Expecting the Unexpected:
Emissions Uncertainty and Environmental Market Design

Severin Borenstein, James Bushnell, Frank A. Wolak, and Matthew Zaragoza-Watkins[1]

January 2014

Abstract: We analyze the demand for emissions allowances and the supply of allowances and abatement opportunities in California's 2013-2020 cap and trade market for greenhouse gases (GHG). We estimate a cointegrated vector autoregression for the main drivers of greenhouse gas emissions using annual data from 1990 to 2011 and use it to forecast BAU emissions during California's program and the impact of the state's other GHG reduction programs. We then consider additional price-responsive and price-inelastic activities that will affect the supply/demand balance in the allowance market. We show that there is significant uncertainty in the business-as-usual (BAU) emissions levels due to uncertainty in economic growth and other factors. Our analysis also suggests that while many GHG abatement programs are in place, most of the planned abatement will not be very sensitive to the price of allowances, creating a steep abatement supply curve. The combination of BAU uncertainty and inelastic abatement supply implies a high probability that the price in the California will either be at the price floor, or high enough to trigger a safety valve mechanism called the Allowance Price Containment Reserve (APCR). We estimate a low probability that the price would end up in an intermediate range between the price floor and the APCR. The analysis suggests that cap and trade markets, as they have been established in California, the EU and elsewhere may be more likely to experience price volatility and extreme low or high prices than is generally recognized.

[1] This research was performed under a contract with the California Air Resources Board. Borenstein, Bushnell, and Wolak are members of the Emissions Market Assessment Committee and the Market Simulation Group that advise ARB. Zaragoza-Watkins works with the EMAC and the MSG as a researcher. We thank Elizabeth Bailey for her contributions on an earlier version of this paper. We also thank participants in the 18th Annual POWER research conference in March 2013 for valuable comments. The opinions in this paper do not represent those of the California Air Resources Board or any of its employees. Emails addresses: Borenstein: borenste@haas.berkeley.edu; Bushnell: jbbushnell@ucdavis.edu; Wolak: wolak@zia.stanford.edu; Zaragoza-Watkins: mdzwatkins@berkeley.edu.

I. INTRODUCTION

Among economists there is a general consensus that a carbon pricing mechanism, through either a tax or a cap-and-trade mechanism, is the preferred choice for a broad-based climate policy. There is also general agreement that a more stable and predictable price into the future will more effectively incent firms and consumers to make long-lived investments in more expensive lower-carbon technologies. A stable and predictable price of carbon will also stimulate innovation in the development of new low-carbon technologies. The ultimate success of any climate policy depends on creating incentives for innovation and investment in new low-carbon technologies.

Existing climate policies have not been very successful in creating a stable and predictable price of carbon, particularly those that use a cap-and-trade mechanism.[2] Prices in existing cap and trade markets for greenhouse gases (GHGs) have been volatile and, most recently, have been so low as to create little incentive to invest in GHG reduction. The European Union Emissions Trading System (EU-ETS), the world's largest GHG market has experienced both a sharp crash in prices (Ellerman and Buchner, 2008) and a long slow decline to barely economically significant levels. The Regional Greenhouse Gas Initiative (RGGI) in the Northeastern U.S. has gone through a similar experience.[3] Although they may meet short-term emissions caps, volatile and low average emissions allowance prices probably do little to achieve the long-term climate policy goals of significant investments in low-carbon technologies.

We argue that there are two reasons for this outcome in cap-and-trade markets. The first is the well-known exogenous volatility of GHG emissions themselves. Such emissions are closely tied to economic activity and also vary with natural conditions such as temperature and rainfall. This uncertainty has long been recognized as an issue when forecasting both damages and mitigation cost,[4]

---

[2] Even regions that have implemented carbon taxes have had a difficult time maintaining their future carbon pricing commitments. In 2008, British Columbia implemented a 10 Canadian dollar (CAD) per ton of CO_2 tax that would increase by $CAD 5 per year. However, in 2012 the province decided to freeze the tax at $CAD 30 per ton. The Australian government implemented a 10 Australian dollar per ton of CO_2 tax on July 1, 2012. However, the recently elected Liberal Government ran on a platform of abolishing this carbon tax.

[3] As of this writing, allowances in the EU-ETS were trading at 5 Euros per metric tonne and in RGGI at 3 dollars per tonne.

[4] When discussing controversies about mitigation costs, Aldy, et. al. (2009) note that "Future mitigation costs are highly sensitive to business-as-usual (BAU) emissions, which depend on future population and Gross Domestic Product (GDP) growth, the energy intensity of GDP, and the fuel mix."

The second reason is more subtle, but may be equally important. Market design features that make the cap-and-trade climate policy politically viable, also steepen the supply curve of abatement and therefore increase the uncertainty in allowance prices for a given amount of exogeneous volatility in GHG emissions. Common policies in cap and trade markets – output-based updating of allowance allocations, refunding of allowance auction revenues to mitigate output price increases in allowance-consuming sectors of the economy, and flexible protocols for issuing emissions offsets – all increase the political attractiveness of cap-and-trade climate policies versus carbon taxes. However, as we demonstrate below, these same mechanisms steepen the supply curve of mitigation, which can increase allowance price volatility.

Partly in recognition of the problems created by uncertain allowance prices, economists have proposed hybrid mechanisms that combine caps with price-collars that can provide both upper (Jacoby and Ellerman, 2004) and lower (Burtraw et al., 2009) bounds on allowance prices. Such hybrid mechanisms can greatly reduce allowance price risk while ensuring a better match between ex-post costs and benefits (Pizer, 2003). While the EU-ETS has no such bounds, the trading system proposed under the stillborn Waxman-Markey bill of 2008, as well as the California cap-and-trade market studied here, both featured price-collars of some fashion. The fact that California's market currently has the highest price among mandatory GHG cap-and-trade programs is likely due to its relatively high floor price level.

While the details of California's price-collars are described in regulations developed by the California Air Resources Board (ARB), proposed regulatory changes would alter the exact manner in which the price ceiling – known as the *allowance price containment reserve* (APCR) mechanism – would be applied and the degree to which it could mitigate uncertainty over prices.[5] A key question relating to this issue is the extent to which either the auction reserve price or APCR price are likely to be relevant, that is, the probabilities that market prices may be near the price floor or the APCR soft price ceiling.[6]

In this paper we develop estimates of the distribution of allowance prices that accounts

[5] The regulations are available at: http://www.arb.ca.gov/cc/capandtrade/september_2012_regulation.pdf. See also the ARB Board resolution dated October 18, 2012 at http://www.arb.ca.gov/cc/capandtrade/final-resolution-october-2012.pdf and an issue analysis from the Emissions Market Assessment Committee dated September 20, 2012 at http://www.arb.ca.gov/cc/capandtrade/emissionsmarketassessment/price-containment.pdf.

[6] As described below, the APCR makes a limited number of extra allowances available if the price hits certain price levels.

for both uncertainty in greenhouse gas emissions and the steepness of the supply curve of abatement. Instead of estimating the full probability distribution of allowance prices, we focus on computing probabilities that allowance prices lie on distinct portions of the abatement supply curve. We compute the probability of price outcomes on four segments of the abatement supply curve: (1) at or near the auction price floor (reserve price), (2) above the auction price floor and below the first step of the APCR (the upward sloping portion of supply curve of abatement), (3) at or above the first step of the multi-step (described below) APCR and at or below the last step of the APCR, and (4) above the last price step of the APCR. We find that both uncertainty in BAU emissions and the steepness of the supply curve of abatement between the auction price floor and first step in the APCR are the key drivers of the probabilities of these four price outcomes.

We show that the steep abatement supply curve between the auction price floor and the first price step of the APCR, implies a bi-modal distribution of prices: most of the probability mass is at either low or high price outcomes. A primary factor determining where in that distribution of prices the market will equilibrate is the "business as usual" (BAU) emission level that would result if there were no GHG reduction policies. BAU emissions are substantially the result of economic activity driving electricity consumption and vehicle travel, as well as the emissions intensities of those activities, and emissions from natural gas combustion in the residential and commercial sectors and industrial processes. In this paper we develop estimates of these drivers of emissions utilizing forecasting techniques from time-series econometrics. We apply these techniques to emissions and economic data from 1990 to 2011 in order to forecast future emissions and the uncertainty of emissions.

Our empirical assessment of the potential demand for allowances and supply of abatement, as well as the offsets that augment this supply, suggests that the market price is most likely to be at or near the price floor through 2020.[7] In all of the scenarios we examine, we also find a low probability that the price will be in the intermediate range, substantially above the auction reserve price floor and still below the APCR prices. Thus, most of the remaining probability weight is on outcomes in which some or all of the allowances in the APCR are needed. Moreover, for all abatement supply curve scenarios that we consider likely, there is a small, but non-trivial probability that – absent further government

[7] Throughout this paper we will refer to an "allowance market price." The trading of allowances and their derivatives will be arranged through several competing and coexisting platforms, including quarterly auction of allowances by the State. We assume that prices between these markets will be arbitraged so that all trading platforms will reflect prices based upon the overall aggregate supply and demand of allowances and abatement.

intervention – allowance prices will be above the highest price in the price containment reserve.

Throughout this analysis, we assume that no market participant is able to exert market power or manipulate the market for emission allowances. That is, we assume that the emissions market is completely competitive; no market participant is able to unilaterally, or collusively, change their supply or demand of allowances in order to profit from altering the price of allowances. In ongoing work, we are analyzing the potential for market power and market manipulation given the characteristics of supply and demand in the market.

The remainder of this analysis proceeds as follows. Section II gives an overview of the possible outcomes in the market for California emissions allowances given the characteristics of the supply and demand for GHG emissions abatement. Section III describes how we model the Business As Usual (BAU) drivers of GHG emissions over the 2013-2020 life of the program using a Vector Autoregression (VAR) model that imposes the restrictions implied by the existence of cointegrating relationships among the elements of the VAR. In Section IV we explain how we incorporate into the simulations the major additional California GHG reduction programs, known in California as "complementary policies," though they may not be complements to the cap-and-trade program in the economic sense. These include a renewable portfolio standard (RPS) that will increase electricity generation from renewable sources, a fuel economy standard that will reduce fuel use per vehicle mile traveled, a low-carbon fuel standard (LCFS) that will reduce the measured emissions intensity of the transport fuel used, and additional programs to improve non-transport and transport energy efficiency. Even though the impacts of these programs should be largely independent of allowance prices, the effects of these programs, as with the allowance market, will be highly dependent on the economic and emissions variables that we model in the VAR.

Section V analyzes the reduction in reported emissions related to other programs and activities in California, including both consumer response to higher prices for electricity, transport fuels, and natural gas, and two other important activities, reshuffling and offsets. Reshuffling, also known as "contract shuffling" or "resource shuffling", occurs when output of an energy product is reallocated among buyers in different regions so that the entities covered by the cap and trade program are buying the lower-carbon version and uncovered entities are buying the higher-carbon version, but no reduction in total emissions results.[8]

[8] We distinguish between reshuffing and classical leakage, because reshuffling typically involves no change in the emissions producing activities in and outside of the region or industry covered by the cap-and-trade program.

Due to the California cap and trade market, there is likely to be significant "reshuffling" of electricity purchases among buyers and sellers across state lines. Offsets are emission reductions from sources not covered by the cap and trade program. Production of such offsets can then be credited to offset buyers against their allowance obligation. As explained below, offsets are envisioned to significantly augment the supply of allowances in the California market, but there is a great deal of uncertainty as to how much offset supply will ultimately occur.

In section VI, we bring together the analysis of abatement pathways with the previous estimates of emissions to forecast the possible supply/demand balance in the market and the probabilities of different price outcomes. We then discuss a number of market design issues in section VII in light of the probabilities we find. We conclude in section VIII with a broader discussion of our findings for the use of cap and trade programs to address climate change.

