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ADVERSE SELECTION IN AN OPT-IN EMISSIONS TRADING PROGRAM: THE CASE OF SECTORAL CREDITING FOR TRANSPORTATION

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Adverse Selection in an Opt-In Emissions Trading Program

The Case of Sectoral Crediting for Transportation

Adam Millard-Ball

Abstract

Sectoral crediting mechanisms such as sectoral no-lose targets have been proposed as a way to provide incentives for emission reductions in developing countries as part of an international climate agreement, and scale up carbon trading from the project-level Clean Development Mechanism to the sectoral level. Countries would generate tradable emission credits (offsets) for reducing emissions in a sector below an agreed crediting baseline. I show that large uncertainties in the regulator's predictions of the counterfactual business-as-usual baseline are likely to render sectoral no-lose targets an extremely unattractive mechanism in practice, at least for the transportation case study presented here. Given these uncertainties, the regulator faces a tradeoff between efficiency (setting generous crediting baselines to encourage more countries to opt in) and limiting transfer payments for non-additional offsets (which are generated if the crediting baseline is set above business-as-usual). I show that the first-best outcome is attainable through setting a generous crediting baseline. However, this comes at the cost of either increased environmental damage (if developed country targets are not adjusted to account for non-additional offsets), or transfers from developed to developing countries that are likely to be too high to be politically feasible (if developed country targets are made more stringent in recognition that many offsets are non-additional). A more stringent crediting baseline still generates a large proportion of non-additional offsets, but renders sectoral no-lose targets virtually irrelevant as few countries opt in.

1 Introduction

The carbon market is the centerpiece of current efforts to engage developing countries in global efforts to reduce greenhouse gas emissions. In particular, the Clean Development Mechanism (CDM), one of the implementation mechanisms of the Kyoto Protocol, allows developed countries to purchase emission reductions (carbon offsets) from projects in developing countries as a partial alternative to domestic action. By equalizing marginal abatement costs across sectors and across countries, the CDM can in principle substantially reduce the cost of achieving a given abatement[1] target, or increase the volume of emission reductions secured at a given carbon price or marginal abatement cost (Anger et al. 2007).

The CDM, however, has come in for substantial criticism in recent years. There is evidence that many of the CDM offsets are not additional, i.e. the project would have been undertaken anyway in the absence of the CDM, and thus no emission reductions are being achieved (Wara and Victor 2008; Haya 2009; Schneider 2009; Fujiwara 2010; He and Morse 2010). Other lines of criticism relate to problems with the methodologies used to quantify emission reductions (Millard-Ball and Ortolano 2010); the lack of broad sustainable development benefits from CDM projects (Sutter and Parreño 2007); and the inability of the CDM to promote innovation and incentivize long-term transformations in energy systems (Sterk 2008).

Sectoral no-lose targets and other sector-based crediting mechanisms have emerged prominently in the policy literature as a way to overcome some of these problems with project-level CDM (Bosi and Ellis 2005; Figueres 2006; Center for Clean Air Policy 2008; Ecofys 2008; Sterk 2008; Baron et al. 2009; IETA 2010). Sectoral approaches have also been seen as a stepping-stone to "graduation," i.e. the assumption of binding emissions targets by developing countries (Michaelowa et al. 2005; Schneider and Cames 2009).

Developing countries would opt-in to a sectoral no-lose targets mechanism on a voluntary basis, and could generate tradable credits (offsets) by reducing emissions to below a sectoral crediting baseline (Figure 1). Emissions above the crediting baseline would not be penalized (hence, the "no lose"

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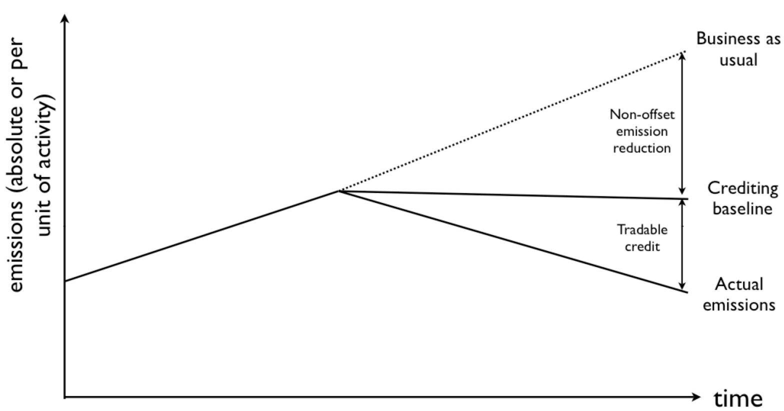
[1] Note that abatement does not necessarily refer to a reduction in emissions from current levels. It only implies a reduction below the business-as-usual counterfactual.

designation). In contrast to project-based CDM, where projects are typically proposed and developed by private investors, offsets from sectoral no-lose targets would accrue to national governments, who would in turn determine whether and how to pass through the carbon price signal or provide other emission reduction incentives to private actors. Offsets would be sold to developed (Annex I) countries that face binding emission caps, or in conjunction with some other source of demand for offsets such as a domestic cap-and-trade program.

Most discussions of sectoral no-lose targets assume that the crediting baseline would be set below the expected business-as-usual (BAU) counterfactual, as implied in Figure 1. This would bring about a net reduction in global greenhouse gas emissions, and ensure that some abatement is funded by developing countries themselves or through multilateral grant programs. However, the crediting baseline could in principle be set at any level, including above BAU.

Figure 1 Concept of Sectoral No-Lose Targets



The opt-in nature of sectoral no-lose targets presents potential problems of adverse selection if there exist information asymmetries between the regulator and individual developing countries. Indeed, this is an issue with any voluntary opt-in emissions trading program; Montero (2000) demonstrates the regulator's trade-off between efficiency (ensuring that all entities with low abatement costs opt in) and information rent extraction (reducing the number of "excess permits" allocated). A stringent crediting baseline can reduce information rents and the number of excess permits, but at an efficiency cost as fewer entities opt in.

In the case of the U.S. Acid Rain Program, generating units with a "generous" baseline (one set above their counterfactual emissions) were more likely to opt in, resulting in increased SO_2 emissions and a net social loss after considering abatement cost savings (Montero 1999). Adverse selection problems have also been raised in the contexts of crediting rules under project-based CDM (Fischer 2005) and under opt-in programs for agriculture and forestry (Kerr and Sweet 2008; van Benthem and Kerr 2010).

This paper uses the transportation sector as a case study to examine how rules for setting crediting baselines affect decisions by developing countries to opt in to a sectoral no-lose targets mechanism. I offer two main contributions to the literature. First, I provide empirical results that quantify the information rents (which have an associated transfer or environmental cost) and efficiency implications of adverse selection in an opt-in emissions trading program. With one main exception (Montero 1999), the impacts of adverse selection in emissions trading have not been estimated empirically. Moreover, in contrast to Montero, the context of this paper is international, and as a result efficiency-improving transfers may be harder to implement for political reasons. I show that while the first-best outcome[2] is attainable, this result requires transfers from developed to developing countries that are likely to be too high to be politically feasible. The higher the abatement costs in developing countries, or the less precision with which business-as-usual emissions can be estimated, the higher the transfers that are required to maintain this first-best outcome. These transfers are assumed to be made through adopting more stringent emissions targets in developed countries, in order to maintain global emissions at the optimum level. If targets are not adjusted, then there may be no efficiency gain at all due to increased environmental damage.

Second, I contribute to the policy literature on emissions trading mechanisms to engage developing countries in greenhouse gas abatement. While sectoral no-lose targets have been widely discussed as a new potential climate policy mechanism, adverse selection has scarcely been mentioned at all, except implicitly as part of a discussion of methodological difficulties in setting crediting baselines (Sterk 2008; Bongardt et al. 2009). Indeed, the literature on sectoral no-lose targets has focused on conceptual design issues with little detailed analysis of how to set the crediting baseline.

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[2] Throughout this paper, I ignore potential inefficiencies from the raising of public funds. For instance, if offsets are purchased by national governments, this may require an increase in distortionary taxes.

