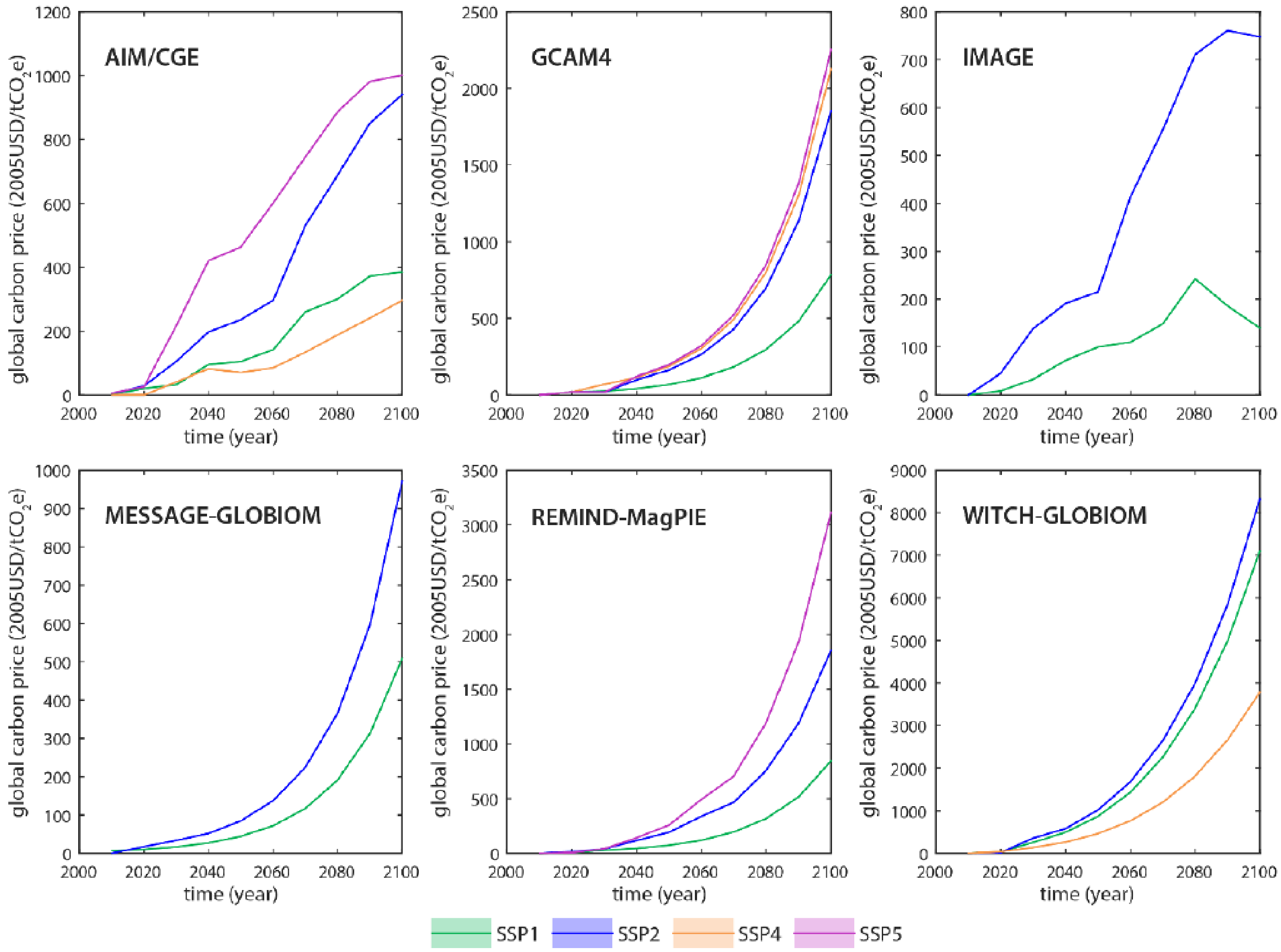
Table 1. Global Social Cost of Carbon in 2005 US Dollars under Different Assumptions (Nordhaus, 2014)

