Online Supplementary Material for:

The Trouble With Voluntary Emissions Trading:

Uncertainty and adverse selection in sectoral crediting programs

Adam Millard-Ball

Appendix A: Comparative Statics

Here, I show that it is ambiguous whether increasing the generosity of the crediting baseline locally increases or decreases the percentage of additional offsets, as given by (4).

$$\mathbf{b}^*_{QUALITY} = \arg\min_{\mathbf{b}} E\left\{\frac{\sum_{i=1}^{N}\max\left(b_i - z_i^0,\ 0\right)}{\sum_{i=1}^{N}\max\left(b_i - z_i^*,\ 0\right)}\right\} \tag{4}$$

For each country *i*, the numerator is the difference between the crediting baseline and BAU emissions, conditional on this value being positive (i.e., conditional on generating non-additional offsets). The denominator is the difference between the crediting baseline and actual emissions, conditional on the crediting baseline being greater than the rent extraction point b_i^r defined in (7) (i.e., conditional on a country's participation).

As in the main text, define the regulator's prediction error $\varepsilon_i = \hat{z}_i^0 - z_i^0$ with the probability density $f_{\mathrm{E}}\left(\varepsilon_i\right)$ common to all countries. The regulator's estimate of the rent extraction point is defined as $\hat{b}_i^r$, and from (7), $\hat{b}_i^r = b_i^r + \varepsilon_i$ assuming that each country knows its own BAU emissions with certainty. Then for each country, the minimand in (4) can be expressed as follows, dropping the *i* subscript for clarity and letting *S* and *T* respectively stand for non-additional and total offsets from all other countries:

$$\begin{aligned} M &\equiv \int_{-\infty}^{\infty}\left[\frac{S + \max\left(b - \hat{z}^0 + \varepsilon,\ 0\right)}{T + \max\left(b - z^*,\ 0\right)}\right] f_{\mathrm{E}}\left(\varepsilon\right) d\varepsilon \\ &= \int_{-\infty}^{\hat{b}^r - b}\left[\frac{S}{T}\right] f_{\mathrm{E}}\left(\varepsilon\right) d\varepsilon + \int_{\hat{b}^r - b}^{\hat{z}^0 - b}\left[\frac{S}{T + b - \hat{z}^0 + q^* + \varepsilon}\right] f_{\mathrm{E}}\left(\varepsilon\right) d\varepsilon + \int_{\hat{z}^0 - b}^{\infty}\left[\frac{S + b - \hat{z}^0 + \varepsilon}{T + b - \hat{z}^0 + q^* + \varepsilon}\right] f_{\mathrm{E}}\left(\varepsilon\right) d\varepsilon \end{aligned} \tag{9}$$

I obtain the derivative of (9) with respect to *b* through Leibnitz's Rule, assuming certain regularity conditions for $f_{\mathrm{E}}(\varepsilon)$, and the quotient rule:

$$\frac{\partial M}{\partial b} =$$

$$\left(\frac{S}{T-\hat{z}^{0}+q^{*}+\hat{b}^{r}}-\frac{S}{T}\right)f_{\mathrm{E}}(\varepsilon)_{|\hat{b}^{r}-b}+\int_{\hat{b}^{r}-b}^{\hat{z}^{0}-b}\left[\frac{-S}{\left(T+b-\hat{z}^{0}+q^{*}+\varepsilon\right)^{2}}\right]f_{\mathrm{E}}(\varepsilon)\,d\varepsilon+\int_{\hat{z}^{0}-b}^{\infty}\left[\frac{T+q^{*}-S}{\left(T+b-\hat{z}^{0}+q^{*}+\varepsilon\right)^{2}}\right]f_{\mathrm{E}}(\varepsilon)\,d\varepsilon \qquad (10)$$

The first term in (10) represents the probability that a country will participate when it did not before. The second and third terms respectively represent the probabilities that a country will generate more additional and non-additional offsets respectively.