Transportation is an important case study in part because of the sheer size of the sector. It accounted for 23% of global energy-related CO_2 emissions in 2007, and this proportion remains unchanged in 2030 under the International Energy Agency's (2009b) reference scenario. Transportation is also useful to consider because the gains of moving to a sectoral approach may be large. The sector has been under-represented in project-level CDM, accounting for just 0.1% of registered CDM projects and the same proportion of projected emission reductions as of March 2010 (UNEP Risø 2010). However, the paucity of transportation CDM projects may not be a reflection of the abatement potential; numerous low-cost opportunities to reduce transportation emissions are likely to exist in developing countries, especially when co-benefits are considered (Sperling and Salon 2002; Wright and Fulton 2005; Johnson et al. 2009). Several authors have called for sectoral no-lose targets or similar approaches for transportation as an alternative to project-based CDM (Bradley et al. 2007; Schneider and Cames 2009; Wittneben et al. 2009)

The paper proceeds as follows. In Section 2, I present a theoretical model that specifies opt-in and abatement decisions by developing countries, and the baseline setting decision by the regulator. Section 3 describes the empirical approach to estimating abatement cost functions and business-as-usual emissions. In Section 4, I present the results of the simulations. Section 5 concludes with policy implications.

2 A Model of an Opt-In Trading Program

2.1 Opt-In and Abatement by Developing Countries

The model presented here is similar in spirit to that of van Benthem and Kerr (2010), who develop it in the context of a forestry program. We have $i = 1 \ldots N$ entities that may choose to opt-in to a trading program. The entities are non-Annex I countries (primarily developing nations) that do not face binding emission targets under the Kyoto Protocol or a similar agreement. I refer to them simply as "countries" or "developing countries" in the following sections. (Annex I countries do not enter into the model, except as an exogenous source of demand for offsets.) For simplicity, I develop a one-shot model of a single compliance period. Provided abatement costs and decisions are independent over different compliance periods, this model generalizes in a straightforward way to multiple compliance periods.

Each country has business-as-usual (BAU) emissions z_{it}^0 in period *t*. For simplicity, in the remainder of this section I drop the *t* subscript and refer only to the compliance period, which might be a single year or, as under the Kyoto Protocol, span multiple years. If a country does not opt in, its emissions are z_i^0 by definition and its abatement cost is zero. It a country opts in, it chooses emission levels z_i and incurs an abatement cost $c_i\left(z_i^0 - z_i\right)$.

Each country is assigned a crediting baseline b_i for the compliance period by an international regulator such as the UN Framework Convention on Climate Change secretariat (UNFCCC). Any reductions below this crediting baseline can be sold on the carbon market as offsets at an exogenous price *p*. Assuming that countries are profit-maximizing and do not care about aggregate emission levels, each country receives the following payoff:

$$\begin{aligned} \pi_i &= p\left(b_i - z_i\right) - c_i\left(z_i^0 - z_i\right) && \text{if } b_i > z_i \\ \pi_i &= -c_i\left(z_i^0 - z_i\right) && \text{otherwise} \end{aligned} \tag{1}$$

Note that the "no lose" provision means that a country never needs to buy offsets, even if emissions are above the crediting baseline. Also note that the payoff is zero if a country does not opt in.

I assume that countries have perfect information, i.e. they know the carbon price p, BAU emissions z_i^0 and cost function $c_i\left(z_i^0 - z_i\right)$ with certainty. (Incidentally, this assumption renders the "no-lose" provision redundant, as a country would not opt in if it knew that it were going to lose out.) A country will opt in for the compliance period if and only if:

$$p\left(b_i - z_i\right) \geq c_i\left(z_i^0 - z_i\right) \tag{2}$$

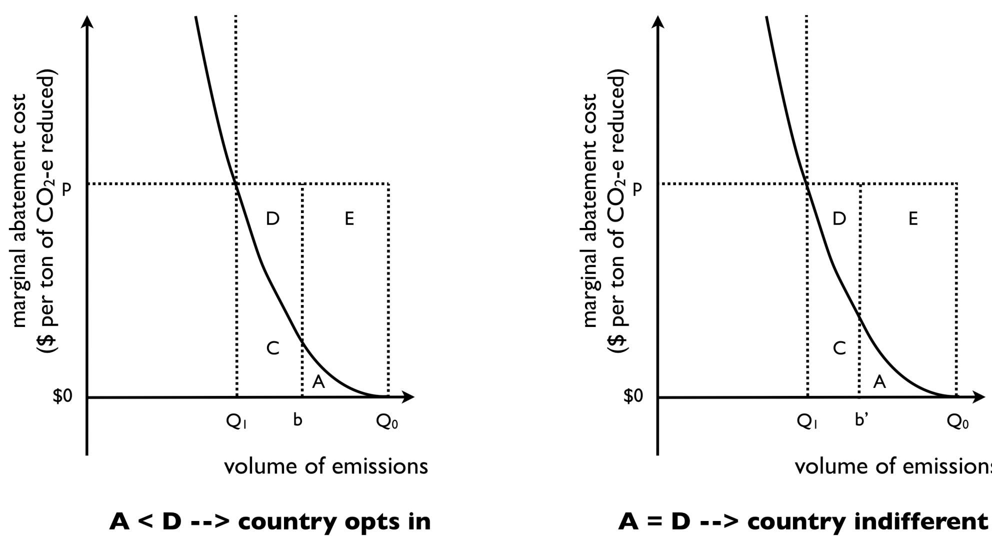
Given the usual conditions on the shape of the cost function, a country that opts in will reduce emissions to z_i^e, defined as the point where price equals marginal abatement cost, i.e. $p = -\frac{\partial c_i}{\partial z_i^e}$.

Thus, a developing country chooses emissions z_i^* as follows:

$$z_i^* = \begin{cases} z_i^e & \text{if } p\left(b_i - z_i\right) \geq c_i\left(z_i^0 - z_i\right) \\ z_i^0 & \text{otherwise} \end{cases} \tag{3}$$

Graphically, this is shown in Figure 2. If the cost of reducing emissions from BAU to the crediting baseline b (area A) is less than the rents earned on emission reductions that can be sold on the carbon market (area D), then a country opts in, as in the left panel. If area A is equal to area D, which occurs if the crediting baseline is changed to b', a country is indifferent regarding opt-in, as in the right panel.

Figure 2 Opt-in Decisions By Developing Countries



2.2 BAU Estimating and Baseline Setting by the Regulator

I assume that the regulator knows the carbon price *p* and country-specific cost function $c_i\left(z_i^0 - z_i\right)$ with certainty. However, it estimates BAU emissions with error as $\hat{z}_i^0 = z_i^0 + \varepsilon_i$. These BAU estimates, in turn, serve as the basis for setting the crediting baseline. Most likely, the crediting baseline would be set as a percentage of estimated BAU.

This asymmetry in information regarding BAU emissions between countries and the regulator is the source of the adverse selection. It might arise as the regulator does not know which transportation infrastructure investments, taxation changes or regulatory measures a country planned to undertake under BAU. In addition, while the regulator makes a one-shot estimate of BAU, the country has the opportunity to update its emissions estimate over time and change its opt-in decision. Moreover, while the regulator can condition a dynamic estimate of BAU on observables such as GDP and population, it cannot use changes in variables that may be the target of transportation policy measures such as public transportation provision or local fuel prices. For example, suppose that a crediting baseline is set as a percentage of BAU, which in turn is estimated dynamically. If local fuel prices are used to make this dynamic estimate, there is no incentive for a country to reduce fuel subsidies or increase fuel taxes as an emission reduction measure. Such an action would simply be reflected in a more stringent crediting baseline.

Setting aside any politically negotiated dimension, we might posit three alternative objective functions that the regulator seeks to optimize when setting the vector crediting baselines **b**:

1. **Maximize average offset quality.** We can define a non-additional offset as one that is generated by virtue of the crediting baseline being set above BAU. A country needs to take no action and incurs no abatement costs to generate these non-additional offsets. We can thus define an average offset quality objective as one that minimizes the proportion of non-additional offsets that are generated. This may be motivated on environmental grounds, or to minimize the proportion of expenditure on offsets that is a pure transfer from Annex I to non-Annex I countries. Formally, the regulator sets

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

The numerator is the volume of non-additional offsets (the difference between the baseline and BAU emissions, if positive). The denominator is the total volume of offsets generated (the difference between the baseline and actual emissions, if positive).

We assume that $E\left\{\sum_{i=1}^{N}\max\left(b_i - z_i^*,\ 0\right) > 0\right\}$, i.e. the regulator does not set the crediting baseline so stringently that no country opts in and no offsets are generated.