Scenario	2015	2020	2025	2030	2050
Base parameters:					
Baseline*	18.6	22.1	26.2	30.6	53.1
Optimal controls†	17.7	21.2	25.0	29.3	51.5
2°C limit damage function:					
Maximum†	47.6	60.1	75.5	94.4	216.4
Max of average†	25.0	30.6	37.1	44.7	87.9
Stern Review discounting:					
Uncalibrated*	89.8	103.7	117.4	131.3	190.0
Calibrated*	20.7	25.0	30.1	35.9	66.9
Alternative high discount*	6.4	7.7	9.2	10.9	19.6

Estimates of the Social Cost of Carbon: Concepts and Results from the DICE-2013R Model and Alternative Approaches

https://www.journals.uchicago.edu/doi/10.1086/676035?mobileUi=0&

Journal of the Association of Environmental and Resource Economists, 2014



Guivarch and Rogelj (2017) "Carbon price variations in 2°C scenarios explored," *Report of the High-Level Commission on Carbon Prices,* World Bank, United Nations.

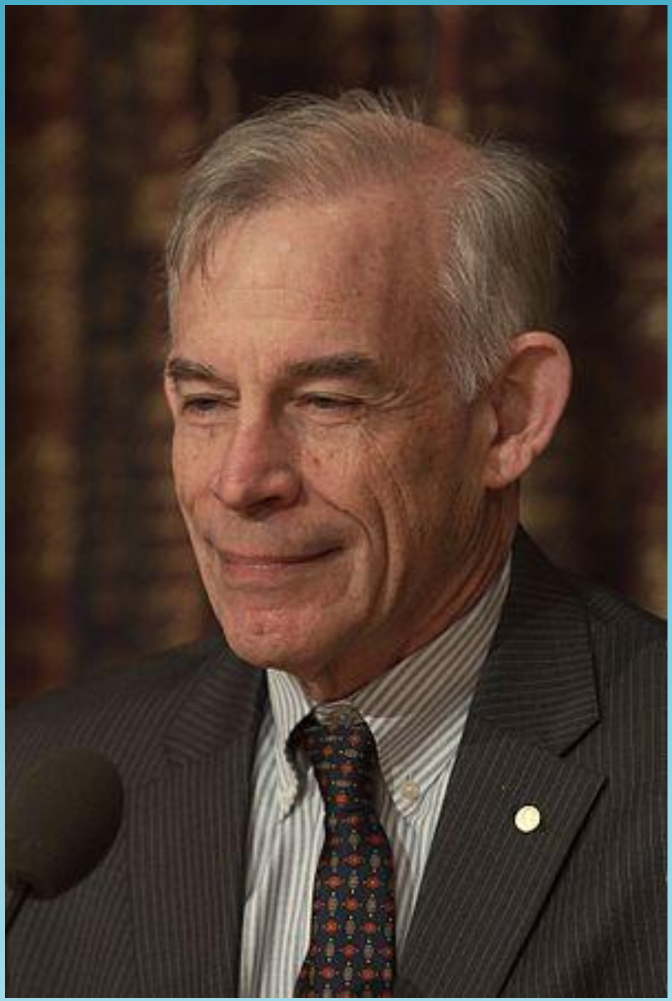
MIT Sloan Management Review

WINTER 2010 VOL. 51 NO. 2

Why Forecasts Fail. What to Do Instead

Spyros Makridakis, Robin M. Hogarth and Anil Gaba

Christopher Sims
2011 Nobel Speech



[VARs] are statistical descriptions of time series, with no accompanying story …. In my earliest work with VAR's (1980a; 1980b) I interpreted them with informal theory…. It was possible, however, to introduce theory explicitly, **but with restraint**, so that VARs became usable for policy analysis.

4 Benefits of VAR Modeling:

1) Fewer variables, lower data requirements to achieve reasonable DoF.