II. THE CALIFORNIA CAP AND TRADE MARKET

We focus on estimating the potential range and uncertainty of allowance prices over the entire 8-year span of the market.[9] The underlying source of demand for allowances will be emissions of GHGs from the covered entities, which will be a function of the levels and intensities of their emissions-producing activities. Banking and borrowing of allowances is permitted among the years of each compliance period and banking is permitted between compliance periods. Because of the relatively generous allowance budgets in the earlier years and a policy change that is likely to be adopted in 2014,[10] under nearly all scenarios, emissions during the first two compliance periods (ending 12/31/14 and 12/31/17) will not exceed the caps, so the eight years of the market are likely to be economically integrated. As a result, we examine the total supply and demand balance over the entire eight years of the program (2013-2020). Because there is a large degree of uncertainty around the level

[9] In late 2013, the ARB finalized plans to link California's cap and trade market with the market in Quebec, Canada as of January 1, 2014. Our analysis does not include Quebec, though it could easily be extended to do so if comparable data were available for Quebec. Quebec's total emissions were roughly 1/7 that of California. The supply-demand balance of allowance in this province could alter the probabilities presented in this paper.

[10] See the ARB Board resolution dated October 18, 2012 at http://www.arb.ca.gov/cc/capandtrade/final-resolution-october-2012.pdf and an issue analysis from the Emissions Market Assessment Committee dated September 20, 2012 at http://www.arb.ca.gov/cc/capandtrade/emissionsmarketassessment/pricecontainment.pdf. Most recently, the ARB Board considered changes to APCR at its October 2013 meeting, but deferred action at that time.

of BAU emissions, we pay particular attention to establishing confidence intervals as well as point estimates.

The number of allowances available in the California GHG cap and trade program derives from the allowance cap, a portion of which is allocated to the APCR.[11] Of the 2,508.6 million metric tonnes (MMT) of allowances in the program over the 8-year period, 121.8 MMT of allowances are assigned to the price containment reserve to be made available in equal proportions at allowance prices of $40, $45, and $50 in 2012 and 2013. In later years, these price levels increase by 5% plus the rate of inflation in the prior year.

The supply of abatement is multi-faceted and features several elements that are either unique, or present in a more extreme form, in California. These elements combine to create an extremely steep abatement supply curve, which we will demonstrate implies the potential for a very wide distribution of price outcomes. Abatement of capped emissions will flow through two mechanisms: a direct effect in which firms or consumers reduce emissions in response to a level of allowance prices, and an independent effect in which emissions are reduced due to additional "complementary policies" outside the cap and trade program.

The supply of relatively price-independent abatement comes from (a) complementary policies that abate GHGs independent of the price in the market, (b) activities that reduce measured GHGs due to the process of accounting for electricity imports ("reshuffling" and "relabeling"[12]), and (c) offsets, which we discuss later (and which might be considered a form of lessening demand rather than increasing supply, but the analysis would be unchanged). While incentives for reshuffling and offsets are affected by the price of allowances, previous analyses suggest that the bulk of this activity would be realized at prices below or just slightly above the auction reserve price.[13]

In its revised scoping plan of 2010, ARB's preferred model projects that 63% of emissions

---

[11] A proposed policy change that the ARB Board will consider would allow reallocation of a large number of allowances from later compliance periods to earlier periods if the allowance price reaches the highest step of the price containment reserve.

[12] Relabeling describes the practice of reselling out-of-state power that comes from a high-emissions source such that the buyer can then import the power into California at the administratively determined default emissions rate. Relabeling might be considered a type of reshuffling. We consider them in combination.

[13] The potential levels of reshuffling and relabeling are examined in Bushnell, Chen, and Zaragoza-Watkins (forthcoming). The offset market is discussed below. Some offset supply may be available at prices somewhat above the auction reserve price.

abatement would arise from complementary policies rather than responses to the cap (four additional sensitivity models project between 30% and 63% of emissions abatement would arise from complementary policies).[14] It is important to recognize that these reductions are not costless, indeed many may impose costs above the allowance price. Rather, these reductions, and the accompanying costs, will occur *approximately independently* of the level of the allowance price. Therefore, while these policies provide reductions, and contribute to the goal of keeping emissions under the cap, they do not provide the price-responsive abatement that can help mitigate volatility in allowance prices.

In this paper, we treat the impact of these complementary policies as influencing the distribution of the supply of abatement. For example, aggressive vehicle fuel-efficiency standards should lead to slower growth in the emissions from the transportation sector, which we represent as a change in the rate at which the emissions intensity of vehicles declines over time. Similarly mandates for renewable energy production decrease the amount of electricity demand that needs to be served by more carbon intensive sources, thereby reducing emissions.

As described below, the supply of price-responsive mitigation is limited by the allocation policies that have been implemented under AB 32. The large amount of allowances allocated using an approach known as output-based updating is expected to limit the impact of allowance prices on production levels and consumer prices for many industries.[15] Most of the remaining reductions in response to allowance prices would therefore come from consumer responses to changes in energy prices, namely transportation fuels (gasoline and diesel), natural gas, and, possibly, electricity consumption. Compared to the aggregate level of reductions needed and expected under AB 32, we show that the reductions from

---

[14] See http://www.arb.ca.gov/cc/scopingplan/economics-sp/updated-analysis/updated_sp_analysis.pdf at page 38 (Table 10).

[15] Output-based updating describes allocation of allowances to a company based on the quantity of output (not emissions) that the firm produces. Output-based updating reduces the firm's effective marginal cost of production and, thus, reduces the incidence of the allowance price on firms and consumers, while retaining the full allowance price incentive for the firm to adopt GHG-reducing methods for producing the same level of production (see Meredith Fowlie, "Updating the Allocation of Greenhouse Gas Emissions Permits in a Federal Cap-and-Trade Program," in Don Fullerton and Catherine Wolfram, ed. *The Design and Implementation of U.S. Climate Policy*, University of Chicago Press. 2012). If applied to a large enough set of industries or fraction of the allowances, the effect can be to inflate allowance prices as higher prices are necessary to offset the diluted incentive to pass the carbon price through to consumers. See Bushnell, James and Yihsu Chen. "Regulation, Allocation, and Leakage in Cap and Trade Markets for CO2." Resources and Energy Economics. 34(4), 2012.

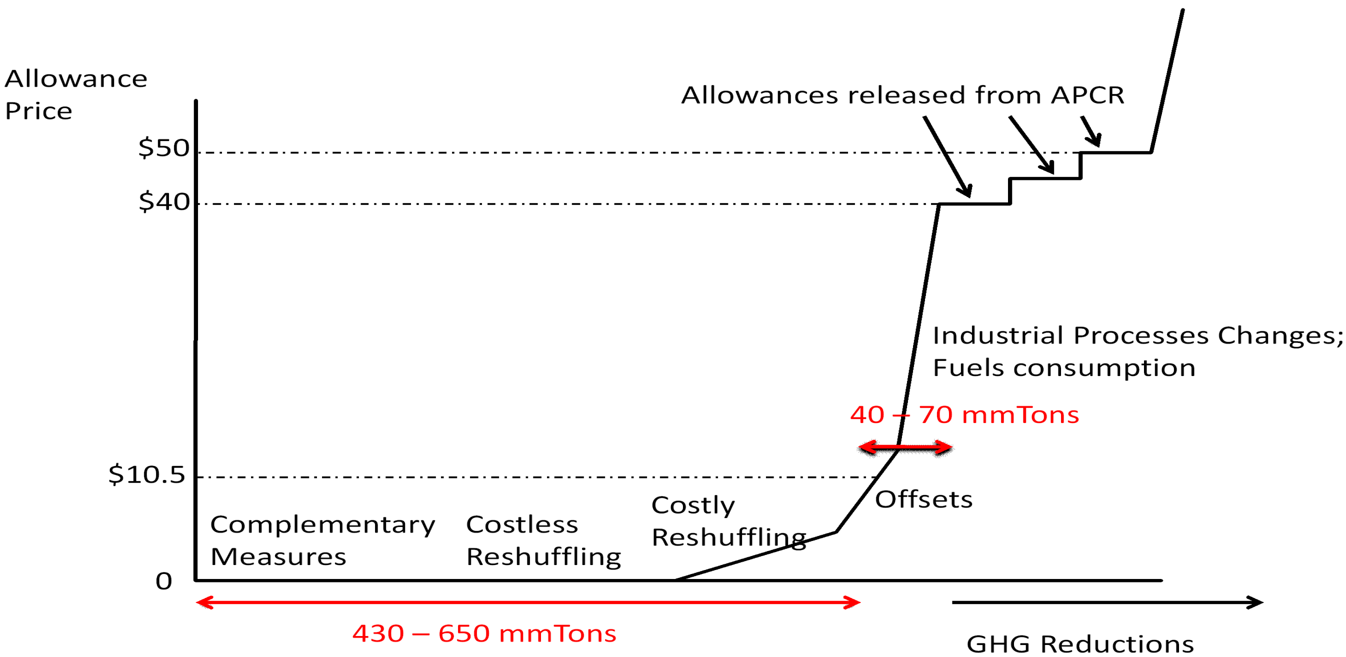

Figure 1: Supply of Abatement

---

these energy price effects are relatively small.[16] This is due in part to a feature of the program that will use the revenues from the sales of allowances to fossil fuel electricity suppliers to limit the magnitude of potential retail electricity price increases. Similar policies are under consideration at ARB for retail natural gas sector and transportation sector. If implemented they would further increase the slope of abatement supply curve.

The combination of large amounts of "zero-price" abatement, and relatively modest price-responsive abatement creates a hockey stick shaped abatement-supply curve (See Figure 1). Analysis undertaken by ARB indicates that the marginal abatement cost curve rises sharply after the relatively low-cost abatement options are exhausted. ARB states in its updated Scoping Plan dated March 2010 that "...GHG emissions in the model show limited responsiveness to allowances prices...This lack of responsiveness results from the limited reduction opportunities that have been assumed to be available in the model."[17]

[16] Offsets and reshuffling/relabeling may also be sensitive to allowance prices, but are considered separately.

[17] Available at: http://www.arb.ca.gov/cc/scopingplan/economics-sp/updated-analysis/updated_sp_analysis.pdf. See also, the ARB analysis contained in Appendix F: Compliance Pathways Analysis available at:

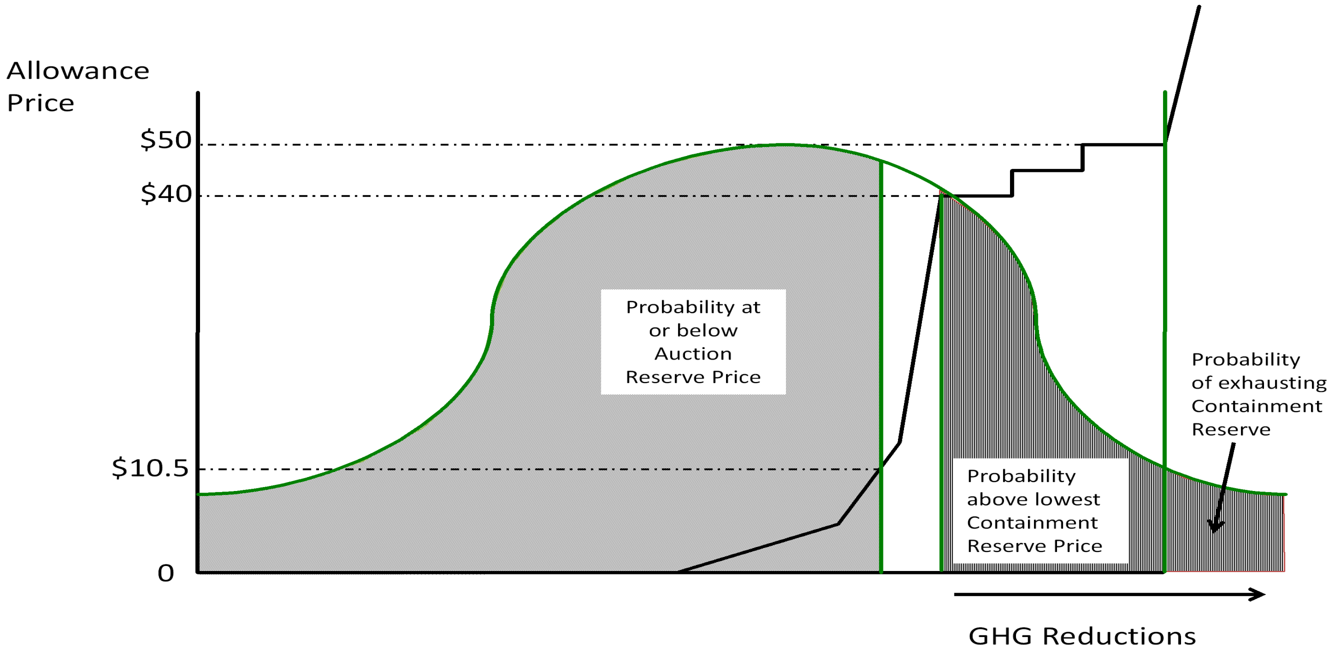

Figure 2: Hypothetical Distribution of Abatement Demand (BAU minus allowances outside price containment reserve) versus Abatement Supply

---

One implication of this is that allowance prices are more likely to be either at or near the level of the auction reserve price or at levels set by the APCR policy than they are to be at some intermediate level. When one considers an uncertain range of BAU emissions, even if strongly centered on the expected level, the probabilities of prices falling at either the APCR ceiling or auction reserve price floor constitutes a large fraction of the overall distribution of potential emissions outcomes.