In the absence of the private information held by each country about their true baseline, the regulator can ensure that all offsets are additional by setting $b_i \leq z_i^0$. However, since z_i^0 is estimated with error, this may not be possible for all countries.

2. Minimize global emissions. This objective has an environmental motivation, in that the regulator wishes to minimize global emissions. It is most applicable in a world where emission reductions targets in Annex I countries are implicitly fixed or set independently of the existence of any offset mechanism. Any non-additional offsets (generated if $z_i^0 < b_i$) will increase global emissions, and may lead to an efficiency loss if Annex I emission caps were set at or above the efficient level. Additional offsets have no impact on aggregate emissions, as any reductions in developing countries are counterbalanced by increased emissions in Annex I countries. However, the regulator may be able to secure a reduction in aggregate emissions; this occurs if the crediting baseline is set below BAU, and the aggregate emission reduction is $z_i^0 - b_i$ from any country that opts in.

Formally, the regulator sets the crediting baseline to minimize the sum of developing country emissions and offsets generated:

$$\mathbf{b}^*_{MIN\_EMISSIONS} = \arg\min_{\mathbf{b}} E\left\{\sum_{i=1}^{N}\left[z_i^* + \max\left(b_i - z_i^*,\ 0\right)\right]\right\} \tag{5}$$

3. Maximize efficiency. Under this objective, the regulator maximizes the emissions-weighted number of countries that opt in. In a world where targets in Annex I countries adjust to the expected supply of non-additional offsets from developing countries, this can be interpreted as an efficiency objective, in that the regulator takes advantage of all developing world abatement opportunities with a marginal cost less than the carbon price. This objective is also equivalent to minimizing emissions in developing countries.

$$\mathbf{b}^*_{EFF} = \underset{\mathbf{b}}{\arg\min}\, E\left\{\sum_{i=1}^{N} z_i^*\right\} \tag{6}$$

2.3 Implications of Alternative Baselines

Note that the crediting baseline only affects the decision to opt in, and not the volume of emission reductions conditional on having opted in. If all countries opt in, we achieve the efficient outcome in the sense that abatement opportunities in all countries can be realized. However, the crediting baseline does matter in terms of affecting the level of transfers between Annex I and developing countries; and aggregate global emissions. We can think of b_i^r as a "rent extraction" point in that it is the most stringent baseline that ensures a country will opt in.

$$p\left(b_i^r - z_i^*\right) = c_i\left(z_i^0 - z_i^*\right) \Rightarrow b_i^r = \frac{c_i\left(z_i^0 - z_i^*\right)}{p} + z_i^* \tag{7}$$

It is straightforward to show that, as demonstrated by Montero (2000), the choice of crediting baseline trades off efficiency for transfer costs (or information rents in Montero's terminology). The number of countries opting in and the transfer costs (payment for non-additional emission reductions) are both increasing in the crediting baseline. Thus, the regulator's efficiency objective is straightforward to achieve by setting a crediting baseline so generous that all countries opt in.

In contrast, it is unclear how a regulator should set a crediting baseline to optimize against the other two potential objectives – maximizing average offset quality, or minimizing global emissions. Both the numerator and denominator of (4) are increasing in **b**, and so the effect of changing the baseline on the proportion of additional offsets is ambiguous. A similar ambiguity applies to (5); global emissions are the sum of developing country emissions z_i^*, which are decreasing in b_i, and offsets $\max\left(b_i - z_i^*, 0\right)$, which are increasing in b_i. The following sections address this issue empirically.

3 Empirical Approach

The broad empirical approach adopted here is to hypothesize that sectoral no-lose targets had been implemented in some prior year, perhaps as part of the 1997 Kyoto Protocol. In order to simulate opt-in and abatement decisions under a sectoral no-lose targets mechanism, we need to specify the abatement cost function, the crediting baseline, BAU emissions, and the carbon price, as is evident from Eq. (3). Section 3.1 discusses estimation of abatement costs. Section 3.2 discusses alternative ways in which the regulator might set the crediting baseline. BAU emissions from transportation are observed[3] and I use data from the International Energy Agency (2009a), with 2007 being the most recent year for which data are available. I do not attempt to estimate the carbon price, but rather undertake simulations under a range of price scenarios.

3.1 Estimating Abatement Costs

I derive regionally specific abatement cost curves from the Global Change Assessment Model (GCAM), an integrated assessment model that models emissions in 15-year time steps from 1990 to 2095 (Kim et al. 2006). The regions modeled are China, Africa, Eastern Europe, Former Soviet Union (FSU), India, Korea, Latin America, Middle East and Southeast Asia (the other five regions in GCAM consist only of Annex I countries). I impose a series of carbon prices for each region from 2020, and use GCAM to simulate abatement in 2020 at that price. This is similar to the procedure used by Böhringer et al. (2005) in a multi-sectoral context, and by Baker et al. (2009) in the context of solar energy technologies. Note that percentage abatement in 2020 is similar to that in 2035, and so the results are scarcely affected by using a longer time period to adjust to the carbon price.

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 the GCAM model are similar in magnitude to those derived from McKinsey engineering estimates of the maximum technical potential of a range of abatement options in several individual developing or emerging market countries – Brazil, China, Mexico and

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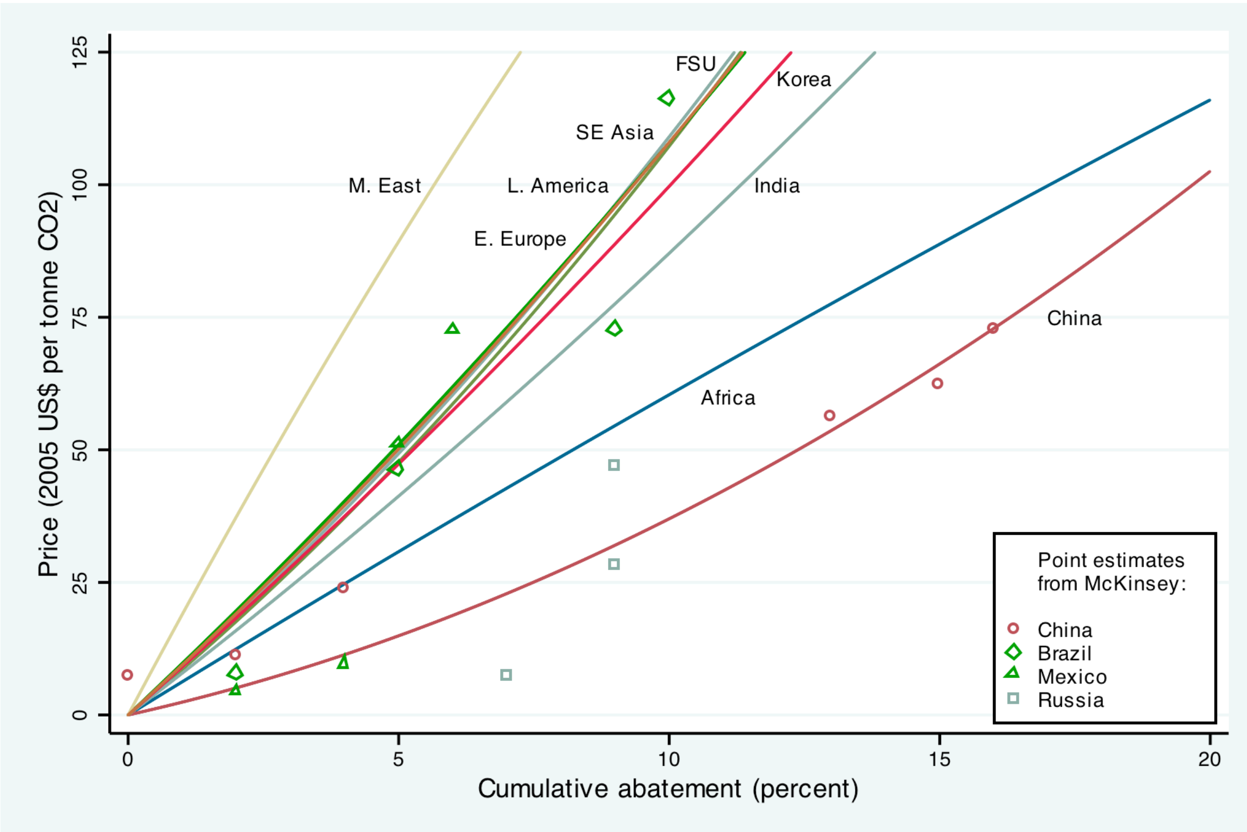
[3] In other sectors, the presence of CDM projects poses a complication, and means that observed emissions will not necessarily correspond to BAU. In the transport sector, however, just two CDM projects had been registered by the end of 2009. I therefore take observed emissions in developing countries as a reasonable approximation for BAU.