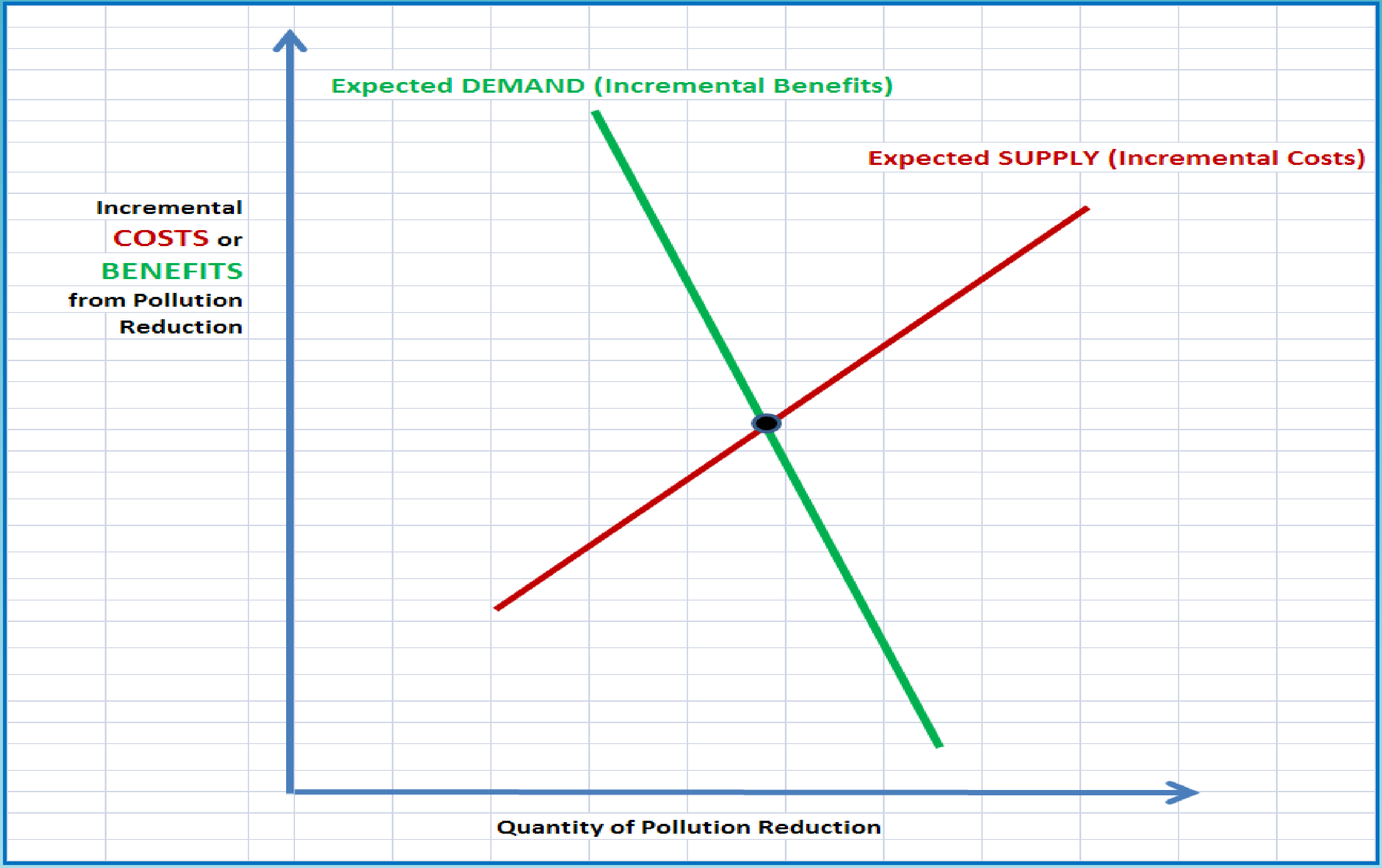
2) Theory is not built-in but implicit, interpreted.

3) All explanatory variables are historical, known. Lags mean fewer 'forecasts within the forecast.'

4) Best of all – 30 years of experience show VARs are usually more accurate than structural models.