The sign of the derivative in (10) is ambiguous. The first term is negative from (7), the second term is negative, and the third term is positive as $T \geq S$ and q^* is positive. As long as S is nonzero and the probability density function $f_{\mathrm{E}}(\varepsilon)$ is sufficiently large below $\hat{z}^{0}-b$, the first two terms will dominate and (10) will be negative. If the mass of $F_{\mathrm{E}}(\varepsilon)$ is concentrated above $\hat{z}^{0}-b$, or if S is zero, then the third term will dominate and (10) will be positive.

In practice, at least with symmetric baselines and regularly shaped error distributions, (10) is likely to be positive – increasing the crediting baseline (making it more generous) will increase the proportion of non-additional offsets. That is because the greater the probability mass of $F_{\mathrm{E}}(\varepsilon)$ at and below $\hat{z}^{0}-b$, the smaller will be S (given the assumption of symmetric baselines). However, two numerical examples demonstrate the formal ambiguity, even with symmetric baselines. Suppose that the initial baseline is the same for the other $N-1$ identical countries, and thus:

$$E[S]=E\left[(N-1)\max\left(b-z^0,\ 0\right)\right]=(N-1)\int_{\hat{z}^0-b}^{\infty}\left(b-\hat{z}^0+\varepsilon\right)f_{\mathrm{E}}(\varepsilon)d\varepsilon$$
$$E[T]=E\left[(N-1)\max\left(b-z^*,\ 0\right)\right]=(N-1)\int_{\hat{b}^r-b}^{\infty}\left(b-\hat{z}^0+q^*+\varepsilon\right)f_{\mathrm{E}}(\varepsilon)d\varepsilon \tag{11}$$

Assume the following values: $N=100, b=92, \hat{z}^0=100, \hat{b}^r=95, q^*=12, T=E[T], S=E[S]$. If $\varepsilon \sim N(0,16)$ then (10) is positive. If $\varepsilon \sim Gamma(2,0.6)$ then (10) is negative (in both cases, solving by numerical integration). The assumptions of symmetry and that each country knows its own BAU emissions with certainty are a special case, so the derivative of (4) can take on either sign.

A similar argument shows the ambiguity of the comparative statics of (5), where the regulator seeks to minimize global emissions. As before, a country participates if $\varepsilon \geq \hat{b}^r-b$; and has emissions $z^0=\hat{z}^0-\varepsilon$ if it does not participate, and $b-\left(z^0-q^*-b\right)$ if it does participate. Given that emissions elsewhere in the world then increase by z^0-q^*-b (the number of offsets generated), the minimand of (5) can be expressed as follows:

$$E\left[z^*+\max\left(b-z^*,\ 0\right)\right]=\int_{-\infty}^{\hat{b}^r-b}\left(\hat{z}^0-\varepsilon\right)f_{\mathrm{E}}(\varepsilon)d\varepsilon+\int_{\hat{b}^r-b}^{\infty}bf_{\mathrm{E}}(\varepsilon)d\varepsilon \tag{12}$$

By Leibnitz's Rule, the derivative of (12) with respect to *b* are as follows:

$$-\left(\hat{z}^0-\hat{b}^r+b\right)f_{\mathrm{E}}(\varepsilon)_{|\hat{b}^r-b}+bf_{\mathrm{E}}(\varepsilon)_{|\hat{b}^r-b}+\int_{\hat{b}^r-b}^{\infty}f_{\mathrm{E}}(\varepsilon)d\varepsilon$$
$$=\left(b^r-z^0\right)f_{\mathrm{E}}(\varepsilon)_{|\hat{b}^r-b}+1-F_{\mathrm{E}}\left(\hat{b}^r-b\right) \tag{13}$$

The first term is negative, and represents the reduction in global emissions as countries participate. The last term represents the increase in global emissions as the crediting baseline rises. Thus, the sign of (13) depends on the shape of $f_{\mathrm{E}}(\varepsilon)$, and is ambiguous.