Russia (McKinsey & Company 2009a, b, c, d). Both the GCAM cost curves and the McKinsey point estimates are shown in Figure 3.

This rough agreement between the McKinsey and GCAM methods increases confidence in the abatement cost curve estimates. The estimates are still highly uncertain, given the implicit assumptions on future energy prices, economic growth, technological progress and consumer preferences, to name just a few. However, sensitivity tests to differences in abatement costs are implicitly performed as the simulations in Section 4 are run with a variety of carbon prices. This will capture any variation in the level of the abatement cost curve; 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 were also run using cost curves derived from the McKinsey country studies referred to above. These sensitivity tests (not shown) lead to almost no change in the decisions of countries to opt in at a given price and crediting baseline. They have a small effect on percentages of additional offsets, but do not change either the conclusions or the magnitude of the quantitative results.

Figure 3 Estimates of Marginal Abatement Cost Curves



Notes: (1) Negative cost measures are excluded from the McKinsey data, as these are unlikely to be influenced by a carbon price. (2) The curves for Eastern Europe, Latin America, South East Asia and Former Soviet Union are practically indistinguishable.

3.2 Setting the Crediting Baseline

Regulatory Approaches

I assume that the regulator sets a dynamic crediting baseline in order to minimize the errors in predicting BAU emissions. In other words, BAU is estimated as a function of exogenous variables such as population or GDP. The formula is determined ex ante, but the absolute level of the baseline is only known ex post once GDP and other relevant variables are observed. I assume that the crediting baseline is set as a percentage of estimated BAU, and simulate crediting baselines of between 70% and 130% of estimated BAU.

I simulate three horizon years of one, five and ten years forward respectively. This corresponds to the hypothetical implementation of sectoral no-lose targets in the years 2006, 2002 and 1997. With the more distant horizon years, prediction errors might be expected to increase considerably. Hence, although a one-year horizon period is unrealistic in practice (apart from anything, it would only leave one year for a country to implement emission reduction measures), it is useful in showing the effects of more accurate predictions. In all cases, the compliance period is taken to be the year 2007, the most recent year for which IEA emissions data by sector are available.

As discussed below, I choose a plausible specification for estimating BAU as a function of GDP, energy prices and related variables. It seems reasonable to think that the UN or another regulator would adopt a similar econometric approach. However, it is possible that the regulator might, through luck or econometric skill, achieve greater accuracy in estimating BAU. For this reason, the Appendix provides details of sensitivity tests using an approximate upper bound for predictive accuracy. Here, I estimate 1,342,276 models for each horizon period and selected the one with lowest mean square error for an out-of-sample prediction in 2007.

This upper bound leads to a modest improvement in predictive accuracy, as shown in Figure 4. However, as detailed in the Appendix, there is no substantive impact on the simulation results.

It is also plausible that the regulator would choose an approach that results in lower predictive accuracy. One possibility is to adopt a politically negotiated crediting baseline, for example a "contraction and convergence" agreement under which per capita emissions from all countries converge by 2050 or 2100 at a level that achieves a long-term atmospheric stabilization target. Another possibility is to use an intensity baseline, under which the regulator estimates BAU emissions $\hat{z}_{it}^{0}$ (or log emissions) in compliance period t only as a function of changes in GDP from the current period t_0:

$$\hat{z}_{it}^{0} = z_{it_0} + \beta\left(GDP_{it} - GDP_{it_0}\right)$$

Neither the politically negotiated nor the intensity baseline option is considered further in this paper. These approaches both result in much larger prediction errors (results not shown), and thus would render sectoral crediting mechanisms even less attractive than under the dynamic baseline approach presented in the remainder of this paper.

Estimating BAU Emissions

I estimate BAU emissions as a function of GDP (measured at purchasing power parity in 2000 U.S. dollars); GDP from manufacturing (MANUF); final consumption expenditure (FINCON); crude oil price (OIL); gasoline price at the Rotterdam spot market (GAS); and time (TIME). I also include a lagged dependent variable. The inclusion of manufacturing GDP accounts for the potential greater emissions intensity of manufacturing activity compared to a services-based economy, due to freight transportation activity. The inclusion of final consumption expenditure may control for influences on GDP that do not directly affect transportation demand, such as petroleum exports. The time trend captures improvements in technical efficiency. The dependent variable is per capita transportation emissions (TPTCO2PC), and so I do not include population as a predictor. Data are from the International Energy Agency's (2009a) databases and the UN National Accounts database (United Nations 2010).

I estimate a small number of plausible specifications for a one, five and ten year horizon period (i.e., using only data through 2006, 2002 or 1997 respectively). Table 1 shows these models, which consist of two fixed-effects and two first-differenced specifications, each with a full and more parsimonious set of predictor variables. I also estimated fixed-effects models with country-specific coefficients for OIL, GDP and the lagged dependent variable, but these performed the worst in predictive terms (results not shown). The fixed-effects models include an AR(1) error term. All variables except time enter in log form, with retransformed predictions made using Duan's smearing estimate (Cameron and Trivedi 2009: 103). Note that the inclusion of various lagged variables and quadratic and cubic terms makes it difficult to interpret the coefficients directly, and so it comes as no surprise that many do not have the sign that one might expect from a cursory glance.

For each horizon period, I assume that the regulator picked the model with the best predictive performance (lowest population-weighted mean square error for the out-of-sample prediction in 2007), either through skill or luck. Predicting one year out, there is little to choose between the models, but the full fixed effects model performs best in predictive terms. Predicting over longer horizon periods, predictive performance declines substantially and the parsimonious fixed effects models (6) and (10) perform best.

Table 1 Model Specifications to Estimate Business as Usual Emissions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	1 year horizon (data through 2006)				5 year horizon (data through 2002)				10 year horizon (data through 1997)			
Lag* Log TPTCO2PC	0.818	0.844	-0.0324	-0.0228	0.0315	0.0320	0.0140	0.0161	0.0296	0.0386	0.0313	0.0425
	(0.00856)	(0.00737)	(0.0159)	(0.0153)	(0.0171)	(0.0166)	(0.0165)	(0.0160)	(0.0239)	(0.0227)	(0.0227)	(0.0215)
Log GDP	0.880	0.392	-4.318	0.328	-2.434	0.415	-4.495	0.361	-2.376	0.450	-4.095	0.431
	(0.672)	(0.0322)	(2.117)	(0.0337)	(2.465)	(0.0410)	(2.512)	(0.0400)	(3.221)	(0.0495)	(3.146)	(0.0478)
Lag 1 Log GDP	-0.251	-0.278	0.258	0.247	0.198	0.193	0.197	0.186	0.186	0.169	0.135	0.127
	(0.0350)	(0.0323)	(0.0355)	(0.0336)	(0.0398)	(0.0387)	(0.0390)	(0.0380)	(0.0508)	(0.0487)	(0.0482)	(0.0460)
Log^2 GDP	-0.0513		0.536		0.336		0.567		0.317		0.512	
	(0.0791)		(0.251)		(0.291)		(0.297)		(0.384)		(0.374)	
Log^3 GDP	0.00162		-0.0211		-0.0137		-0.0225		-0.0126		-0.0199	
	(0.00307)		(0.00982)		(0.0114)		(0.0116)		(0.0151)		(0.0147)	
Log MANUF	0.00217		0.0396		0.0142		0.0300		0.0449		0.0502	
	(0.00902)		(0.0184)		(0.0202)		(0.0199)		(0.0260)		(0.0249)	
Log FINCON	0.0250		0.182		0.173		0.182		0.199		0.187	
	(0.0209)		(0.0304)		(0.0344)		(0.0336)		(0.0438)		(0.0414)	
Log OIL	-0.0207	-0.0124	-0.0333	-0.00984	-0.00668	-0.00970	-0.00446	-0.00745	-0.0244	-0.0103	-0.0191	-0.00705
	(0.0248)	(0.00432)	(0.0237)	(0.00649)	(0.0251)	(0.00817)	(0.0242)	(0.00777)	(0.0302)	(0.0105)	(0.0289)	(0.00948)
Log GAS	0.00287		0.0485		0.0106		0.0120		0.0419		0.0412	
	(0.0274)		(0.0276)		(0.0297)		(0.0286)		(0.0394)		(0.0378)	
TIME	-0.00356	0.000969	0.0274	0.00954	0.000144	0.00706	0.0183	0.00960	-0.0481	0.00876	-0.000178	0.00912
	(0.00232)	(0.000253)	(0.00819)	(0.00220)	(0.0189)	(0.00184)	(0.00967)	(0.00239)	(0.0270)	(0.00239)	(0.0150)	(0.00275)
$TIME^2$	7.09e-05		-0.000294		0.000108		-0.000150		0.000909		0.000190	
	(3.54e-05)		(0.000124)		(0.000266)		(0.000154)		(0.000407)		(0.000251)	
Constant	-1.615	0.0109			7.452	0.644			8.059	0.494		
	(1.817)	(0.0719)			(1.175)	(0.0633)			(1.827)	(0.0945)		
Country fixed effects?	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No
Differenced?	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
ρ (autocorrelation coefficient)	.032	.018			.829	.836			.794	.803		
N	3809	4162	3809	4162	3015	3194	3015	3194	1898	2048	1898	2048
R-squared	.989	.990	0.078	0.066	.834	.833	0.069	0.060	.843	.851	0.079	0.072
RMSE for 2007 prediction**	31.2	32.0	31.5	32.3	90.0	85.5	100.9	102.4	264.8	111.6	203.4	150.8