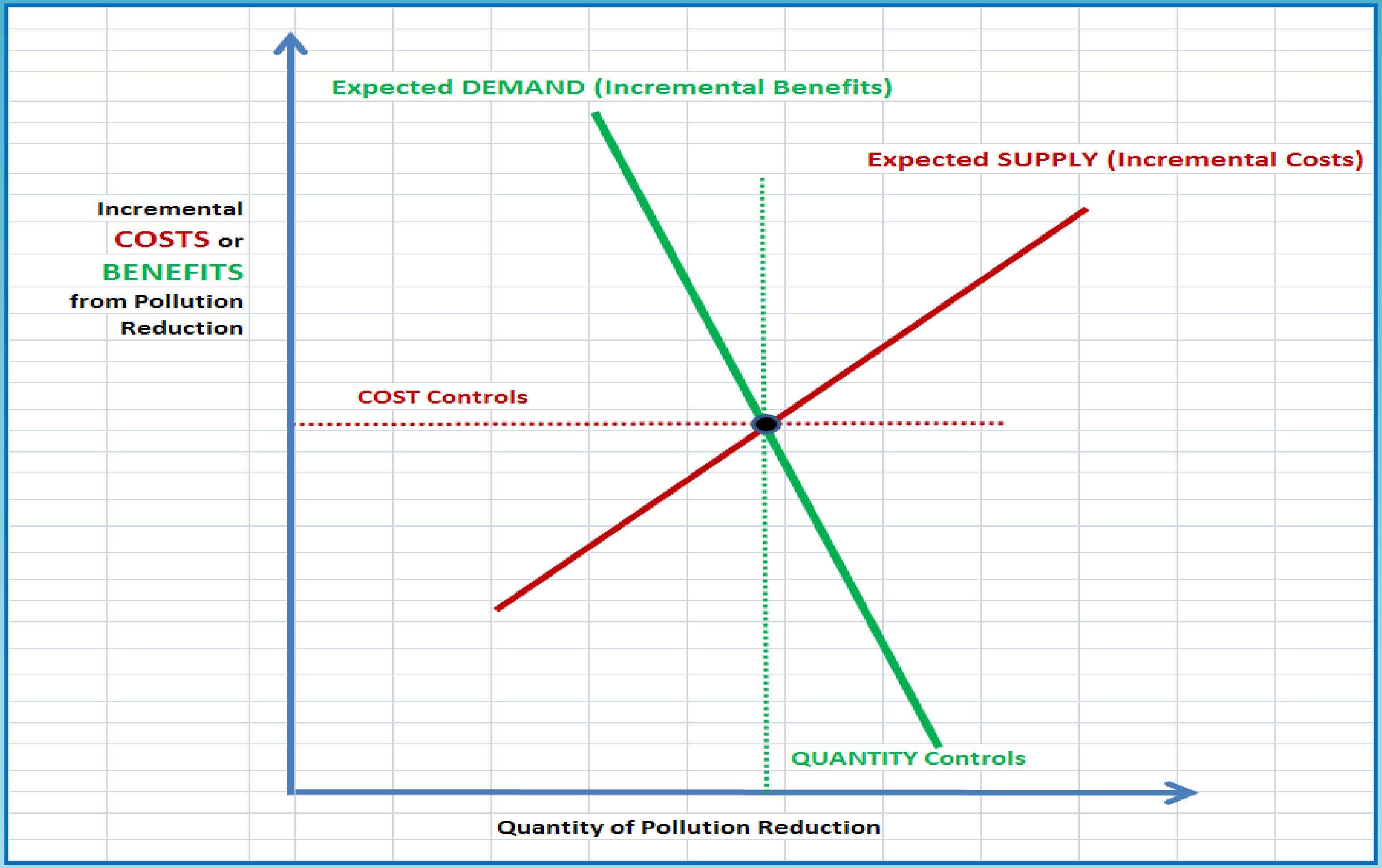
* **Points 1), 2) and 3)** help **explain 4).** VARs focus on the final whats, not all the intervening whys & hows. For predictions, this Less is often More.

Quantiy vs. Price Controls: Good Old Supply & Demand!