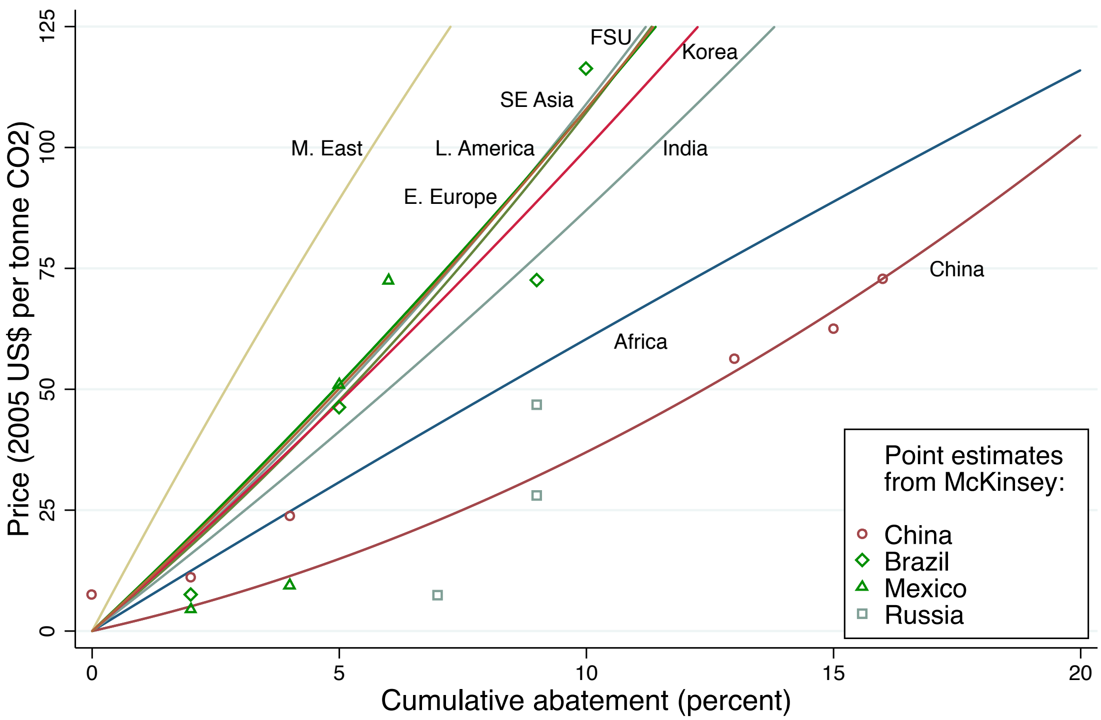
Appendix B: Derivation of Abatement Costs

As discussed in the main text (Section 3.1), I derive regionally specific abatement cost curves from the Global Change Assessment Model (GCAM). I impose a series of carbon prices for each region from 2020 onwards, and use GCAM to simulate abatement in 2020 at that price (percentage abatement in 2035 is very similar). This method of deriving abatement costs is similar to that of Böhringer et al. (2005) and Baker et al. (2009).

Large differences in abatement cost estimates are often observed between bottom-up engineering studies and top-down integrated assessment models (Jaccard et al. 2004; van Vuuren et al. 2009). In this instance, however, estimates from GCAM are similar in magnitude to those derived from McKinsey engineering estimates of abatement potential in several countries – Brazil, China, Mexico and Russia (McKinsey & Company 2009a, b, c, d). Figure B-1 shows the GCAM cost curves and the McKinsey point estimates.

This rough agreement between the McKinsey and GCAM methods increases confidence in the abatement cost curve estimates. Moreover, sensitivity tests to differences in abatement costs are implicitly performed as the simulations in Section 4 are run with a variety of carbon prices – doubling the carbon price is equivalent to halving abatement costs. Another form of sensitivity analysis involves using different shaped cost curves, rather than simply changing their level. Simulations (not shown) run with cost curves derived from the McKinsey country studies do not change the qualitative conclusions or the magnitude of the quantitative results.