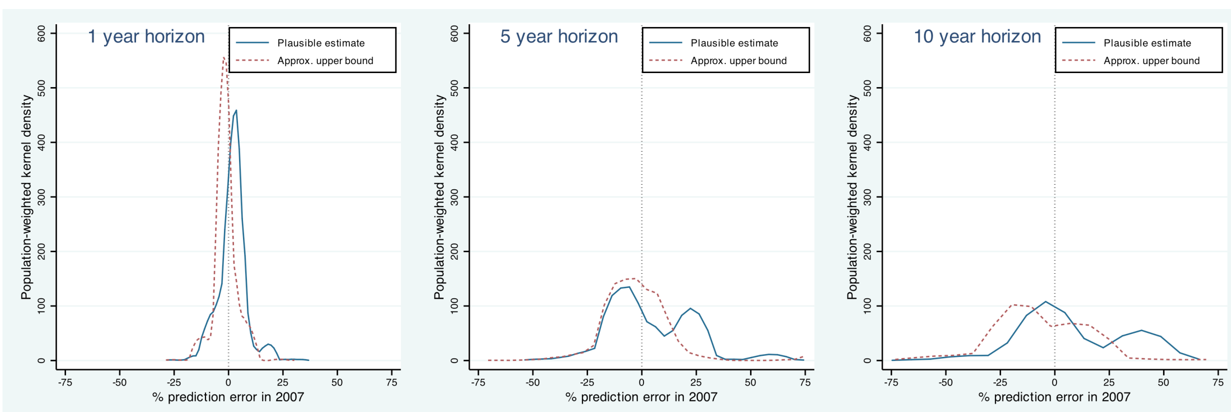
Standard errors in parentheses
*Dependent variable is lagged one year (models 1 through 4), five years (models 5 through 8) and ten years (models 9 through 12) respectively
** Non-Annex I countries only, weighted by population.

Predictive Performance

Figure 4 provides kernel density plots that show the predictive performance of the models, in terms of the distribution of percentage errors in the estimate of BAU for 2007 for each non-Annex I country. For comparison, the approximate upper bound (discussed in the Appendix) is also shown.

The ability of the regulator to predict BAU emissions declines precipitously as the horizon year extends and the regulator needs to predict further in the future. While reasonable accurate predictions (within about 5%) can be made with a one-year horizon period, this is not the case when predicting five or ten years out. The approximate upper bound does not markedly improve predictive performance, suggesting that the particular econometric specifications employed here are not at fault. Rather, the issue is the inherent unpredictability of transportation emissions in rapidly growing developing countries.

Figure 4 Errors in Predicting BAU Emissions



4 Simulation Results

4.1 Illustrative Scenarios

Figure 5 illustrates the essential structure of the results through showing the impacts of alternative crediting baselines for two scenarios. The first, shown in the two left panels, is a highly optimistic scenario – a one-year horizon period which minimizes the prediction error, coupled with a high carbon price of $50 per tonne of CO_2 reduced. The second, shown in the two right panels, is a more realistic scenario using a five-year horizon period and a carbon price of $20. In each case, the crediting baseline is set as a percentage of estimated BAU, ranging from 70% to 130%.

The top left panel (optimistic assumptions) clearly illustrates the tradeoff between efficiency and transfer costs, and how increasing the generosity of the baseline improves efficiency at the expense of greater transfers. (Recall that efficiency is achieved when all countries opt in. Transfer costs are calculated as the volume of non-additional offsets multiplied by the carbon price, on the assumption that developed countries adjust their own caps downwards to reflect the supply of non-additional offsets.)

With a stringent baseline of 74% of estimated BAU, all offsets are additional (light blue line), but just two countries, Azerbaijan and Lebanon, opt in. Below 74%, no country opts in. With a generous baseline of 116% of estimated BAU, almost all countries opt in (yellow line) but only 28% of the offsets generated are additional. The top right panel (more realistic assumptions) shows similar trends, but the share of additional offsets is substantially reduced. Even at the maximum level of additionality, which is achieved when the crediting baseline is set at 83% of estimated BAU, less than one-quarter of offsets are additional.

Both scenarios also indicate that it is difficult to secure net reductions in global emissions (red line). In the left panel, net reductions are maximized through setting the crediting baseline at 92% of BAU, but even here, at 24 Mt CO_2 per year the volume is minimal and it quickly becomes negative as the baseline is made more generous. While emission reductions in developing countries (green line) grow as the baseline is made more generous and more countries opt in, this is more than countered by the growing volume of offsets (dark blue line) that enable higher emissions in Annex I countries. In the right panel, net reductions are always negative, i.e. the volume of offsets is always greater than the volume of emission reductions in developing countries, regardless of the stringency of the crediting baseline.

Note that making the crediting baseline more stringent does not guarantee a greater share of additional offsets, as the relationship is not monotonic. In the left panel, moving from a crediting baseline of 93% of estimated BAU to one of 89% reduces the share of additional offsets from 86% to 52%. While making the crediting baseline more stringent in this way does reduce the volume of non-additional offsets, it also reduces the volume of additional offsets as fewer countries opt in.