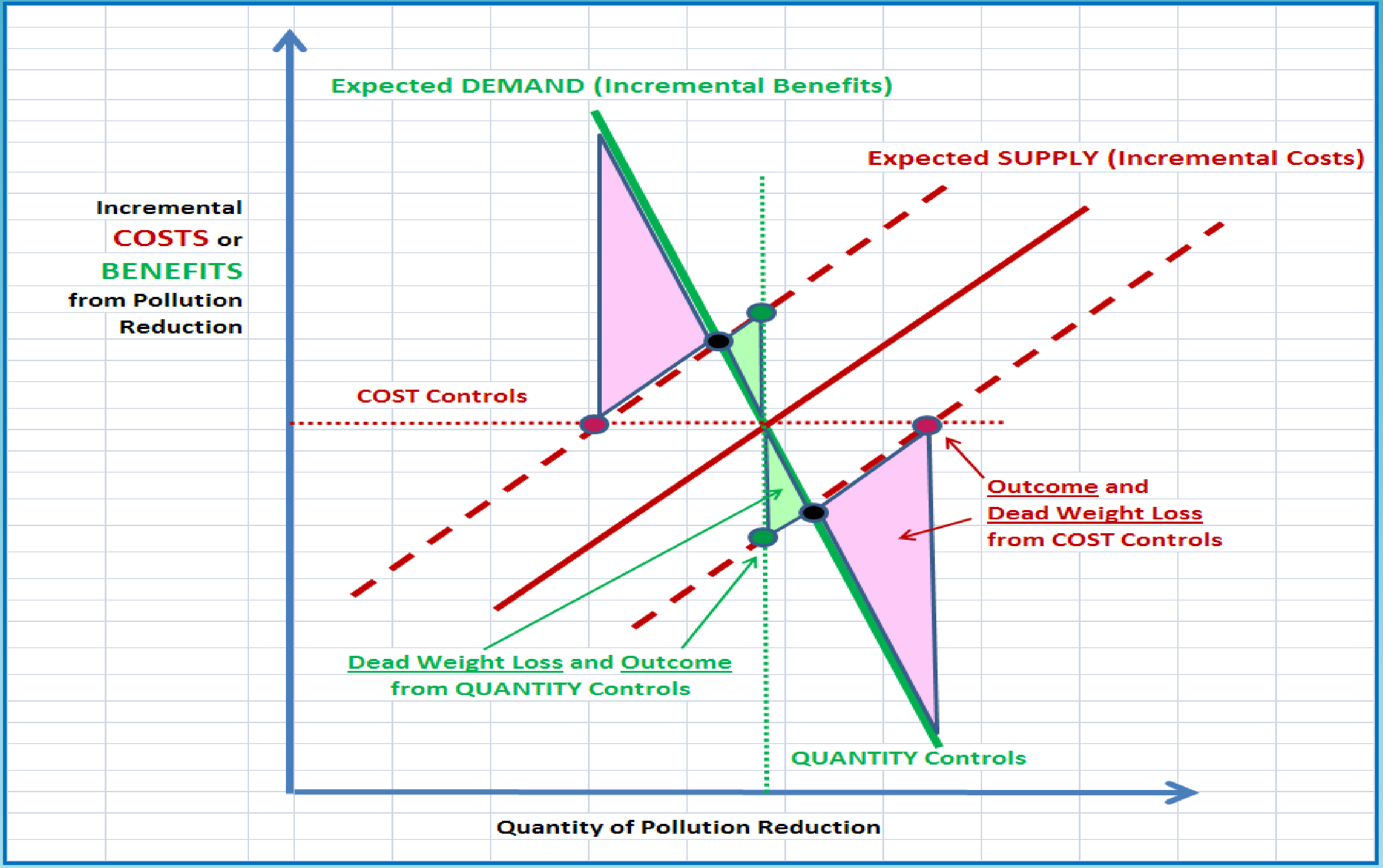


"Prices vs. Quantities," Weitzman (1974)