Figure B-1 Estimates of Marginal Abatement Cost Curves for Transportation



Notes: (1) Negative-cost measures are excluded from the McKinsey data. These tend to be vehicle efficiency measures where barriers are institutional or informational. Sweeney & Weyant (2008: 21-22) argue that these types of negative-cost measures are at best only partially responsive to a carbon price, and I assume that implementation would not be affected by sectoral no-lose targets. (2) Curves for Eastern Europe, Latin America, SE Asia and FSU (Former Soviet Union) are practically indistinguishable.

References

Baker, E., H. Chon and J. Keisler (2009). "Advanced solar R&D: Combining economic analysis with expert elicitations to inform climate policy " Energy Economics **31**: 537-549.

Böhringer, C., T. Hoffmann, A. Lange, A. Löschel and U. Moslener (2005). "Assessing Emission Regulation in Europe: An Interactive Simulation Approach." Energy Journal **26**(4): 1-21.

Jaccard, M., R. Murphy and N. Rivers (2004). "Energy-environment policy modeling of endogenous technological change with personal vehicles: combining top-down and bottom-up methods." Ecological Economics **51**(1-2): 31-46.

McKinsey & Co. (2009a). China's Green Revolution: McKinsey & Company.

McKinsey & Co. (2009b). Low-Carbon Growth. A Potential Path for Mexico: McKinsey & Co.

McKinsey & Co. (2009c). Pathways to a Low-Carbon Economy for Brazil. Sao Paulo: McKinsey & Co.

McKinsey & Co. (2009d). Pathways to an energy and carbon efficient Russia: McKinsey & Company.

Sweeney, J. and J. Weyant (2008). Analysis of Measures to Meet the Requirements of California's Assembly Bill 32. Stanford, CA: Precourt Institute for Energy Efficiency.

van Vuuren, D. P., M. Hoogwijk, T. Barker, K. Riahi, S. Boeters, J. Chateau, S. Scrieciu, J. van Vliet, T. Masui, K. Blok, E. Blomen and T. Kram (2009). "Comparison of top-down and bottom-up estimates of sectoral and regional greenhouse gas emission reduction potentials." Energy Policy **37**(12): 5125-5139.

Appendix C: Sensitivity to Estimates of BAU Emissions

The estimates of business-as-usual (BAU) emissions employed here, upon which the crediting baseline is predicated, correspond to a method that would likely be used by a regulator in practice. However, the regulator might estimate an alternative specification with better predictive performance, either through luck or econometric skill. In this appendix, I therefore estimate an approximate upper bound on the regulator's predictive ability in order to suggest how sensitive the results are to more accurate predictions of BAU.

I estimate a total of 1,342,276 specifications for the three horizon periods (i.e., using only data through 1997, 2002 or 2006), and select the one with the lowest population-weighted mean square error for an out-of-sample prediction in 2007. As with the plausible specification discussed in the main text, the crediting baseline is then set as a percentage of estimated BAU. Where a log dependent variable specification was used, predictions were made with Duan's smearing estimate.

Table C-1 shows the universe of 12 specifications and 19 sets of predictor variables that are used in the search. The total number of specifications estimated (1,342,276) is substantially less than these values imply (2^{19} sets of predictors * 12 specifications * 3 horizon periods = 18,874,368) for two reasons. First, some combinations of predictor variables are assumed to be mutually exclusive or would be perfectly colinear: examples include country-specific GDP and regional GDP, and variables in untransformed and log form. Second, some specifications failed to converge.

Table C-2 shows the specifications of the models with the lowest population-weighted mean square error in the out-of-sample prediction for 2007. While all the models include GDP in various forms and lagged dependent variables, there is no clear specification that performs best across all horizon periods. Nor is there any obvious rationale to choose these three models in the absence of ex-post data on predictive performance. This simply highlights the difficulties for the regulator in selecting the best predictive model ex ante.