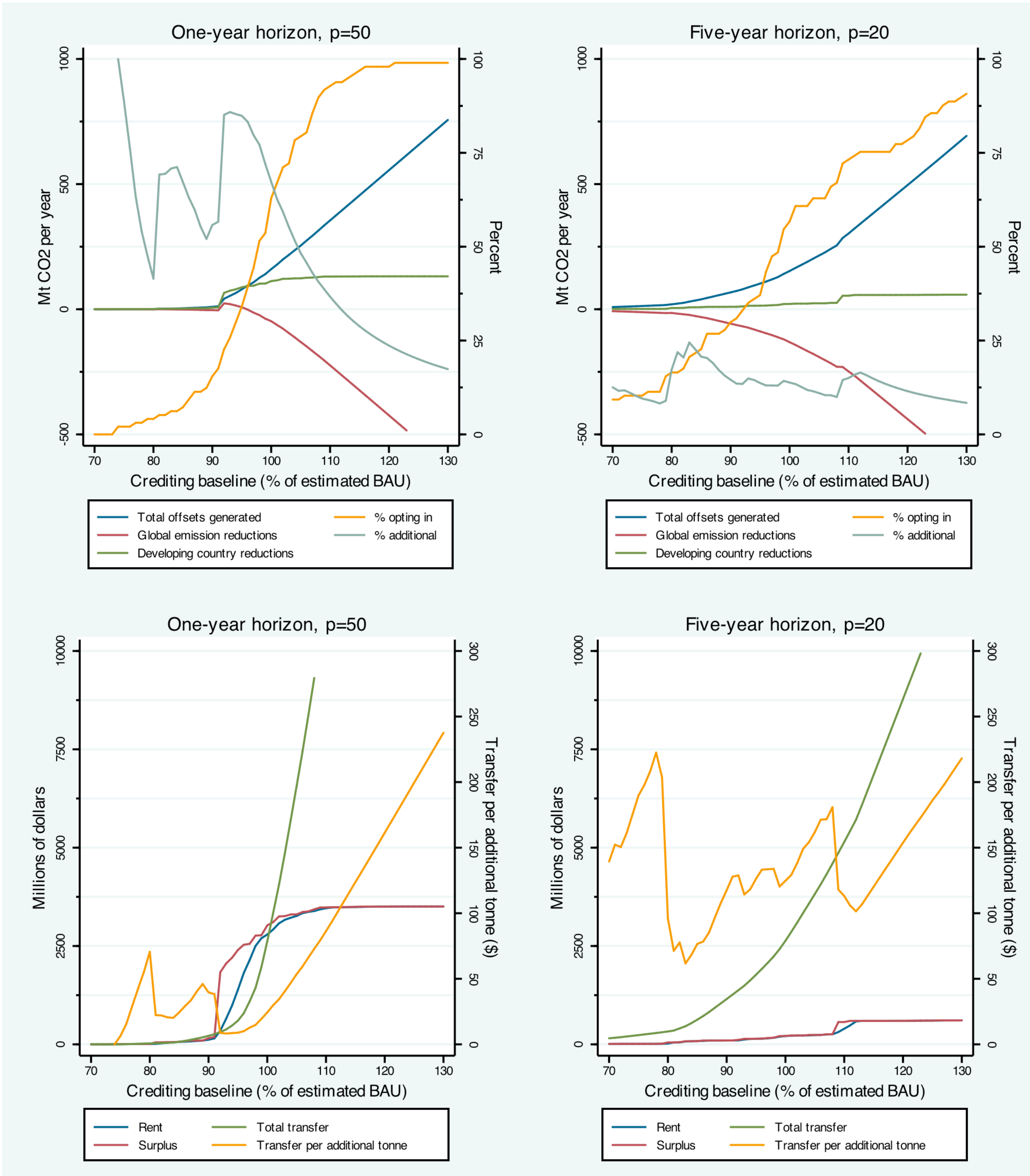
The lower panels of Figure 5 explicitly show the efficiency gains and transfers from the same two scenarios. Surplus (red line) is the total economic gain from capturing lower-cost abatement opportunities in developing countries, assuming that the exogenously specified carbon price reflects constant marginal environmental damages and abatement costs in Annex I countries. It is calculated as the sum of areas D and E in Figure 2. Rent (blue line) is the share of this surplus that is captured by developing countries, i.e. area D minus area A in Figure 2. The simulation results in Figure 5 suggest that developing countries capture the vast majority of the surplus. Separate from the surplus is the transfer (green line). The transfer represents payment to developing countries for non-additional offsets; when divided by the volume of additional offsets, it gives transfer per additional tonne (yellow line, plotted on the right axis).

The optimistic assumptions in the left panel suggest that there are substantial economic gains to be made from sectoral no-lose targets at a relatively modest transfer cost. With a crediting baseline set at 109% of BAU, the total surplus almost reaches its maximum of about $3.5 billion, with almost all of this accruing as rent to developing countries. At about $79 per additional tonne, the transfer at this crediting baseline is relatively large but can be reduced to less than $25 by making the crediting baseline slightly more stringent, while losing just a small part of the surplus. With the more realistic scenario in the right panel, however, these gains largely disappear. The lower carbon price reduces the maximum potential surplus to about $610 million, which is far outweighed by the transfers required to ensure that countries opt in. Even at its minimum of $62, the transfer per additional tonne is more than triple the carbon price, effectively quadrupling the cost of the offsets to Annex I countries.

The relative positions of the green (total transfer) and red (total surplus) lines indicate whether there is potential for a Pareto-improving arrangement between Annex I and non-Annex I countries. In the left panel, total transfers are less than the surplus for some crediting baselines, implying that it may be possible for non-Annex I countries to repay the transfer – leaving both sets of countries better off. However, it is difficult to see how a politically feasible and practical mechanism could be developed to achieve this, given that it would involve some form of side payments from developing to developed countries.

With the more realistic assumptions in the lower-right panel, no Pareto improvement is possible. That is, there is no side payment that could make sectoral crediting advantageous to pursue for both developed (Annex I) and developing countries, at least within the framework of the model presented here.

Figure 5 Impacts of Alternative Crediting Baselines



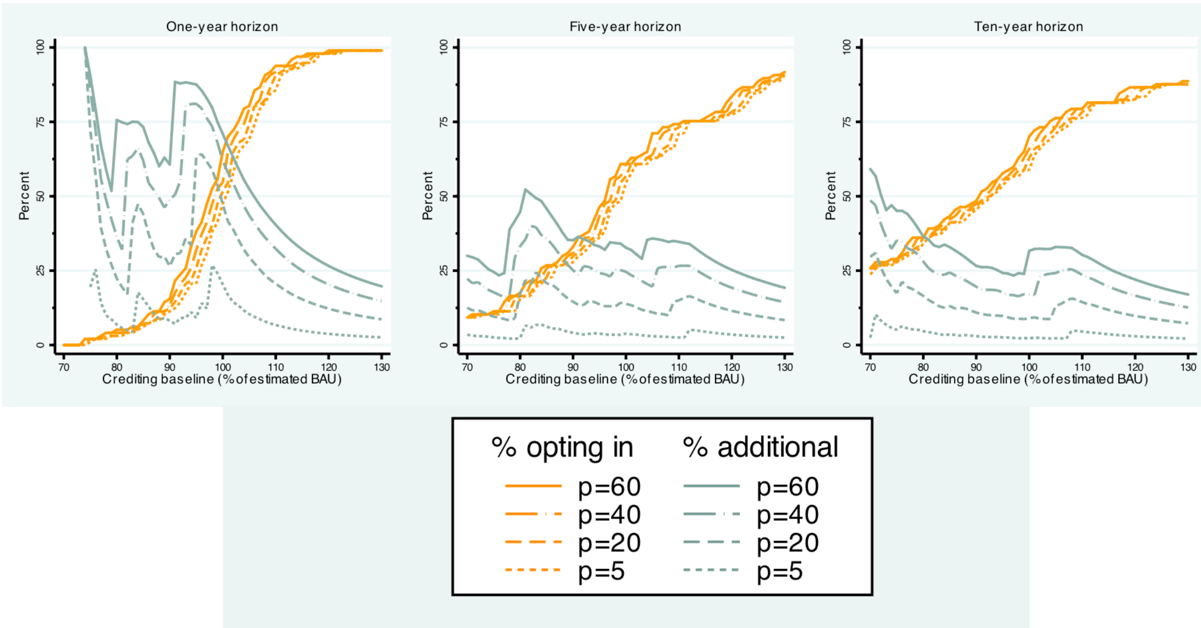
4.2 Impacts of Carbon Price and BAU Estimation

The tradeoff between efficiency and transfer costs can be approximately captured by two variables – the percentage of countries opting in, and the percentage of additional offsets. The three panels in Figure 6 plot these two variables for a range of carbon prices – $5, $20, $40 and $60 per tonne of CO_2 reduced, indicated by the different dashed lines. Each panel uses an alternative horizon period (from left to right: one, five and ten years). Thus, prediction errors tend to increase when moving from the left towards the right panel.

First, note that the decisions of countries to opt in are relatively stable. They hardly change with the carbon price, although there is some flattening of the curve as prediction errors increase. This flattening happens as the increased variance of prediction errors means that more countries receive a baseline of more than 100% of actual (not necessarily estimated) BAU, and thus will opt in at any carbon price.

The percentage of additional offsets, in contrast, exhibits large shifts in response to relatively small changes in either prediction errors or carbon prices. As noted above, making the crediting baseline more stringent (a lower percentage of estimated BAU) does not always increase the proportion of additional offsets. At the lowest carbon prices, additionality is somewhat of a lost cause, as the amount of abatement induced and thus the volume of additional offsets is small in relationship to the volume of non-additional offsets, the latter being by definition independent of the carbon price. At a price of $5 per ton of CO_2 reduced, it is rare for additional offsets to account for more than 10% of the total offset supply, and then only in the case of the one-year horizon where prediction errors are small.