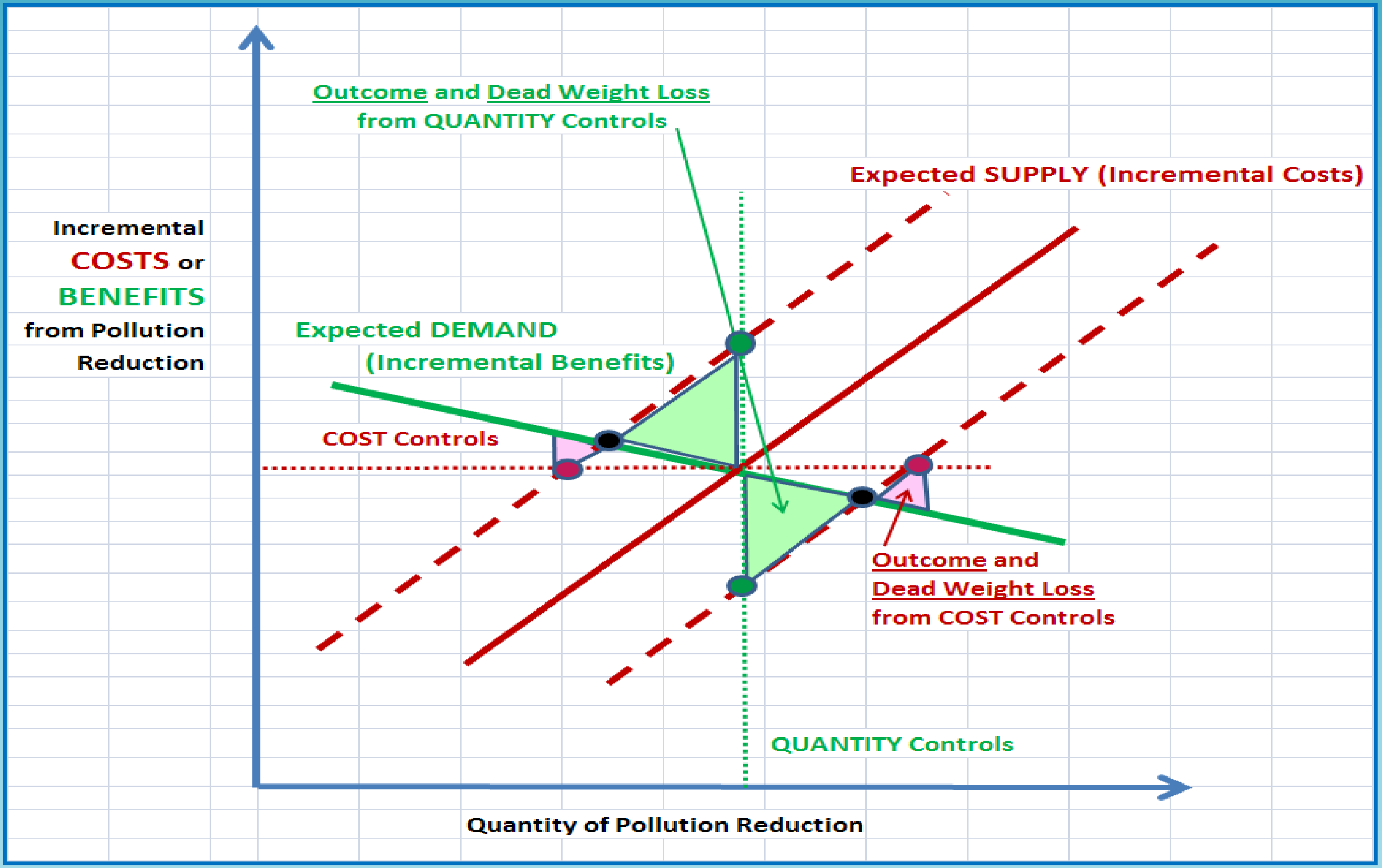
Either Control Equivalent – If No Uncertainty!



Steep Decline in Marginal Benefits => Quantity Controls (Market Permits)



Gradual Decline in Marginal Benefits => Cost Controls (Carbon Taxes)



Vector Error Correction Estimates

Sample (6 lag-adjusted): 1987M01 – 2018M0;

Included observations: 368 after adjustments;

t-statistics in [ ]; **, **, and *** =>*

10%, 5%, and 1% level of significance

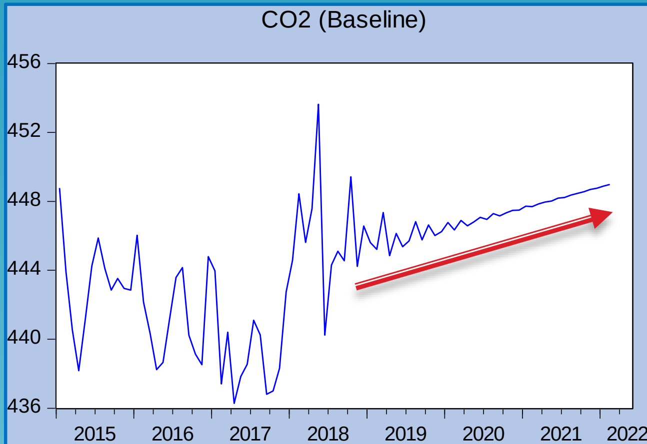
Cointegrating Equation:	CO2(-1)	GASAV_QC(-1)	PETAV_QC(-1)	COALAV_QC(-1)
	1.0000	-5.52E-05	-0.017606	-0.001495
		[-5.02987]***	[-10.7610]***	[-10.0958]***
Error Correction	D(CO2)	D(GASAV_QC)	D(PETAV_QC)	D(COALAV_QC)
Response:	-1.198501	51.44285	0.302807	2.896766
	[-8.72333]***	[0.87700]	[1.32202]	[1.56038]
R-squared	0.330816	0.497483	0.63725	0.273663
Adj. R-squared	0.242004	0.430791	0.589108	0.177266