Figure C-1 shows the simulation results using predictions of BAU from these approximate upper bounds; a crediting baseline set between 70% and 130% of estimated BAU; and various carbon prices. These simulations parallel those presented in Figure 7 of the main text. The comparison between Figure C-1 and Figure 7 indicates that the improvements in predictive accuracy from using the approximate upper bound bring a minimal payoff in terms of efficiency gains and reduced transfer costs. In the 5- and 10-year horizon scenarios, it is rare for more than 50% of offsets to be additional, even at the highest carbon price of $60 per tonne of CO_2 reduced. The shapes of the curves relating participation decisions to the generosity of the crediting baseline are almost indistinguishable between Figure C-1 and Figure 7, indicating that the improvement in predictive power has almost no benefit for efficiency.

These sensitivity tests suggest that the results are not driven by the econometric specifications for predicting BAU employed in the main body of the paper. Rather, the obstacles to sectoral crediting mechanisms for transportation can be seen as product of the inherent difficulties in predicting BAU emissions, with prediction errors being large in relation to expected abatement.

Figure C-1 Alternative Price Scenarios (Approximate Upper Bound for BAU Prediction)

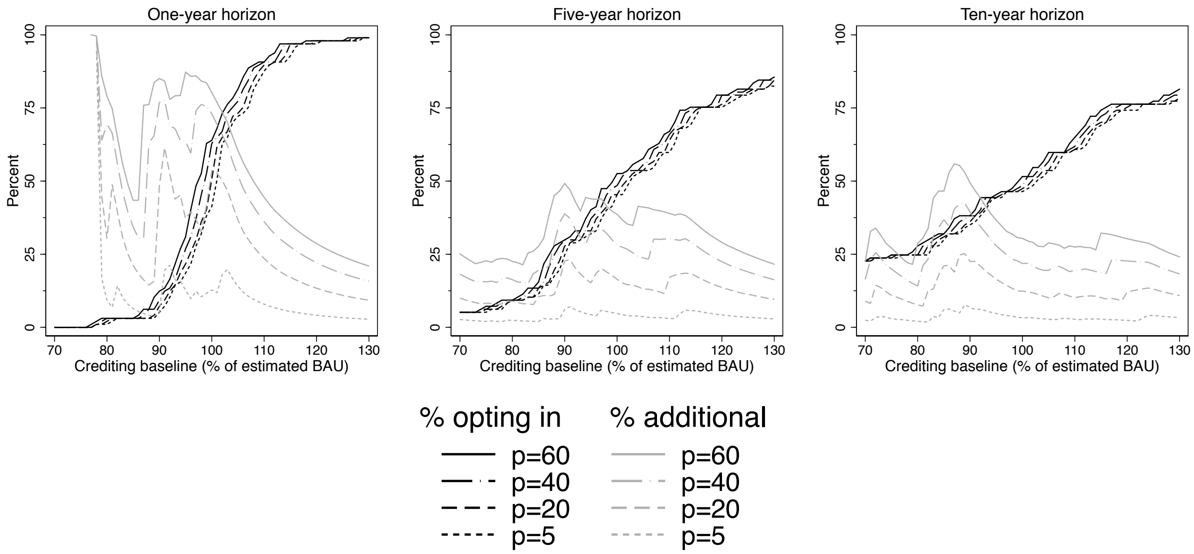


Table C-1 Combinations of Models Estimated

Variable Sets	GDP	Lag GDP	GDP^2	GDP^3	GDP*Annex I
	GDP*Region (10 variables)	GDP*Country (97 variables)	Log GDP	MANUF	FINCON
	OIL	GAS	Log OIL and Log GAS	Lag OIL and Lag GAS	Lag log OIL and Lag log GAS
	Lagged dependent variable*	TIME	TIME^2	TIME*Country (97 variables)	