Figure 6 Alternative Price Scenarios



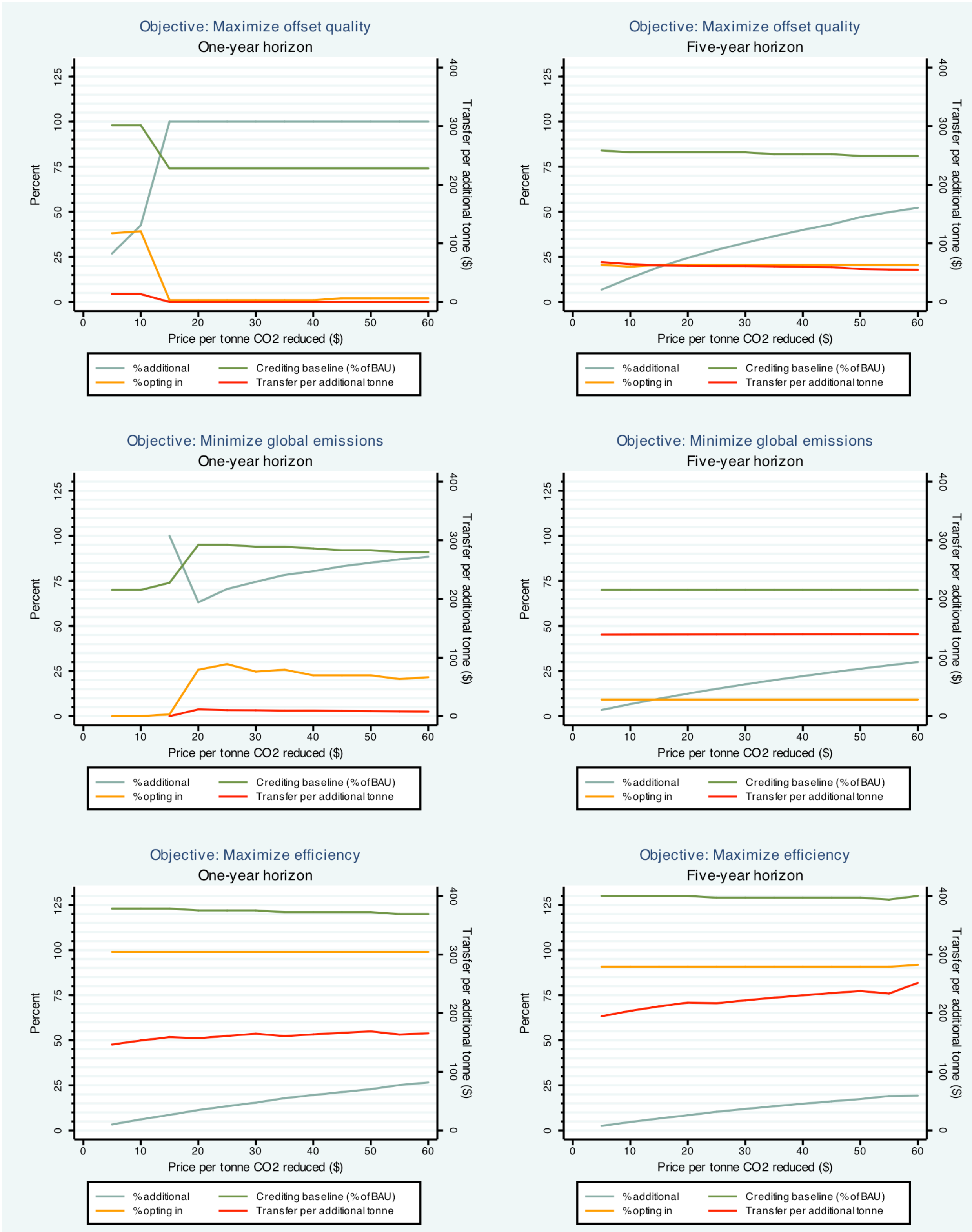
4.3 Optimized Crediting Baselines

In this section, I return to the three potential objectives of the UNFCCC or other regulator, discussed in Section 2.2. For each objective (maximize average offset quality, minimize global emissions and maximize efficiency), I calculate the optimal crediting baseline (as a percentage of estimated BAU, constrained to be within 70% and 130%) for the one- and five-year horizon periods. Results are calculated for prices of between $5 and $60 in increments of $5. Note that these results are ex post optimal, in that the regulator may not be able to achieve them without knowing the precise emissions-weighted distribution of BAU prediction errors.

In these scenarios, the offset quality objective is usually best served by setting a very stringent crediting baseline of just over 70%. In the optimistic scenario shown on the left panel, the regulator can ensure that all offsets are additional, except at the lowest carbon prices of $5 or $10, but at the expense of just one or two countries opting in (depending on the price). The more realistic scenario (right panel), however, shows that this success in ensuring additionality is difficult to sustain as BAU prediction errors increase. At low-to-moderate carbon prices of $30 or less, it is impossible to ensure that more than one-third of offsets are additional. There is also a high efficiency penalty for promoting offset quality, with less than one-quarter of countries opting in under this scenario.

Minimizing global emissions requires the regulator to set a slightly different but still stringent baseline, at the price of generating more non-additional offsets. The efficiency objective, meanwhile, requires the baseline to be set as generously as possible to maximize the emissions-weighted number of countries that opt in. The tradeoff is a very high transfer payment of more than $150 per additional tonne in most instances. Depending on the horizon period and the carbon price, the total transfer can exceed $38 billion per year in payment for non-additional offsets.

Figure 7 Optimized Crediting Baselines



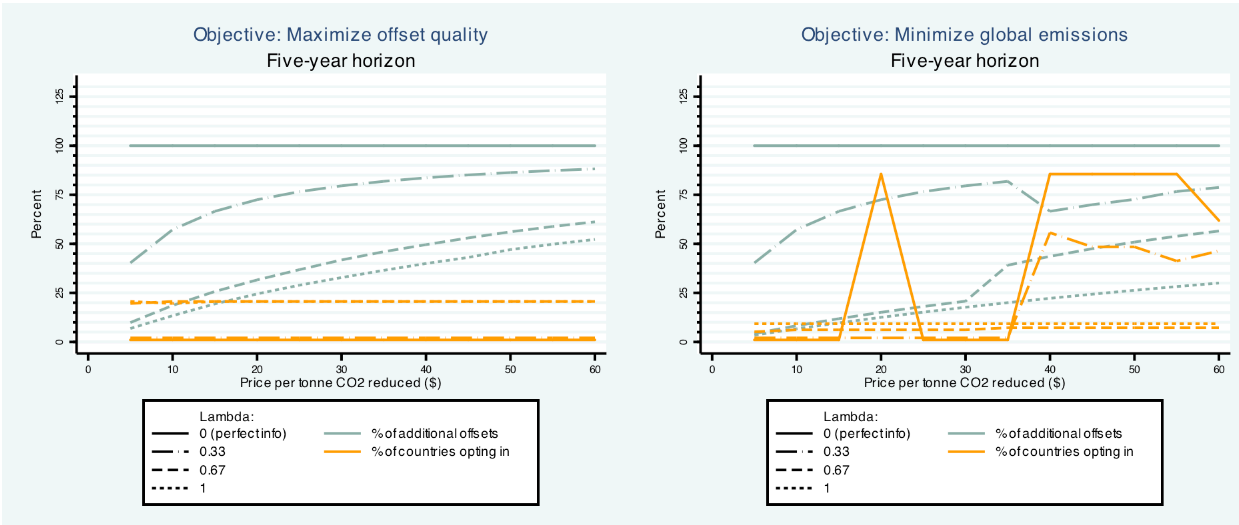
4.4 Reducing Information Asymmetries

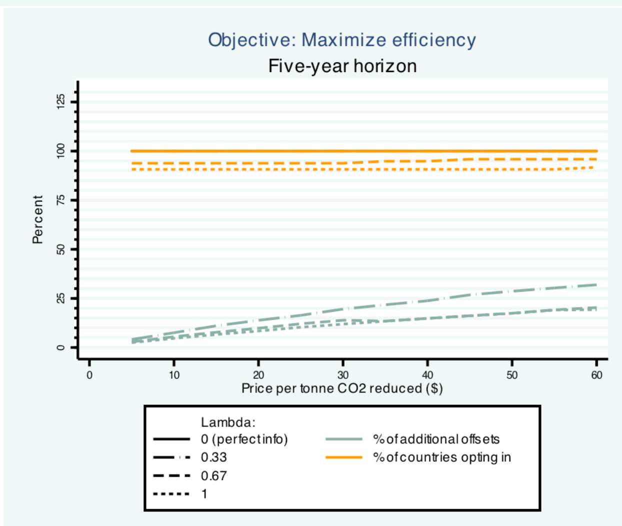
Information asymmetries between the regulator and individual developing countries drive the tradeoff between efficiency and transfer costs, as discussed in Section 2. Here, I relax this assumption by increasing the information available to the regulator, so that the regulator estimates BAU as $\hat{z}_i^0 = z_i^0 + \lambda\varepsilon_i$, $\lambda \in [0,1]$. In Sections 4.1 through 4.3, $\lambda = 1$, while $\lambda = 0$ represents the perfect information case.