This intuition is illustrated in Figure 2, which superimposes a hypothetical symmetric distribution of the amount of abatement needed (BAU emissions less the cap) onto the same horizontal axis as our supply curve. Note from Figure 2 that the range of abatement quantity that falls between the auction reserve price ($10.50/tonne in this illustration) and the first-step of the price-containment "ceiling" ($40/tonne in this illustration), which is the area with no pattern, is relatively small.

The implications of California's abatement supply curve is therefore that the vast majority

http://www.arb.ca.gov/regact/2010/capandtrade10/capv3appf.pdf.

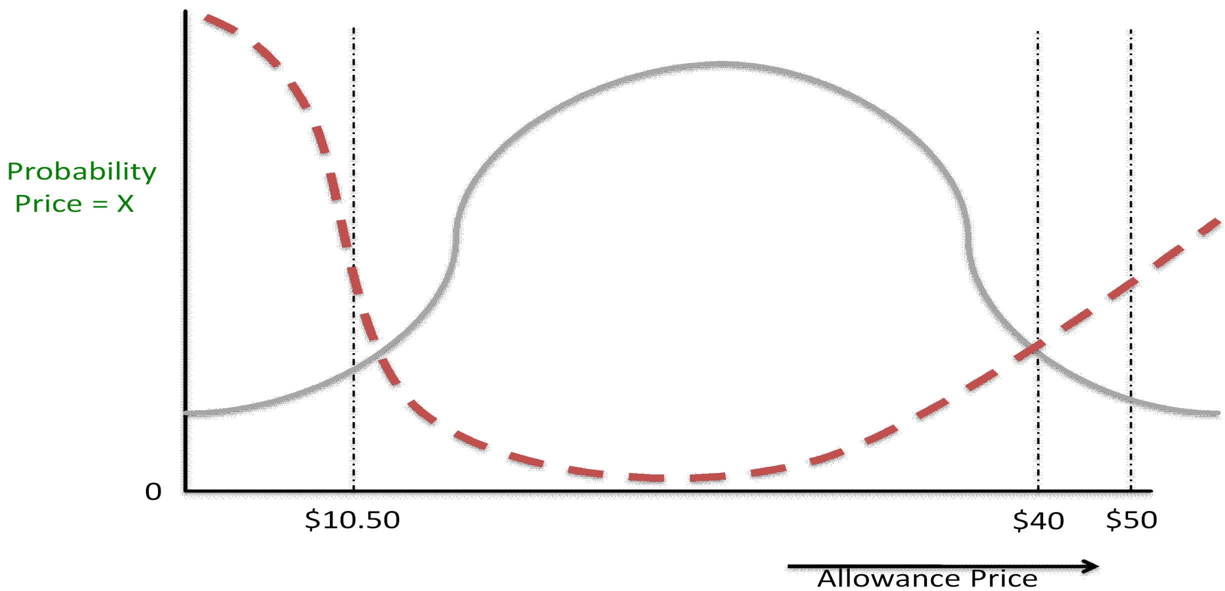

Figure 3: Possible Density Functions of Allowance Price

of probability for a given price outcome falls either at the auction reserve price or in the range in which the price containment policy is likely to be triggered. Rather than the intuitive bell-shaped distribution of possible prices, it is more appropriate to think of the probabilities as distributed according to the dashed line of Figure 3, which has the same mean as the solid line, but this mean is generated by a high probability of a "low" (auction reserve) price balanced by a somewhat lower probability of a "high" (price containment reserve) price.

a. Price Evolution and Estimated Equilibrium Price in the Market

The analysis we present here models supply and demand that evolves and is aggregated over the 8 year span of the market. We calculate the equilibrium as the price at which the aggregate demand over the 8 years is equal to the aggregate supply. We analyze this program alone, assuming that the market is not continued after the 8 years or integrated into some other program. At this point there is not clarity about how the program will evolve after 2020.

At any point in time, two conditions will drive the market price, an intertemporal arbitrage condition and a market equilibrium condition. If the markets for emissions at different points in time are competitive and well integrated, then intertemporal arbitrage enabled by banking and borrowing will cause the *expected* price change over time to be equal to the nominal interest rate (or cost of capital).[18] At the same time, the price *level* will be determined by the condition that the resulting expected price path – rising at the nominal interest rate until the end of 2020 – would in expectation equilibrate the total supply and demand for allowances.[19]

Throughout the market's operation, new information will arrive about the demand for allowances (*e.g.,* weather, economic activity, energy prices and the energy intensity of GSP) and the supply of abatement (*e.g.,* supply of offsets, response of consumers to higher fuel prices, and the cost of new technologies for electricity generation). These types of information will change expectations about the supply/demand balance in the market over the length of the program and thus change the current equilibrium market price. The price at any point in time reflects a weighted average of all the possible future prices that may occur in order to equilibrate supply and demand.

For instance, while high allowance prices are a possibility if the economy grows rapidly and abatement efforts are less effective than anticipated, early in the market operation that would be only one of many possible future outcomes that the market price would reflect. Over time, however, if economic growth were stronger and abatement weaker than expected, this would become an increasingly likely scenario and price would rise faster than had been anticipated. Thus, if lower-probability outcomes were to occur over time, their impact would become evident gradually in the adjustment of the market price. In that case, an extremely high market price would probably not occur until the later years of the program.

---

[18] This is the outcome envisioned when banking was first developed (Kling and Rubin, 1997). See also Holland and Moore (forthcoming), for a detailed discussion of this issue.

[19] Because of lags in information and in adjustment of emissions-producing activities, supply and demand will not be exactly equal at the end of the compliance obligation period (December 31, 2020). At that point, the allowance obligation of each entity would be set and there would be no ability to take abatement actions to change that obligation. The supply of allowances would have elasticity only at the prices of the APCR where additional supply is released and the level at which a hard price cap is set, if one is enacted. Thus, the price would either be approximately zero (if there is excess supply) or at one of the steps of the APCR or a hard price cap (if there is excess demand). Anticipating this post-compliance inelasticity, optimizing market participants would adjust their positions if they believed the weighted average post-compliance price outcomes were not equal to the price that is expected to equilibrate supply and demand. Such arbitrage activity would drive the probability distribution of post-compliance prices to have a (discounted) mean equal to the equilibrium market price in earlier periods.

Source	1990 Emissions	2011 Emissions
Electricity (domestic)	44.76	38.25
Electricity (imports)	29.65	46.13
Transportation (on road)	134.70	147.10
Industrial	79.77	75.40
Nat. Gas and Other	69.94	67.90

Table 1: Aggregate Emissions from Key California Sectors in 2010 (MMT)

Market participants are likely to employ an analysis similar to ours to decide the allowance price that they should use when choosing how much GHG to emit and whether an investment to abate emissions is likely to be cost effective. Analyses like this will also determine the price at which participants' are willing to buy and sell in the allowance market.

III. ESTIMATING THE BUSINESS AS USUAL EMISSIONS

Perhaps the largest factor driving the supply/demand balance in the GHG market will be the level of emissions that would take place under business as usual (BAU). There is, however, considerable uncertainty about BAU emissions over the period 2013 to 2020. The scope of the cap-and-trade program is very broad, and will be implemented in two phases. The first phase, which began January 1, 2013 covers large stationary sources, which are dominated by power plants, oil refineries, and other large industrial facilities. The second phase, to begin January 1, 2015, will expand the cap to include emissions associated with the combustion of transportation fuels and natural gas at non-industrial facilities. Table 1 summarizes the aggregate emissions from the key sectors during 2010.

Historically, there has been considerable variability in the level of economic activity in each of these sectors, which in turn implies considerable uncertainty in the production of GHG emissions from these activities. Figure 4 illustrates the annual emissions from each sector over a 22-year period beginning in 1990. Predicting the level of economic activity from each of these sectors only one year in advance has the potential for significant forecast errors. Forecasting the level of economic activity and GHG emissions nine years into the future involves even greater forecast errors, which implies a greater potential for very low or high allowance price realizations.

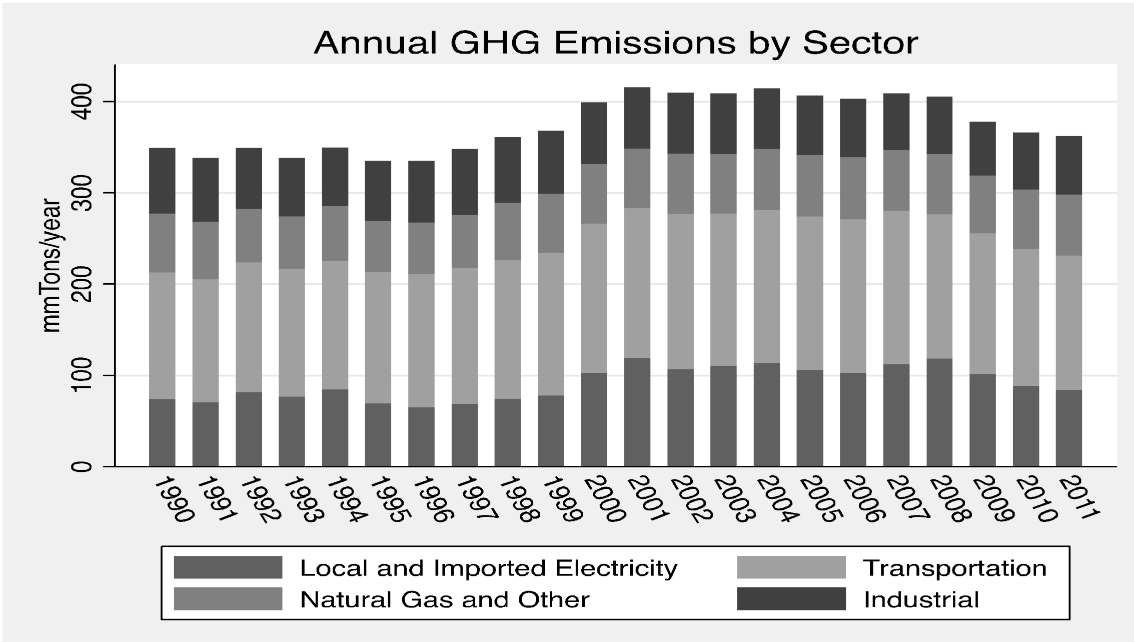

Figure 4: California Emissions Data 1990-2011

An important category of emissions to highlight is those associated with imported electricity. Although these emissions are substantial, because they are from sources located outside of California their measurement is uncertain and subject to potential avoidance through reshuffling or relabeling of sources. As described below, we apply ARB-derived emissions levels from imports as BAU and consider scenarios of reshuffling in determining the net value of GHG emissions from electricity imports.

To derive estimates of the expected future time path of GHG emissions and the uncertainty associated with this forecast, we estimate a seven-dimensional Vector Autoregression (VAR) model with determinants of the three major components of state-level GHG emissions that are covered under the program and the key statewide economic factors that impact the level and growth of GHG emissions.[20] Due to the short time period for which the necessary disaggregated GHG emissions data have been collected, the model estima-

[20] Vector Autoregressions are the econometric methodology of choice among analysts to construct short to medium-term (from 1 to 10 time periods into the future) forecasts of macroeconomic variables and for this reason are ideally suited to our present task. Stock and Watson (2001) discuss the successful use of VARs for this task in a number of empirical contexts.

tion is based on annual data from 1990 to 2011. Because data are available for 2012 on real Gross State Product (GSP), in-state electricity production by source, and the real price of gasoline in California, we condition on these values in forecasting the expected future time path of GHG emissions and the computing the uncertainty in the future time path of GHG emissions.