Specifications	1	$y_{it} = \alpha + X_{it}\beta + \varepsilon_{it}$	Basic linear regression model
	2	Same as (1), but prediction is calculated as difference from last in-sample observation**	
	3	$\log y_i = \alpha + X_{it}\beta + \varepsilon_{it}$	Basic linear regression model with log DV
	4	Same as (3), but prediction is calculated as difference from last in-sample observation**	
	5	$y_{it} = \alpha_i + X_{it}\beta + \varepsilon_{it}$	Fixed effects model
	6	Same as (5), but prediction is calculated as difference from last in-sample observation**	
	7	$\log y_{it} = \alpha_i + X_{it}\beta + \varepsilon_{it}$	Fixed effects model with log DV
	8	Same as (7), but prediction is calculated as difference from last in-sample observation**	
	9	$y_{it} = \alpha_i + X_{it}\beta + \varepsilon_{it}, \quad \varepsilon_{it} = \rho\varepsilon_{it-1} + \mu_{it}$	Fixed effects model with AR(1) term
	10	$\log y_{it} = \alpha_i + X_{it}\beta + \varepsilon_{it}, \quad \varepsilon_{it} = \rho\varepsilon_{it-1} + \mu_{it}$	Fixed effects model with AR(1) term and log DV
	11	$y_{it} - y_{it-1} = \left(X_{it} - X_{it-1}\right)\beta + \varepsilon_{it}$	First differenced model
	12	$\log y_{it} - \log y_{it-1} = \left(X_{it} - X_{it-1}\right)\beta + \varepsilon_{it}$	First differenced model with log DV

DV = dependent variable

Country-specific coefficients (e.g. GDP*Country) are for Annex 1 countries only.

*Dependent variable is lagged 1 and 2 years (for 1-year horizon), 5 years (for 5-year horizon) and 10 years (10-year horizon)

**Calculated by adding the residual from the last in-sample observation to the prediction.

Table C-2 Estimates of BAU – Approximate Upper Bound

	1-year horizon (data through 2006)	5-year horizon (data through 2002)	10-year horizon (data through 1997)
Specification	(3) – Linear regression with log DV	(4) – Linear regression with log DV. Residual from last in-sample observation added to prediction	(10) – Fixed effects with AR(1) term and log DV
GDP			0.000182
			(2.00e-05)
Lag GDP		-6.85e-06	1.01e-05
		(8.05e-06)	(5.36e-06)
GDP^2	-7.69e-10	-4.39e-09	-6.29e-09
	(9.67e-11)	(2.50e-10)	(9.13e-10)
GDP^3	8.76e-15	5.22e-14	6.86e-14
	(1.31e-15)	(3.71e-15)	(1.30e-14)
GDP*Annex I			1.94e-05
			(1.04e-05)
MANUF		-3.87e-05	-1.28e-05
		(8.25e-06)	(1.80e-05)
FINCON	-6.08e-06	-2.83e-05	
	(1.76e-06)	(4.09e-06)	
OIL			-0.00142
			(0.00102)
GAS			0.00132
			(0.000891)
Log OIL	-0.0388		
	(0.0288)		
Log GAS	0.0523		
	(0.0317)		
Lag log OIL	0.0560		
	(0.0283)		
Lag log GAS	-0.0815		
	(0.0333)		
$TIME^2$	1.43e-06	7.93e-06	
	(5.02e-06)	(1.08e-05)	
Lag 1 dependent variable	0.973		
	(0.0161)		
Lag 2 dependent variable	-0.00984		
	(0.0158)		
Lag 5 dependent variable		0.813	
		(0.00772)	
Lag 10 dependent variable			0.0468
			(0.0241)
GDP*Region	Yes	Yes	No
Constant	0.209	0.764	4.886
	(0.0360)	(0.0342)	(0.0371)
ρ (autocorrelation coefficient)			.798
Observations	3839	3254	1898
R-squared	0.990	0.958	0.784
RMSE for 2007 prediction*	26.2	80.3	95.5

Standard errors in parentheses * Non-Annex I countries only, weighted by population