Figure 8 shows the impacts of varying λ for one of the scenarios presented in Section 4.3 (five-year horizon), using the three alternative regulatory objectives. In the left panel, the regulatory objective is maximizing offset quality, or the percentage of additional offsets. In the right panel, the regulator seeks to maximize global emission reductions, and in the lower panel, to maximize efficiency. (The discontinuities in the right panel are due to the extreme sensitivity of opt-in decisions to small changes in the crediting baseline under perfect information. At $20/tonne, increasing the crediting baseline from 96% to 100% of estimated (and actual) BAU increases the proportion of countries opting in from 0% to 100%.)

Even substantial improvements in the regulator's predictive ability do not necessarily have a commensurate impact on efficiency (as indicated by opt-in decisions) or transfer costs (as indicated by the percentage of additional offsets), particularly when carbon prices are low. Except where information asymmetries are completely eliminated ($\lambda = 0$), a regulator that maximizes offset quality will still set relatively low baselines so that few countries (here, never more than 21%) opt in. Where the regulator maximizes efficiency, improvements in predictive ability have little impact on the percentage of additional offsets. The regulator still sets a very generous baseline in order to maximize the percentage of countries that opt in.

Figure 8 Impact of Reduced Information Asymmetries





Note: solutions for perfect information cases are not unique, and the most stringent crediting baseline that optimizes against the objective is shown here.

5 Conclusions

In principle, sectoral no-lose targets are a compelling mechanism to provide incentives for emission reductions in developing countries. However, their feasibility is conditional on the ability of an international regulator to make reasonably accurate predictions of business-as-usual emissions. The results presented in this paper suggest that, at least for the transportation sector, the uncertainties in predicting business-as-usual are extremely large relative to expected abatement, rendering sectoral no-lose targets an unattractive option.

The efficient solution requires setting an extremely generous baseline to encourage as many countries as possible to opt in. The baseline must be generous enough to compensate for the regulator's prediction error. However, in this case, almost all of the resultant offsets will be non-additional. If Annex I countries do not tighten their own emission caps in response, which is perhaps the most likely outcome, global emissions will be higher on the order of 500 Mt CO_2 per year. If Annex I caps are tightened, then environmental impacts are avoided but large transfers (payment for non-additional offsets) that can exceed $10 billion per year are required. For comparison, the total mitigation assistance pledged under the Copenhagen Accord was just $30 billion.

The large transfer payments may be justifiable from an ethical or equity point of view, in that they will tend to flow from some of the largest emitters to countries that bear little historical responsibility for CO_2 emissions. Politically, however, monetary transfers of this magnitude are almost certainly unacceptable, even if it were politically feasible to tighten emission caps in Annex I countries – itself a highly questionable assumption. Moreover, as BAU cannot be calculated ex post, neither can additionality or the amount of transfer to a particular country; thus, transfers cannot be made in lieu of direct overseas development assistance for mitigation or adaptation.

An alternative regulatory approach would be to focus not on efficiency, but on environmental goals or minimizing transfer payments. The regulator might seek to maximize global emission reductions, or the percentage of additional offsets. These objectives are particularly attractive in a world in which Annex I targets are fixed, or in which large transfer payments are politically unacceptable. However, such an approach will leave a sectoral no-lose targets mechanism largely irrelevant, as the baseline would be set so stringently that few countries opt in. At low carbon prices, moreover, even such stringent baselines are insufficient to ensure that most offsets are additional.

The results here assume that governments can pass on the carbon price signal in full to firms and consumers, or enact regulations to achieve the same goal. They assume that governments have a long-term outlook rather than heavily discounting future outcomes beyond their period in office. They ignore the potential for national governments to manipulate emissions data or the variables that are used in calculating the dynamic estimate of BAU. They also assume that both the regulator and individual developing countries have perfect information on abatement cost curves. To the extent that these assumptions do not hold, the efficiency/transfer tradeoff may be even starker than suggested here. The transport sector suffers from numerous pricing and other distortions, not least fuel subsidies, and so it is perhaps naïve to believe that governments will respond in an efficient manner to a CO_2 price signal.

The results do rely on information asymmetries between the regulator and national governments. If national governments are equally bad as the UNFCCC at predicting BAU, no adverse selection will occur, although some non-additional offsets will still be generated. However, in practice, governments will be able to predict significantly better than an international regulator: not least, they know what policies they intend to implement under BAU, and can observe the trajectory of emissions after the baseline is set. Moreover, countries with little or no predictive ability are likely to be those without the institutional capacity to respond to a carbon price signal, meaning that sectoral no-lose targets will have little impact in any case.

The inability to make precise predictions about transportation emissions, particularly over a 5 to 10 year time horizon, is hardly surprising. Part of the prediction difficulties may be due to errors in measuring transport emissions, but this bodes equally poorly for the feasibility of sectoral crediting mechanisms. And even without the restrictions imposed here that exclude variables such as vehicle ownership and infrastructure investment, the predictions of regional travel demand models often diverge significantly from realized vehicle travel and gasoline consumption. In the relatively static and data-rich setting of the U.S., predicted vehicle travel can differ from the actual values by 6% (Rodier 2004; see also Flyvbjerg et al. 2005; Flyvbjerg et al. 2006; Transportation Research Board 2007). Despite a sophisticated energy modeling system, aggregate five-year U.S. transport energy forecasts were off by an average of 4.5% during the 1980s and 1990s (Winebrake and Sakva 2006; see also Fischer et al. 2009).

Nor is the problem of predictive performance limited to transportation, which suggests that similar analyses might reveal problems of adverse selection in other sectors. Even in those considered more "straightforward", such as the electricity generation sector with its uniform product, there are large uncertainties in estimating baselines (Zhang et al. 2006). Thus, while this paper analyses only the case of transportation, it would be wise to be cautious about the feasibility of similar crediting mechanisms in other sectors.

Market mechanisms such as sectoral no-lose targets and project-level CDM have the theoretical attraction of equalizing marginal abatement costs across sectors and across countries. Critiques of these approaches to reducing emissions in developing countries have already identified a wide range of challenges, such as inattention to sustainable development cobenefits; the focus on shorter-term, measurable projects; and payment of the market clearing price rather than incremental cost for emission reductions, which reduces the abatement that can be secured for a given sum of money. This paper provides further evidence that the more we study offsets and similar crediting mechanisms, the more problems we uncover. Other climate policy instruments such as grant programs may be less efficient in principle, but more robust in practice.

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Appendix: 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 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.

Table A-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.

Where a log dependent variable specification was used, predictions were made with Duan's smearing estimate (Cameron and Trivedi 2009: 103).

Table A-2 shows the specifications of the models with the lowest 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 A-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 6. As before, the figure illustrates the tradeoff between efficiency and transfer costs as indicated by two variables – the percentage of countries opting in, and the percentage of additional offsets. The three panels in Figure A-1 plot these two variables for a range of carbon prices – \$5, \$20, \$40 and \$60 per tonne of CO_2 reduced, indicated by the different dashed lines. Each panel uses an alternative horizon period (from left to right: one, five and ten years). Thus, prediction errors tend to increase when moving from the left towards the right panel.

The comparison between Figure A-1 and Figure 6 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 opt-in decisions to the generosity of the crediting baseline are almost indistinguishable between Figure A-1 and Figure 6, 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 transport can be seen as product of the inherent difficulties in predicting BAU emissions, with prediction errors being large in relation to expected abatement.

Table A-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	$y_{it} - y_{it-1} = (X_{it} - X_{it-1})\beta + \varepsilon_{it}$			First differenced model	
	12	$\log y_{it} - \log y_{it-1} = (X_{it} - X_{it-1})\beta + \varepsilon_{it}$			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 A-2 Estimates of BAU – Best-Case Dynamic Baseline

	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			0.00132
			(0.000891)
GAS			-0.00142
			(0.00102)
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)		
time2	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

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