The short time series puts a premium on parsimony in the model. As a result, we use a 7-variable model that includes the three drivers of GHG emissions–in-state fossil-fuel electricity production, vehicle-miles traveled (VMT), and non-electricity natural gas combustion and industrial process GHG emissions–and the two economic factors that influence those drivers–real gross state product and the real price of gasoline in California. To facilitate forecasting the future time path of GHG emissions in the transportation and electricity sectors under different sets of complementary policies for reducing GHG emissions in these sectors, we also model the behavior of the emissions intensity of the transportation and electricity sectors in California. Our approach is to estimate a VAR for these seven variables, simulate them through 2020 and apply a range of emissions intensities to the economic drivers of transportation and electricity emissions in order to simulate future GHG emissions under different complementary policies in these two sectors.

Several features of our VAR model are chosen to match the time series relationships between the seven variables implied by economic theory and existing state policies to limit GHG emissions. We allow for the fact that all seven variables exhibit net positive or negative growth over our sample period and model them as stochastic processes that are second-order stationary in growth rates rather than second-order stationary in levels. The results of unit root tests reported in the Appendix for each of individual time series are consistent with this modeling assumption. We also impose restrictions on the parameters of the VAR model implied by the cointegrating relationships between these seven variables that are supported by the results of preliminary hypothesis tests. Engle and Yoo (1987) show that imposing the parameter restrictions implied by cointegrating relationships between variables in a VAR improves the forecasting accuracy of the estimated model.

a. Model

Let $X_t = (X_{1t}, X_{2t}, ..., X_{7t})'$ denote the vector composed of the seven annual magnitudes included in the VAR for year t, $t = 1990, 1991, ..., 2011$. The elements of X_t are:

X_{1t} = CA electricity production net of hydroelectric generation (terawatt-hours (TWh))
X_{2t} = Total vehicle-miles travelled (thousands of miles)

X_{3t} = Industrial GHG and other natural gas emissions. (millions of metric tones (MMT))
X_{4t} = Real Retail Gasoline price ($2011/gallon)
X_{5t} = Real Gross State Product ($2011)
X_{6t} = Emissions Intensity of In-State Thermal Generation (metric tonnes/MWh)
X_{7t} = Emissions Intensity of Vehicle Miles Travelled (metric tonnes/thousand miles)

All real dollar magnitudes are expressed in 2011 dollars. All GHG emissions are in metric tonnes of CO2-equivalents. As noted above, we include real GSP in the model is to capture the empirical regularity observed both over time and across jurisdictions that a higher level of economic activity leads to greater energy consumption and GHG emissions. The price of gasoline reflects the fact that movements in transport fuel prices change the energy intensity of economic activity and the value of VMT.

Estimating this VAR produces parameters that allow us to construct simulations of the elements of $X_t = (X_{1t}, X_{2t}, ..., X_{7t})$ from 2013 to 2020. Note X_{3t} is already in terms of metric tonnes of GHG. However, in order to get the total GHG emissions covered under the program, we do two further calculations. First, from X_{1t}, the simulation of the production of electricity in California net of hydroelectric generation, we subtract the anticipated amount of renewable and nuclear energy, described in more detail below. The remaining residual production is assumed to be provided by thermal generation and it is this residual amount that is multiplied by the thermal intensity, X_{6t}. Emissions from in-state electricity generation are included in the cap and trade program in all years, 2013 to 2020. Second, we parse X_{3t} – industrial GHG and other natural gas emissions – for 2013 and 2014 into the portion of these emissions that are and are not covered by the program during those years. Essentially, industrial processes and natural gas combustion by large industrial sources are covered in the first two years of the program, while off-road diesel consumption, and residential and small business emissions from natural gas consumption are not covered until 2015.

We do not include the GHG emissions from electricity imports in the VAR because this is largely an administratively determined number. All that can actually be measured is the aggregate GHG emissions outside of California and total electricity produced outside of California. The specific energy deemed to be "delivered" to California is largely the choice of the importing firm. Because incentives for this choice will change dramatically with the start of the cap and trade program, historical data on imports are not predictive of future trends. We instead take the ARB's forecast for emissions from electricity imports and then adjust total electricity emissions for reshuffling, as described later.

Define $Y_{it} = ln(X_{it})$ for $i = 1, 2, ..., 7$ and $Y_t = (Y_{1t}, Y_{2t}, ..., Y_{7t})'$. In terms of this notation a first-order autoregression or VAR that is stationary in first-differences can be written as

$$\Theta(L) \cdot Y_t = \mu + \epsilon_t \tag{3.1}$$

where L is the lag operator which implies, $L^k Y_t = Y_{t-k}$, I is a (7x7) identity matrix, $\Theta(L)$ is (7x7) matrix function in the lag operator equal to $(I - \Theta_1 L)$ where Θ_1 is a (7x7) matrix of constants, μ is a (7x1) vector of constants, and ϵ_t is a (7x1) white noise sequence with (7x1) zero mean vector and (7x7) covariance matrix Ω. Recall that white noise series are uncorrelated over time. In terms of the lag operator notation $(1 - L) = \Delta$, so that $\Delta Y_t = Y_t - Y_{t-1}$.

Although model (3.1) allows each element of Y_t to be non-stationary, reflecting the fact that each element exhibits net positive or negative growth over the sample period. A linear time series process that is stationary in first-differences is also called an integrated process with the order of integration equation equal to 1. For each of the elements of Y_t we performed a Dickey-Fuller (1979) test of the null hypothesis that the time series contained a unit root and was unable to reject that null hypothesis at $\alpha = 0.05$ level of significance for each series.[21] These hypothesis testing results are consistent with our decision to model the vector ΔY_t as 2nd-order stationary process.

It is often the case that stationary linear combinations of non-stationary economic time series exist because of long-run economic relationships between these variables. This logic suggests that linear combinations of the elements of Y_t are likely to be 2nd-order stationary in levels. Times series processes that are 2nd-order stationary in first-differences (*i.e.,* ΔY_t is 2nd-order stationary) and have stationary linear combinations of their elements are said to be cointegrated.[22] For a k-dimensional VAR in first-differences of Y_t, the number of stationary linear combinations of the elements of Y_t is called the cointegrating rank of the VAR. The cointegrating rank is also equal to the rank of the matrix $(I - \Theta_1)$. The existence of cointegrating relationships among elements of Y_t imposes restrictions on the elements of Θ_1. Suppose that the rank of the matrix $(I - \Theta_1)$ is equal to r $(0 < r < 7)$. This implies that the following error correction representation exists for Y_t:

$$\Delta Y_t = \mu - \gamma Z_{t-1} + \epsilon_t \tag{3.2}$$

[21] Dickey and Fuller, 1979. Results of the Dickey-Fuller tests are shown in the Appendix.

[22] See Engle and Granger, 1987, for a complete discussion of this concept and its implications.

where $Z_t = \alpha' Y_t$ is a (r x 1) vector of 2nd-order stationary random variables (these are the stationary linear combinations of Y_t) and γ is a (7 x r) rank r matrix of parameters and α is a (7 x r) rank r matrix of co-integrating vectors, and $(I - \Theta_1) = -\gamma\alpha'$.

Johansen (1988) devised a test of the cointegrating rank of a VAR that is 2nd-order stationary in first-differences. Following the multi-step procedure recommended by Johansen (1995) for determining the rank of a VAR, we find that the null hypothesis that the rank of $(I - \Theta_1)$ is equal to 1 can be rejected against the alternative that the rank is greater than 1 at 0.05 level.[23] However, the null hypothesis that the rank of $(I - \Theta_1)$ is 2 against the alternative that it is greater than 2 cannot be rejected at a 0.05 level. According to Johansen's procedure, this sequence of hypothesis testing results is consistent with the existence of 2 stationary linear combinations of the elements Y_t. We impose these co-integrating restrictions on the parameters of VAR model (3.2) that we estimate to forecast future GHG emissions. Imposing the restrictions implied by the two cointegrating relationships between the elements of Y_t reduces the number of free parameters in the (7x7) matrix $(I - \Theta_1)$ from 49 to 28 = (7x2) x 2, the total number of elements in γ and α.

We utilize Johansen's (1988) maximum likelihood estimation procedure to recover consistent, asymptotically normal estimates of μ, Ω, and Θ_1 with these co-integrating restrictions imposed. The coefficient estimates from this model written in the notation of equation (3.2) are given in the Appendix.

Using these parameter estimates we can then compute an estimate of the joint distribution of $(X'_{2013}, X'_{2014}, ..., X'_{2020})'$ conditional on the value of X_{2011} that takes into account both our uncertainty in the values of μ, Ω, γ, and α because of estimation error and uncertainty due to the fact that $(X'_{2013}, X'_{2014}, ..., X'_{2020})'$ depends on future realizations of ϵ_t for $t = 2012, ..., 2020$. Because we have 2012 data for instate electricity production net of hydroelectric generation (X_1), the real price of gasoline in California (X_4), and real State GSP (X_5), we compute our estimate of the distribution of $(X'_{2013}, X'_{2014}, ..., X'_{2020})'$ conditional on the values of these three elements of X_t for $t = 2012$ as well as the observed value of X_{2011}.

We employ a two-stage smoothed bootstrap approach to compute an estimate of this distribution.[24] The first step computes an estimate of the joint distribution of the elements

[23] Results of these tests are shown in the Appendix.

[24] For a discussion of the smoothed bootstrap, see Efron and Tibshirani, 1993.

of μ, Ω, γ and α by resampling from the smoothed empirical distribution of the (7x1) vector of residuals from the estimated Vector Autoregression (VAR) and re-estimating μ, Ω, γ, and α using Johansen's (1988) maximum likelihood procedure. We use the following algorithm. Let $\hat{\mu}$, $\hat{\Omega}$, and $\hat{\Theta}_1$ equal the estimates of the elements of the VAR imposing the cointegration rank restriction that $(1 - \Theta_t) \;=\; -\gamma\alpha'$. Compute

$$\hat{\epsilon}_t = Y_t - \hat{\mu} - \hat{\Theta}_1 Y_{t-1} \tag{3.3}$$

for t =1991 to 2011. Note that we can only compute values of $\hat{\epsilon}_t$ for t =1991 to 2011, because our sample begins in 1990 and the $(t-1)$th observation is required to compute the value of $\hat{\epsilon}_t$ for period $t = 1991$. Construct the kernel density estimate of the $\hat{\epsilon}_t$ as

$$\hat{f}(t) = \frac{1}{Th^7} \sum_{t=1}^{T} K\{\frac{1}{h}(t - \hat{\epsilon}_t)\} \tag{3.4}$$

where T is the number of observations, h is a user-selected smoothing parameter, and $K(t)$ is a multivariate kernel function that is everywhere positive and integrates to one. We use the multivariate normal kernel

$$K(x) = \frac{1}{(2\pi)^{7/2}} exp(-\frac{1}{2}x'x) \quad \text{where} \quad x \in \Re^7$$

and $h = 0.5$. We found that our results were insensitive to the value chosen for h, as long as it was less than 1.

We then draw $T = 21$ values from (3.4) and use the parameter estimates and these draws to compute re-sampled values of Y_t for $t = 1, 2, ..., T = 21$. Let $(\hat{\epsilon}_1^m, \hat{\epsilon}_2^m, ..., \hat{\epsilon}_{21}^m)'$ denote the mth draw of the 21 values of $\hat{\epsilon}_t$ from $\hat{f}(t)$. We compute the Y_t^m, the 21 resampled values of Y_t for t =1991 to 2011, by applying the following equation starting with the value of Y_t in 1990 ($Y_{1990}^m = Y_{1900}$ for all m)

$$Y_t^m = \hat{\mu} + \hat{\Theta}_1 Y_{t-1}^m + \hat{\epsilon}_t^m. \tag{3.5}$$

We then estimate the values of μ, Ω, and Θ_1 by applying Johansen's (1988) ML procedure using the Y_t^m and imposing the cointegration rank restriction that $(1 - \Theta_t) \;=\; -\gamma\alpha'$. Call the resulting estimates $\hat{\mu}^m$, $\hat{\Omega}^m$, and $\hat{\Theta}_1^m$. Repeating this process $M = 1000$ times yields the bootstrap distribution of $\hat{\mu}$, $\hat{\Omega}$, and $\hat{\Theta}_1$. This step accounts for the uncertainty in future values of Y_t due to the fact that true values of the of μ, Ω, and Θ_1 are unknown and must be estimated.