Cointegrating Equation:	GASAV_QC(-1)	PETAV_QC(-1)	COALAV_QC(-1)	GAS_PCT_PT(-1)	PET_PCT_PT(-1)	COAL_PCEIT_PT(-1)	CO2(-1)
	1.0000	305.5484	48.78128	34457.1	-6742.623	-9104.467	-28644.33
		[3.78299]***	[7.31423]***	[1.08550]	[-2.80778]***	[-1.56436]	[-10.711]***
Error Correction	D(GASAV_QC)	D(PETAV_QC)	D(COALAV_QC)	D(GAS_PCT)	D(PET_PCT)	D(COAL_PCEIT)	D(CO2)
Response:	:-0.00357	-1.26E-06	-1.49E-04	2.12E-07	-2.46E-06	-1.32E-07	4.04E-05
	[-1.66351]*	[-0.14910]	[-2.21786]**	[1.74550]*	[-3.05754]***	[-0.46106]	[8.1054]***
R-squared	0.330816	0.497483	0.63725	0.273663	0.403839	0.370257	0.556133
Adj. R-squared	0.242004	0.430791	0.589108	0.177266	0.324719	0.28668	0.497224

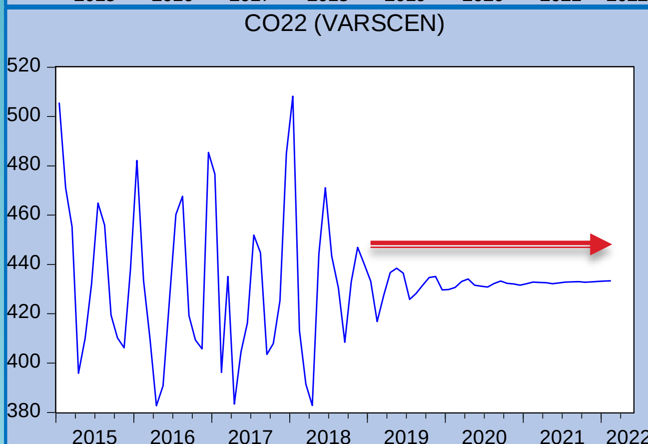
COAL GAS OIL


COALAV_QC (Baseline)
No Treatment
COALAV_QC (Scenario 1)
Price Control
COALAV_QC (Scenario 1)
Quantity Control
GASAV_QC (Baseline)
No Treatment
GASAV_QC (Scenario 1)
Price Control
GASAV_QC (Scenario 1)
Quantity Control
PETAV_QC (Baseline)
No Treatment
PETAV_QC (Scenario 1)
Price Control
PETAV_QC (Scenario 1)
Quantity Control
2015 2016 2017 2018 2019 2020 2021 2022