To account for the uncertainty in Y_{T+k} due to future realizations of ϵ_t, for each m and set of values of $\hat{\mu}^m$, $\hat{\Omega}^m$, and $\hat{\Theta}_1^m$, we draw nine values from $\hat{f}(t)$ in equation (3.4). Call these values $(\hat{\epsilon}_{T+1}^m, \hat{\epsilon}_{T+2}^m, ...\hat{\epsilon}_{T+9}^m)'$. Using these draws and $\hat{\mu}^m$, $\hat{\Omega}^m$, and $\hat{\Theta}_1^m$ compute future values Y_{T+k} for $k = 1, 2, ..., 9$ given Y_T using the following equation:

$$Y_{T+k|T}^m = \hat{\mu}^m + \hat{\Theta}_1^m Y_{T+k-1|T,T-1}^m + \hat{\epsilon}_{T+k}^m \quad \text{for} \quad k = 1, 2, ..., 9 \tag{3.6}$$

This yields one realization of the future sample path of Y_t for t =2012, 2013,..., 2020. The elements of Y_t are then be transformed to X_t by applying the transformation $X_{it} = exp(Y_{it})$ to each element of Y_t to yield a realization of the future time path of X_t. The elements of X_t are then transformed to produce a realization of the future time path of GHG emissions by each covered sector. This two-step process of computing $\hat{\mu}^m$, $\hat{\Omega}^m$, and $\hat{\Theta}_1^m$ and then simulating $Y_{T+k|T}^m$ for $k = 1, 2, ..., 9$ and doing this $m = 1$ to $M = 1000$ times produces 1,000 realizations from the simulated distribution of $(X_{2012}', X_{2013}', ..., X_{2020}')'$.

The procedure for simulating the value X_{2012} is slightly different from the procedure for simulating values for 2013 to 2020 described above because we know the values of X_1, X_4, and X_5 for 2012. Simulating the value of $(X_{2013}', X_{2014}', ..., X_{2020}')'$ conditional on the values of instate electricity production net of hydroelectric generation (X_1), the real gasoline price in California (X_4), and real State GSP (X_5) in 2012, requires constructing the smoothed conditional density of $(\hat{\epsilon}_{2t}, \hat{\epsilon}_{3t}, \hat{\epsilon}_{6t}, \hat{\epsilon}_{7t})'$ conditional on $(\hat{\epsilon}_{1t}, \hat{\epsilon}_{4t}, \hat{\epsilon}_{5t})' = (\hat{\epsilon}_{1,2012}, \hat{\epsilon}_{4,2012}, \hat{\epsilon}_{5,2012})'$, the elements of $\hat{\epsilon}_t$ corresponding to instate electricity production net of hydroelectric generation (X_1), the real price of gasoline in California (X_4), and real State GSP (X_5) in 2012 that reproduce the observed values of these variables in 2012 given the values of all of the elements Y_t in 2011. We draw $(\hat{\epsilon}_{2t}, \hat{\epsilon}_{3t}, \hat{\epsilon}_{6t}, \hat{\epsilon}_{7t})'$, the remaining elements of $\hat{\epsilon}_t$ from this conditional density for 2012 in computing the simulated value of Y_t for 2012. This re-sampling process ensures that the simulated value of instate electricity production net of hydroelectric generation, the real price of gasoline, and real GSP in California in 2012 are always equal to the observed value for each of these variables. It also ensures that the simulated value of $\hat{\epsilon}_t$ for 2012 is consistent with the smoothed joint distribution of $\hat{\epsilon}_t$ in (3.4) when drawing the remaining elements of this vector.

Although California's cap and trade program phases in the entities under the cap over time, our approach forecasts emissions from Phase I entities (narrow scope) and Phase II entities (broad scope) over the entire post-sample period. Phase I, in effect during the first compliance period of 2013 and 2014, covers electricity generation and emissions from large industrial operations. Phase II, in effect for the second and third compliance periods, 2015-2017 and 2018-2020, expands the program to include combustion emissions from transportation fuels and emissions from natural gas and other fuels combusted at residences and small commercial establishments.

a. Data

To compute the GHG emissions intensities of the instate electricity sector and transportation sector from 1990 to 2011 that enter the VAR model, we require data on the annual emissions from instate electricity production and annual emissions from the transportation sector to enter the numerator of each of these intensities. Annual emissions from the large industrial processes and the residential and commercial natural gas sector from 1990 to 2011 is the final GHG emissions-related time series required to estimate the VAR.[25] To construct these data, we start with data on annual emissions for each covered sector in California for 1990 to 2011. The remaining data that enter the VAR come from a variety of California state and federal sources, discussed below.

Annual emissions levels for each covered sector are taken from the 1990-2004 Greenhouse Gas Emissions Inventory and the 2000-2011 Greenhouse Gas Emissions Inventory (hereafter, Inventory).[26] The longest series of consistently measured emissions data and the basis for developing the 1990 statewide emissions level and 2020 emissions limit required by AB 32, the annual Inventory data was prepared by ARB staff and relies primarily on state, regional or national data sources, rather than individual facility-specific emissions. The Inventory's top-down approach to quantifying emissions differs importantly from the bottom-up method of accounting for facility-specific emissions under the cap and trade program. In particular, the Inventory likely overstates emissions from industrial activity relative to those covered in the first compliance period of the cap and trade program. That is, the Inventory methodology may attribute some emissions to the industrial sector, such as natural gas combustion from small industrial or commercial sources that are not covered until the second compliance period. We investigate the impact of this difference by comparing the Inventory data to annual data collected under the Mandatory Reporting Regulation (MRR), the methodology used to calculate an entity's compliance obligation under cap and trade.[27]

[25] Emissions from the off-road consumption of diesel also comprises a small component of the "other" category.

[26] California's GHG emissions inventory is available at: http://www.arb.ca.gov/cc/inventory/inventory.htm.

[27] Information on the ARB mandatory reporting regulation is available at: http://www.arb.ca.gov/cc/reporting/ghg-rep/ghg-rep.htm.

	mean	S.D.	min	max	year min	year max
California Electricity Generation (TWh)	191.20	15.80	158.90	216.80	1991	2006
California Hydroelectric Gen (TWh)	34.60	9.30	20.20	49.50	1992	1998
Vehicle Miles Travelled (Billions)	300.60	26.84	257.98	329.27	1991	2005
Emissions from Industry, Natural Gas and Other Sources (mmTons CO2)	141.90	4.83	131.98	145.60	1995	1998
Gross State Product (Nominal $Trillion))	1.36	0.43	0.77	2.00	1990	2012
Gasoline Price (Nominal $/gallon)	2.20	0.96	1.09	4.03	1990	2012
In-state Fossil Generation Intensity (tons/MWh)	0.483	0.045	0.402	0.529	2011	1990
Vehicle Emissions Intensity (tons/1000 VMT)	0.507	0.02	0.459	0.534	2011	1990

Note: Data are for 1990-2011

Table 2: Summary Statistics of Data for Vector Autoregression

Comparing the 2008-2011 MRR and Inventory industrial emissions data series shows annual differences of 8.98 to 13.24 MMT, with Inventory industrial emissions fifteen percent higher than MRR industrial emissions, on average. We address this difference by forecasting industrial capped source emissions in the first compliance period using the Inventory industrial emissions data series adjusted downward by fifteen percent. We use the unadjusted Inventory data as our measure of industrial capped source emissions covered in the second and third compliance periods. This approach does not appear to impact either our expected time path or the degree uncertainty in the future time path. Because our maintained assumption is that the first compliance period difference is due to differences in accounting, as opposed to classical measurement error, using the Inventory emissions estimates for the second and third compliance periods should not bias our emissions estimates upward.

California GSP is collected from the Bureau of Economic Analysis (BEA).[28] Gasoline prices are collected from the Energy Information Administration (EIA).[29] In-state electric generation is also collected from the EIA.[30]

[28] Gross Domestic Product by State is available at: http://www.bea.gov/regional/index.htm#data.

[29] Retail fuel price by State is available at: http://www.eia.gov/dnav/pet/pet_pri_gnd_dcus_sca_w.htm.

[30] In-state California electric generation and consumption are available from the CEC at http://energyalmanac.ca.gov/electricity/index.html.

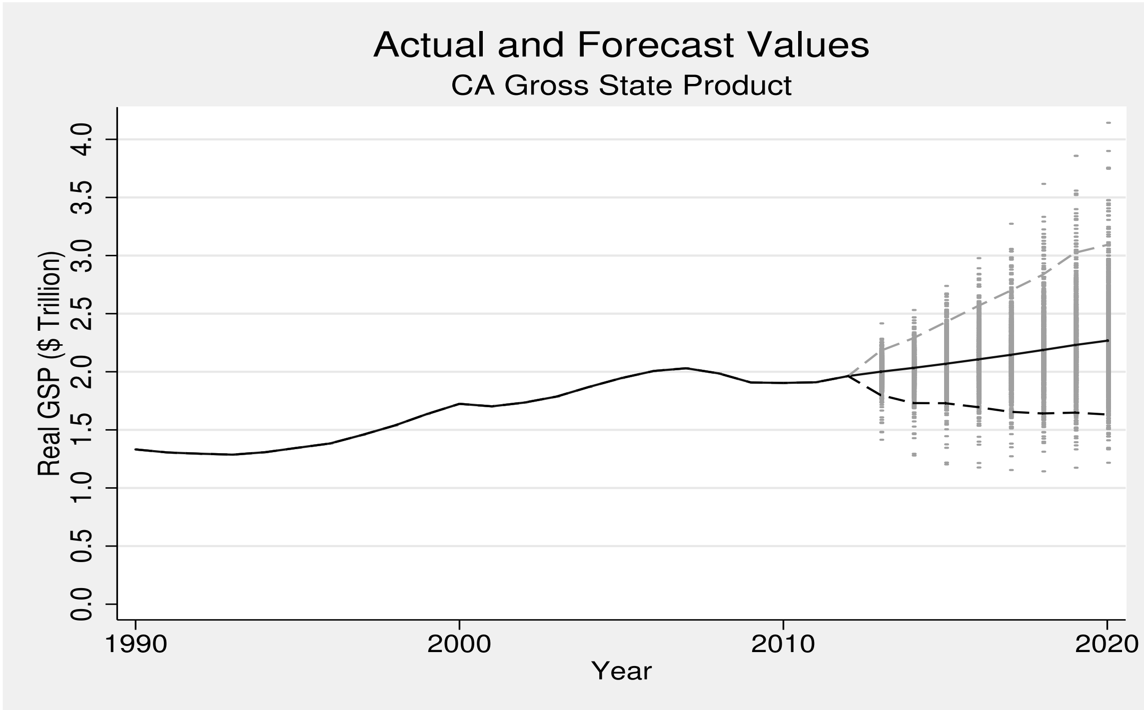

Figure 5: Forecast Results – Gross State Product

Our primary measure of Vehicles Miles Traveled (VMT) is compiled from a series of state-level transportation surveys administered by the National Highway Transportation Safety Administration's (NHTSA) Office of Highway Information (OHI). These data capture on-road VMT and were independently constructed and reported by the states, rather than centrally calculated by OHI.

While these data measure on-road VMT, the cap and trade program caps emissions from all diesel and gasoline combusted as transportation fuel in California, regardless of whether the fuel is combusted on-road or off-road. To address this potential source of bias we deviate from ARB's emissions categorization of "transportation" by excluding GHG emissions from off-road vehicle activities, in favor of categorizing them into "Natural Gas and Other." Therefore, beginning with total transportation sector combustion emissions, we partition emissions into on-road and off-road activities using the more granular activity-based emissions values reported in the combined 1990-2004 and 2000-2011 Emissions Inventories. The emissions levels reported in Table 1 reflect this partition of on-road and off-road emissions.

Finally, to adjust the emissions from natural gas, off-road diesel, and industrial processes for partial coverage under the cap of these emissions in 2013-14, we multiply the value of $X^m_{3,T+k}$ for each simulation by $0.53 \cdot 0.85 (= 0.4675)$ for the values in 2013 and 2014.

This adjustment reflects that over the last 20 years, the industrial sector has consistently accounted for approximately 53% of emissions from non-electricity-generation natural gas combustion and other industrial processes (X_3) (min: 51.5% and max: 56.5%), and the Inventory accounting difference (discussed above), which leads us to attribute 85% of industrial emissions to sources covered under the first compliance period.

Summary statistics for all data of the VAR are in table 2.

b. Results

The parameter estimates from estimating the 7-variable VAR are shown in the Appendix. The parameter estimates are reported in the error-correction model notation of the VAR as:

$$\Delta Y_t = \mu + \Lambda Y_{t-1} + \epsilon_t \tag{3.7}$$

where Λ is (7x7) matrix that satisfies the restriction $\Lambda = -\gamma\alpha'$. Repeating the two-step procedure described above, yields 1000 simulations of the elements of X_t. Table 3 lists the means and standard deviations of simulated value of each element of X_t for each year from 2013 to 2020, as well as the coinciding annual and cumulative emissions resulting from those values. Figure 5 shows actual data (up to 2012) and forecast from VAR for GSP, with 95% confidence intervals for the forecast. The vertical dots show the distribution of simulation outcomes. The next section describes the details of our procedure for simulating future values of annual emissions covered by the program for each year from 2013 to 2020.

IV. ACCOUNTING FOR COMPLEMENTARY POLICIES IN FORECASTS

While the Air Resources Board (ARB) has identified many categories of complementary policies and stated the reductions in GHG emissions that are expected to result from each policy, it is unclear how the baseline from which such estimates are claimed relates to the simulations we obtain from the VAR. Thus, rather than incorporating potential reductions from an uncertain baseline, we proceed by applying emissions intensities of electricity generation and VMT that reflect the likely outcomes of the complementary policies. That is, the effects of complementary policies are incorporated into our simulations of GHG emissions from 2013 to 2020 through changes in the ratios we use to translate forecasts of X_{1t} and X_{2t}, instate electricity production minus hydroelectric energy production and vehicle miles traveled respectively, into GHG emissions.

Year	California Electricity Production net of Hydro Twh	Vehicle Miles Travelled Million Miles	Nat. Gas, Ind. & Other Emissions mmTons	Gasoline Price $2011	Gross State Product 2011 $ Trillion	Thermal Intensity tons/MWh	Transport Intensity tons/1000 Miles	Broad Scope Emissions mmTons	Cumulative Emissions mmTons
2013	170.06	321.41	153.90	4.36	2.00	0.37	0.47	402.73	168.17
	(27.00)	(10.66)	(12.23)	(0.95)	(0.10)	(0.05)	(0.03)	(18.82)	(15.91)
2014	175.49	323.81	154.35	4.37	2.03	0.37	0.46	402.04	334.76
	(26.96)	(12.57)	(14.74)	(0.95)	(0.14)	(0.05)	(0.03)	(20.21)	(29.69)
2015	175.68	326.95	154.49	4.55	2.07	0.37	0.46	399.82	734.55
	(29.74)	(14.11)	(16.91)	(1.21)	(0.18)	(0.05)	(0.03)	(23.02)	(47.88)
2016	178.90	330.05	154.59	4.71	2.11	0.36	0.46	400.58	1135.10
	(30.01)	(15.71)	(18.77)	(1.41)	(0.22)	(0.06)	(0.04)	(24.39)	(68.68)
2017	180.27	333.42	154.75	4.86	2.15	0.36	0.46	400.14	1535.21
	(32.49)	(17.44)	(20.68)	(1.58)	(0.26)	(0.06)	(0.04)	(27.55)	(93.25)
2018	182.67	336.82	154.72	5.07	2.19	0.35	0.45	400.80	1935.98
	(33.88)	(19.23)	(22.23)	(1.88)	(0.30)	(0.06)	(0.04)	(29.25)	(119.61)
2019	185.95	340.37	154.58	5.27	2.23	0.35	0.45	402.51	2338.46
	(36.96)	(21.10)	(23.75)	(2.08)	(0.34)	(0.06)	(0.04)	(31.54)	(148.30)
2020	187.51	343.46	154.51	5.42	2.27	0.35	0.45	403.19	2741.62
	(37.61)	(22.80)	(25.44)	(2.33)	(0.38)	(0.07)	(0.05)	(33.61)	(178.53)

Note: Estimates are mean values of 1000 draws, values in parenthesis are Std.Dev. of 1000 draws.

Table 3: Summary Statistics of Simulated VAR Variables and Emissions

In the case of electricity, the main complementary policies are energy efficiency (EE) investments and the Renewables Portfolio Standard (RPS). Consistent with the regulatory practice of translating sector-wide intensity based policy into fixed quantity targets, we treat both of these measures as impacting the *quantity of non-zero* carbon-emissions-producing power generation, rather than the intensity of overall generation.

In the case of the RPS, two important recent changes imply that historical trends of zero-carbon-emissions generation are not satisfactorily predictive of future supply. These two changes are the imposition of the 33% RPS and the recent unexpected retirement of the San Onofre Nuclear Generation Station (SONGS) in Southern California. To get from a simulation of X_{1t} for 2013-2020 to a simulation of GHG emissions from in-state non-hydro electricity generation, we first subtract off estimates of *future* renewable and nuclear power generation from each simulation of X_{1t}. These values are taken from external data sources rather than generated within the VAR. What remains is a simulation of instate fossil fuel electricity generation. We then multiply this number by the simulated value of the emissions intensity of in-state fossil-fuel generation from our two-step procedure.

For the RPS, we apply a California Public Utilities Commission (CPUC) forecast of new renewable generation (MWh) taken from the 2012 Long-term Procurement Plan-

	Zero-Carbon Power		Low	Medium	BAU Forecast
Year	*RPS*	*Nuclear*	*VMT Intensity*	*VMT Intensity*	*VMT Intensity*
	TWh	*TWh*	*tons/1000 miles*	*tons/1000 miles*	*tons/1000 miles*
2013	30520	17530	0.482	0.492	0.467
2014	41369	17530	0.471	0.484	0.465
2015	48217	17530	0.457	0.472	0.462
2016	50586	17530	0.438	0.456	0.460
2017	54268	17530	0.419	0.440	0.457
2018	56054	17530	0.400	0.423	0.455
2019	56054	17530	0.382	0.407	0.453
2020	56151	17530	0.364	0.391	0.450

Table 4: Assumed Zero-Carbon Electricity Output and Vehicle Emissions Intesities

---

ning process.[31] These estimates of renewable power generation incorporate the impact of the 33% target for the RPS by 2020. We then add this annual quantity of new renewable energy to the average level of renewable generation (taken from EIA) over the last 20 years of about 24 TWh.[32]

For in-state generation of nuclear power, we assume that the Diablo Canyon Nuclear Power Plant will continue to operate during 2013-2020 and that it will produce an average of 17.53 TWh per year, which is its average production for the 10-year period 2003-2012. These values are summarized in the second and third columns of Table 4. The remaining in-state generation is assumed to be from fossil fuel generation sources.

We then multiply this simulated value of instate fossil-fuel electricity production by X_{6t}, the emissions intensity factor produced by the simulation of future values from the VAR, to translate the simulation of instate electricity production into GHG emissions. More formally, we calculate electricity emissions from instate electricity production to be

$$ElecGHG_{m,T+k} = (TWH_N hydro_{m,T+k} - RPS\_TWH_{T+k} - Nuke\_TWH_{T+k}) \cdot EI_{m,T+k}$$

where $TWH_N hydro$ is the realization of $X_{1,T+k}$ for simulation draw m of the instate production of electricity net of hydro production. The variables RPS_TWH and $Nuke\_TWH$

[31] Specifically, we utilize the annual forecast of additional renewable energy from the RPS Calculator developed by E3 for the LTPP process found at http://www.cpuc.ca.gov/PUC/energy/Procurement/LTPP/-2012+LTPP+Tools+and+Spreadsheets.htm. This forecast shows increased renewable energy to provide an additional 32 TWh of renewable energy per year by 2020.

[32] Note that the EIA value of 24 TWh of renewable energy is lower than the official current level of RPS compliant energy. The difference is due to certain existing hydro resources that qualify under current rules. The EIA lists this energy as "hydroelectric" rather than renewable.

are the values of renewable and nuclear annual TWH described in Table 4 and $EI_{m,T+k}$ is $X_{6,T+k}$, the realization of emissions intensity for thermal generation in California for simulation draw m.

Reflecting California's longstanding commitment to energy efficiency, there is a strong pre-existing trend of efficiency improvements already present in the time-series data we used to forecast the BAU emissions. Total emissions per unit of GSP declined at an average rate of about 1.83% per year from 1990 to 2011. We are therefore concerned that further reductions from our forecast to account for energy efficiency improvements would double count the reductions that are already part of the forecast. Indeed, as table 3 indicates, emissions per unit of GDP decline under our BAU forecast by about 1.74% per year from 2013 to 2020. We therefore make no further adjustments in addition to energy efficiency effects already integrated into our forecasts.

To incorporate the impact of complimentary policies targeting the transportation sector, we interact the forecast of VMT from the VAR with three possible values of emissions intensity per mile. The first value, essentially a business-as-usual intensity, takes $X_{7,T+k}$, the VMT intensity forecast by the VAR without any further adjustment. The second and third emissions intensities we use are based upon expectations of the impacts of AB 32 transportation policies derived from EMFAC 2011, the ARB tool for forecasting fleet composition and activity in the transportation sector. Our derivations are summarized here but described in more detail in the Appendix.

Using EMFAC, we derive anticipated emissions intensities (essentially fleet average miles per gallon) under two assumptions about transport policy. The first scenario assumes that all LCFS and miles per gallon (MPG) standards are met. This reduces emissions-per-mile both through improved MPG and through a higher percentage of biofuels, which are treated as zero under the cap, in the transportation fuel mix. The second scenario assumes that the mileage standards for new vehicles are met, but that the penetration of biofuels remains at 10%.[33] Thus, under this scenario the emissions per mile are reduced solely due to the increased fuel-efficiency of vehicles.

The EMFAC 2011 model provides, for each of our transportation policy scenarios, a point estimate of fleet average emissions intensity. Columns 4-6 of table 4 summarize these two

[33] The carbon content of that 10% of biofuels may in fact be lower due to the LCFS, but from an emissions cap perspective that does not matter, since all biofuels are treated equally as zero emissions under the cap, and the current level of biofuels is already around 10%.

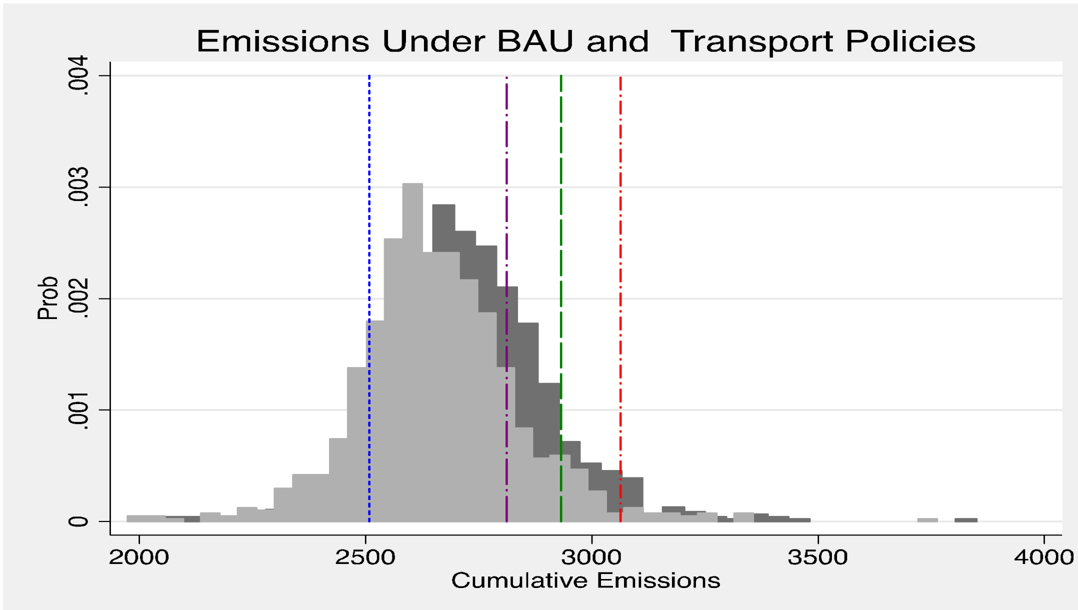

Figure 6: Targeted Transportation Policies Shift Emissions Distribution

---

values, along with the mean transport intensity value forecast by the VAR, for each year. However, even though the standards may be fully complied with, considerable uncertainty remains as to the emissions intensity of the full transportation emissions. Among other factors, a substantial minority of transport emissions come from commercial trucking and other heavy-duty vehicles that will not be subject to the same kind of binding fuel economy standards as the passenger vehicle fleet.