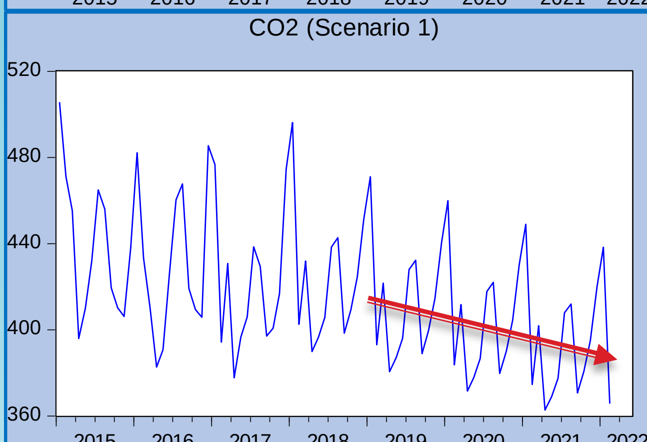
CO2 Output



No
Treatment



Price
Controls



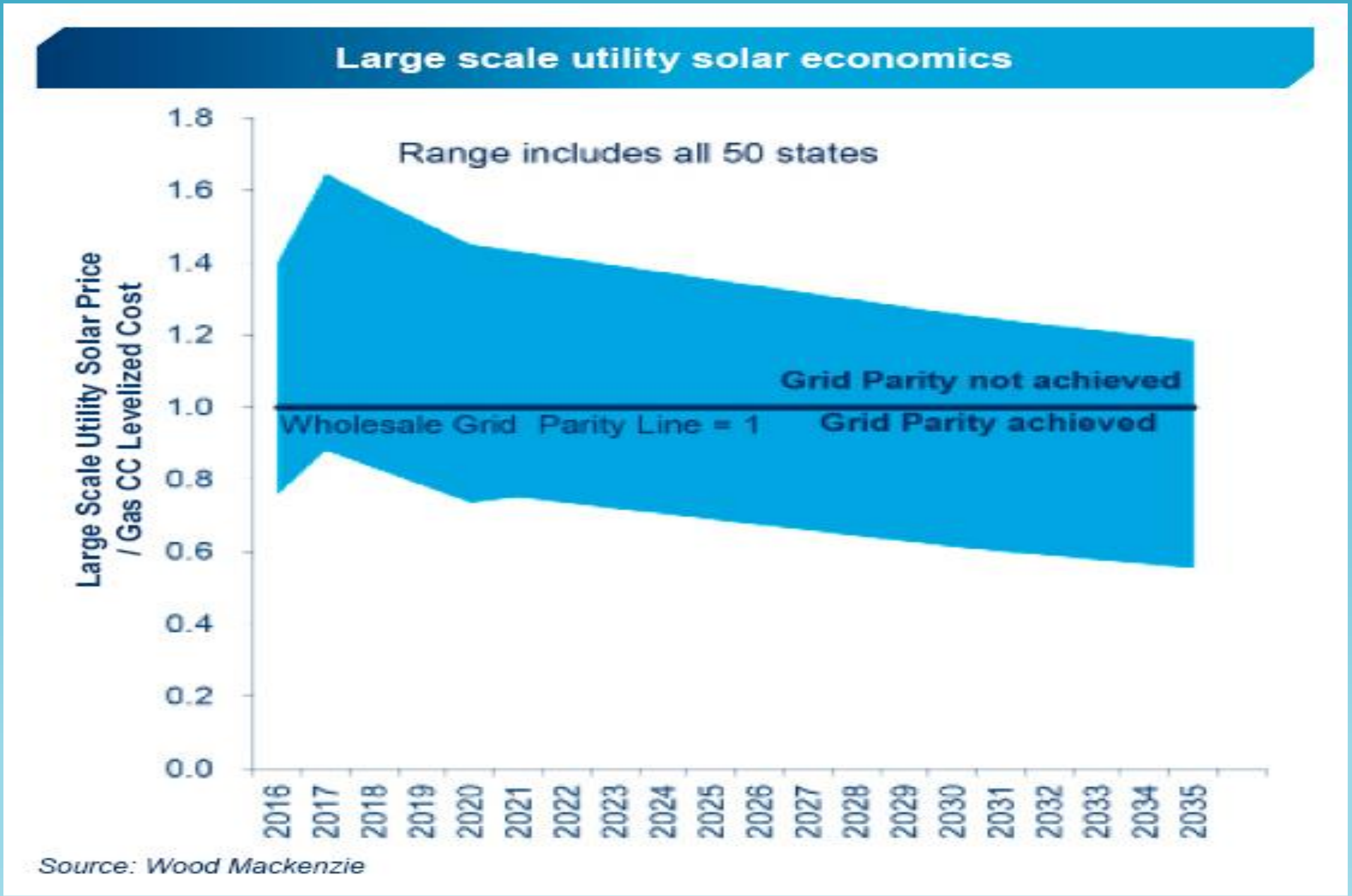
Quantity
Control

The growing importance of renewables <u>not modeled</u> here. (Time series are too short.)

But a carbon tax boost for renewables implies both:

* <u>lower fossil-fuel use</u> (for all 3 fuels), and
* <u>lower CO_2 output</u> than forecast here.

Solar 'Levelized' (*i.e., Marginal*) Costs



http://public.woodmac.com/public/views/solar-next-shale

For Paper or Questions, please contact me at

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