In order to reflect the underlying random aspects of vehicle emissions, even with successfully implemented complementary policies, we model the effect of these policies as a shift in the distribution of emissions intensity from a BAU level to a level achieved, on average, by the policies. This is accomplished by shifting each VMT intensity realization, $X_{7,T+k}$, by an amount equal to the difference between the BAU mean intensity level and the EMFAC forecast of the policy-induced point estimate. This adjusted emissions intensity is then multiplied by the coinciding VMT realization for the same VAR simulation draw to calculate total transport sector emissions for year t. More formally, transport emissions can be expressed as

$$TransportCO2_{m,T+k} = VMT_{m,T+k} \cdot (TI_{m,T+k} - (E_j(TI) - TI_{policy}))$$

where $VMT_{m,T+k}$ and $TI_{m,T+k}$ are the vehicle miles travelled and transport emissions intensity from simulation draw m of the VAR during year t, respectively, and TI_{policy} is the transport emissions intensity derived by EMFAC 2011 for the given policy assumption. This effect is illustrated in Figure 6, which shows the distribution of transportation sector emissions for 2020 under the BAU intensity forecast (dark), as well as the shifted distribution (light) that incorporates the "low" vehicle intensity values from table 4. The three vertical lines are, from left to right, the total allowance budget, along with the abatement available at a price at the top of the APCR under low, medium and high scenarios, which we discuss in the next section.[34]

Both of these adjustments–shifting MWh of in-state electricity generation and adjusting the intensity of VMT emissions–yield estimates of the emissions that will result from the three sectors covered in the California economy. These reductions will be independent of the price of allowances. Three other adjustments are necessary, however, before comparing this demand for allowances with the supply that is available under the cap and trade program: the impact of imported electricity, emissions offsets, and changes in the price of allowances. We incorporate these effects in the next section.

Figure 7 shows actual data (up to 2011) and forecast from VAR for Broad Scope Emissions, with 95% confidence intervals for the forecast. The vertical dots show the distribution of simulation outcomes. Figure 8 shows the forecast cumulative covered emissions – narrow scope for 2013-2014, broad scope for later years – along with pointwise 95% confidence intervals for the value for each year from 2013 to 2020.

V. ADDITIONAL SOURCES OF EMISSIONS ABATEMENT

While the VAR estimation and simulations described in the previous section account for the trend in emissions and changes in transport emissions intensities, the price of allowances and other government policies will also affect total emissions. In this section we analyze these other sources of emissions abatement and compliance opportunities.

[34] The lines are all for cases with more stringent fuel economy standards.

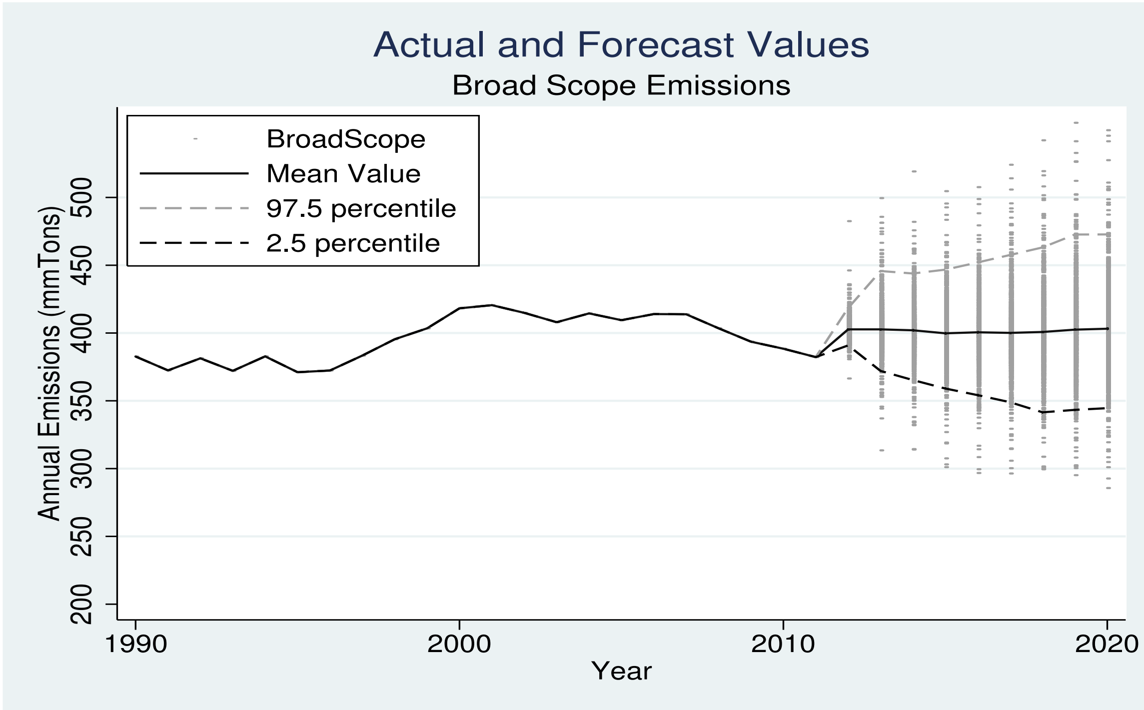

Figure 7: Forecast Results – Broad Scope Emissions

A cap and trade system is based on the presumption that as the allowance price rises, the implied increased production costs will change consumer and producer behavior. In order to assess the impact of the change in the emissions price on quantity demanded in the allowance market, we first analyze such price-elastic demand for allowances in four areas on the consumer side: demand for gasoline, diesel, electricity, and natural gas. For each of these areas, we calculate the emissions reduction that would occur with the price at the auction reserve price floor, at the price to access the first (lowest) tier of the allowance price containment reserve (APCR), and at the price to access the third (highest) tier of the APCR.[35] We also consider responses of industrial emissions to allowance prices.

It is important to recognize that the actual allowance price path will evolve over time as more information suggests whether the market is likely to have insufficient or excess allowances over the life of the eight-year program, as discussed in section II. Prices at these very low or high levels may not be observed until much later in the program, when participants are fairly certain of whether the market will be short or long allowances. Furthermore, there may be considerable uncertainty about future prices throughout the

[35] Each of these price levels escalates over time in real terms, so we calculate the price-sensitive abatement for each year separately.

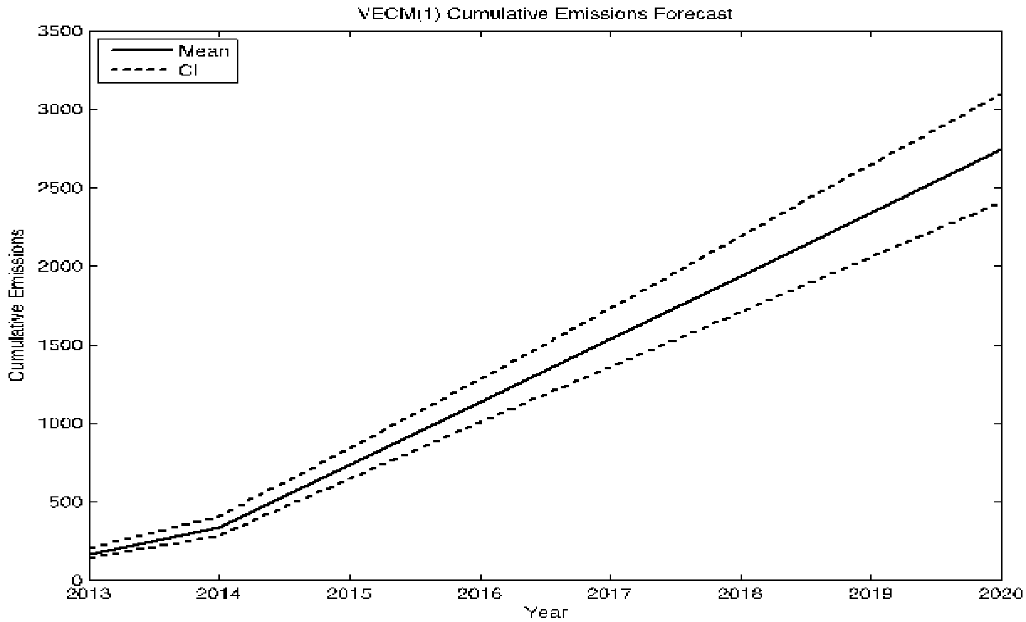

Figure 8: Forecast Results: Cumulative Covered Emissions

program. Thus, to the extent that response to high allowance prices involves irreversible investments, there may be significant option value in waiting to make those investments until more of the uncertainty is resolved. For these reasons, while we use the APCR price levels to calculate potential responses to high prices in every year, we consider low to medium elasticities in recognition that APCR-level prices are very unlikely until later years and delayed responses of market participants – due to uncertainty and option value – may reduce responses to those prices.

a. Demand for Fuels

The potential impact of the allowance price on consumption of transportation fuels – gasoline and diesel – is a function of short-run effects, such as driving less and switching among vehicles a family or company owns, and longer-run effects, such as buying more fuel-efficient vehicles and living in areas that require less use of vehicles. If, however, fuel-economy standards have pushed up the average fuel-economy of vehicles above the level consumers would otherwise voluntarily choose (given fuel prices), then raising fuel prices will have a smaller effect, because the fuel-economy regulation has already moved some customers into the vehicle fuel economy they would have chosen in response to higher gas prices. For this reason, in jurisdictions with effective fuel-economy standards, such as California, the price-elasticity of demand for transportation fuels is likely to be lower. Short-run price elasticity estimates are generally -0.1 or smaller.[36] Long-run elasticities are generally between -0.3 and -0.5.[37] Furthermore, the fuel-economy standards would reduce the absolute magnitude of emissions reductions in another way: by lowering the base level of emissions per mile even before the price of allowances has an effect. Recall that we incorporate the direct impact of fuel-economy standards on emissions holding constant vehicle miles traveled when we account for transport emissions intensities in the VAR simulation.[38]

We recognize that improved fuel-economy standards will phase in gradually during the cap and trade compliance periods. To balance these factors, we assume that the base level of vehicle emissions is unchanged from 2012 levels in calculating the price response, and we assume that the price elasticity of demand will range from -0.1 to -0.2.[39] Our fuel price elasticity value is linked to our assumption about the effectiveness of the fuel-economy regulations. If these regulations move consumers into the higher-MPG vehicles they would have bought in response to higher fuel prices, then that emissions savings occurs regardless of the price of allowances. If fuel prices then rise, we wouldn't expect as great a quantity response, as consumers have already purchased cars that are optimized for higher fuel prices.

At the highest price in the price containment reserve in each year (which, in 2012 dollars, is \$50 in 2013 going up to \$70.36 in 2020),[40] the result with a -0.1 elasticity is a reduction of **10.6 MMT** over the life of the program from reduced use of gasoline and diesel. Assum-

[36] See Hughes, Knittel and Sperling, 2008.

[37] See Dahl, 2012

[38] The VAR also accounts for estimates of uncertainty in the change in gasoline prices absent GHG costs.

[39] We also assume that the cost of tailpipe CO_2 emissions is passed through 100% to the retail price.

[40] These allowance prices translate to an increase of about \$0.45 to \$0.63 per gallon at the pump in 2012 dollars.

ing an elasticity of -0.2 about doubles the reduction to **21.1 MMT**.[41] We also consider the potentially more-elastic response if vehicle fuel economy standards are not separately increased; assuming an elasticity of -0.4 yields a reduction of **44.1 MMT**.[42] (Note the fuels will be under the cap only in 2015-2020, so we calculate reductions for only these six years.) We combine this last case with the business-as-usual transport emissions intensity described in the previous section, essentially assuming this higher price elasticity if higher fuel-economy standards have not been effectively implemented.

If policy is changed to give free allowances to refiners with output-based updating, to incent them not to pass along allowance prices in the price of gasoline, then this source of abatement elasticity will be reduced or eliminated as we discuss in section VII.

b. Demand for Electricity

The impact of a rising allowance price on emissions from electricity consumption depends primarily on the pass-through of allowance costs to retail prices of electricity. As noted earlier, regulated investor-owned utilities (IOUs) receive free allocations of allowances that they must then sell in the allowance auctions, resulting in revenues to the utilities. Those revenues must then be distributed to customers. They can be used to reduce the retail rate increases that would otherwise occur due to higher wholesale electricity purchase prices caused by generators' allowance obligations. Publicly-owned utilities are not obligated to sell their allowances, but are effectively in the same position of deciding how much of the value of the free allowances will be used to offset rate increases that would result when wholesale prices rise.

Based on a resolution from the CPUC in December 2012,[43] a best guess seems to be that the revenues from utility sales of allowances will be used first to assure that cap and trade causes no price increase to residential consumers. In addition, the revenues will be allocated to dampen price increases for small commercial customers and likely greatly reduce them for energy intensive trade exposed large industrial and commercial customers. Remaining revenues will be distributed to residential customers through a semi-annual lump-sum per-customer credit. It appears that most electricity sold to commercial and industrial

[41] Each of these estimates assumes that the LCFS has already raised the biofuel share of retail gasoline to 15%.

[42] This calculation also assumes that biofuels remain at 10% of retail gasoline.

[43] http://docs.cpuc.ca.gov/PublishedDocs/Published/G000/M040/K841/40841421.PDF. The full decision is at http://docs.cpuc.ca.gov/PublishedDocs/Published/G000/M039/K594/39594673.PDF.

customers will see the full pass-through of energy price increases due to allowance costs.[44]

The CPUC estimates that 85% of revenues will go to residential customers, who make up about 34% of demand.[45] Conversely, 15% of revenues will go to non-residential customers, that is, customers who comprise 66% of demand. If the total allocation of allowances is about equal to 100% of a utility's associated indirect (*i.e.,* through power providers) obligation, and the utility is allowed to cover its cost of compliance, this means that the 66% of demand that is not residential will bear associated costs equal to 85% of the total cost of allowances that cover the utility's obligation.

With a statewide *average* GHG intensity of 0.350 metric tonnes per MWh (based on the 2011, most recent, GHG inventory), this means that the price of electricity per MWh would increase for non-residential customers by an average of $(0.85/0.66) \cdot 0.350 \cdot$ allowance price. At an allowance price of \$50/tonne, this raises average non-residential rates by \$22.54/MWh and at \$70.36/tonne by \$31.55/MWh.[46] We apply these increases to the state average retail rates for commercial and industrial customers, based on EIA data, to get a percentage price response. Commercial and industrial electricity demand elasticity estimates are few and not at all consistent. The only study we found in the last 20 years is Kamerschen and Porter (2004), which estimates a long-run industrial price elasticity of demand of -0.35 when controlling for heating and cooling degree-days. We use this figure, though we recognize that it could be too large because the long-run assumption imparts an upward bias to the impact if price is actually increasing over time and we cal-

---

[44] It is worth noting that it is far from straightforward once the program begins for a regulator to know what the counterfactual price of electricity would have been if allowances had sold for a different price or for a price of zero. The price of allowances has a complex impact of wholesale electricity expenditures depending on the emissions intensity of the marginal supplier versus the average supplier and the competitiveness of the wholesale electricity market. Thus, it is not clear how the CPUC would make good on a promise not to pass through the cost of allowances without a detailed study of the impact that cost of equilibrium wholesale electricity prices.

[45] The 34% figure is based on 2012 EIA data for all of California.

[46] The 0.350 MT/MWh figure is arrived at by taking total 2011 GHG electricity emissions measured for in-state (38.2 MMT) and assumed for imports (53.5 MMT) and dividing by total consumption (261.9 MMWh). Two assumptions are implicit in this calculation. First, we calculate the impact by spreading the cost of the allowances over all non-residential customers, rather than calculating a slightly higher increase for a slightly smaller set of customers by excluding trade exposed large customers and reducing the obligation of small customers. This is unlikely to make a noticeable difference. Second, we assume that the wholesale price obligation is increased by the cost of the allowances, when it could be more or less depending on the GHG intensity of the marginal versus the average producer and the share of contracts with prices set prior to or independent of the impact of GHG costs on market price.

culate the elasticity based on same-year average price.[47] On the other hand, some earlier studies–reviewed in Taylor 1975–find much larger long-run elasticities, in some cases above 1 in absolute value.

The -0.35 elasticity is then applied to the share of IOU-served demand subject to this price change, which we take to be 66%, to calculate the resulting reduction in demand. Because the resulting impact on electricity consumption would be a reduction at the margin, we multiply the demand reduction by an assumed *marginal* GHG intensity–which we take to be 0.428 tonne/MWh–to calculate the reduction in emissions at different prices. The result is a reduction of **7.7 MMT** when the price is at the auction reserve throughout the program, **27.3 MMT** when price is at the lowest step of the containment reserve, and **33.4 MMT** when price is at the highest step of the containment reserve.[48]

Electricity prices, however, are likely to rise for all customers over the years of the program for reasons independent of the price of allowances–increased renewables generation, rising capital costs, and replacement of aging infrastructure, among others–and these increases will reduce consumption.

Taking an average statewide retail electricity price of $149/MWh in 2012,[49] we assume that this price will increase by 2.15% (real) per year due to exogenous (to cap and trade) factors.[50] Again assuming a long-run demand elasticity of -0.35 and a marginal CO2e intensity of 0.428 tonne/MWh, yields a reduction of **24.1 MMT** (if allowance price is at the highest price in the price containment reserve) over the life of the program.[51]

Thus, at the highest level of the price containment reserve we estimate total abatement

---

[47] In particular, because the price at any time should reflect all expectations of future changes, the increase in price over time, if it were to occur, would be due to a series of unpredicted upward shocks. Thus, one would not expect market participants to behave as if they had foreseen these shocks.

[48] For an elasticity of -0.2, the reductions are, respectively, 4.6, 15.8, and 19.3 MMT, while for an elasticity of -0.5 the reductions are, respectively, 10.9, 38.6, and 47.2 MMT. We use these elasticities as a high and low case. The baseline price on which all price increases are calculated is the average price over the life of the program assuming a 2.15% annual real increase in electricity prices during this period, as discussed next.

[49] http://www.eia.gov/electricity/monthly/epm_table_grapher.cfm?t=epmt_5_6_a

[50] This increase is based on a projected real increase from 144/$MWhin2012to$211/MWh in 2030, an average increase of 2.15% per year.

[51] Ito (forthcoming) estimates a medium-long run price elasticity for residential electricity demand of -0.2. The reduction from the exogenous price increase drops to 13.9 MMT at an elasticity of -0.2.

from electricity demand reduction of **57.5 MMT** over the life of the program. Both the price elasticity we assume and the marginal CO2e intensity figures may be on the high side. Using an elasticity of -0.2 reduces the impact of electricity demand reduction to **33.2 MMT** at the highest price of the containment reserve. The marginal GHG intensity of 0.428 is based on a combine-cycle gas turbine generator. If some of the reduction comes out of renewable, hydro or nuclear generation the marginal intensity will be lower. The impact scales linearly with the assumed marginal GHG intensity.

c. Demand for Natural Gas

It appears very likely that the ARB will vote in 2014[52] to give natural gas suppliers (who are virtually all investor-owned regulated utilities in California) free allowances equal to the obligation associated with their 2011 supply, but then declining at the cap decline factor. If this were done, then nearly all of the suppliers' obligations could be covered with the free allowances (or the revenue from selling them in the allowance auction). From discussions with industry participants and CPUC staff, it appears the most likely outcome is there would be almost no impact of emissions pricing on retail natural gas price, and therefore almost no price-responsive emissions reduction by consumers in this sector. That outcome is not certain, however, so we also explore the impact of emissions prices being passed through to consumers. "Consumers" in this case include all emissions sources not covered in the industrial categories. (Large industrial customers, which are in the program beginning with the first compliance period, are discussed in subsection e.)

If the cost of natural gas emissions were fully passed through to these consumers, then an allowance price at the auction reserve would raise natural gas prices by an average of \$0.71/MMBTU (in 2012 dollars) over the 2015-2020 period. At the lowest price in of the APCR, the allowance cost would raise the price of natural gas by an average of \$2.71/MMBTU and at the highest price of the APCR, the effect would be to raise the natural gas price by an average of \$3.40/MMBTU. We assume an average retail price of \$8.49/MMBTU across all nonindustrial types of natural gas customers[53] before allowance costs, and 100% pass-through of the allowance cost to retail. It's difficult to know the

[52] See http://www.arb.ca.gov/regact/2013/capandtrade13/capandtrade13isor.pdf. At the October 2013 ARB Board meeting, a decision on these proposals was postponed.

[53] According to the EIA (http://www.eia.gov/dnav/ng/ng_pri_sum_dcu_SCA_a.htm) in 2012 residential averaged \$9.22/MMBTU, commercial about \$7.13/MMBTU for the about half of commercial customers in their data. These are likely the smaller customers because larger customers probably have proprietary contracts, which the price data don't cover. The \$8.49/MMBTU price is the quantity-weighted average based on EIA estimated quantities.

elasticity of retail demand for natural gas. We take a low-end estimate of -0.2 and a high-end estimate of -0.4 over the 6-year time frame of natural gas in the program.[54] We assume a baseline emissions rate of 49.7 MMT/year for each of the six years that non-industrial customers are in the program. Based on these assumptions, at the highest price in the price containment reserve, the low-elasticity estimated abatement is **19.4 MMT** and the high-elasticity scenario is **37.5 MMT**. If policy is indeed changed to give free allowances to utilities with the effect of reducing or eliminating the associated retail price increase, then this source of abatement elasticity will be approximately zero.

d. Abatement from Out-of-State Electricity Dispatch Changes

To the extent that some high-emitting out-of-state coal plants are not reshuffled or declared at the default rate, there is possible elasticity from higher allowance prices incenting reduced generation from such plants. We considered this, but the most recent ARB policy suggests that short-term energy trades would fall under a safe harbor and would not be considered reshuffling. If that is the case, then an operator would be better off carrying out such trades than actually reducing output from the plant. This suggests that allowance price increases might incent some changes in reported emissions. In any case, we consider that as part of the reshuffling and relabeling analysis.

e. Industrial Emissions

For the industries covered under output-based updating, there may still be some emissions reductions as the allowance price rises. This could happen in two ways. First, once a baseline ratio of allowances to output is established, these firms have an incentive to make process improvements that reduce GHG emissions for a given quantity of output. It is unclear how much of such improvement is likely to occur. At this point we have no information on this. Our current estimates assume this is zero. ARB's analysis of compliance pathways suggests that at a price of up to $18/tonne (25% of the highest price of the APCR in 2020), the opportunity for industrial process reduction is at most 1-2 MMT per year.[55] Second, because the output-based updating is not 100%, additional emissions that result from marginal output increases do impose some marginal cost on the firms.

[54] Though some estimates of the price elasticity of gas and electricity demand are higher than those we use here, such estimates generally include substitution from gas to electricity and vice versa, which would have a much smaller net impact on emissions.

[55] See figures F-3 through F-9 of Appendix F, "Compliance Pathways Analysis," available at http://www.-arb.ca.gov/regact/2010/capandtrade10/capv3appf.pdf.

That impact is likely to be small, however, because the effective updating factors average between 75% and 90% over the program, which implies that the firm faces an effective allowance price of 10% to 25% of the market price for emissions that are associated with changes in output. At this point, we have not incorporated estimates of this impact, but it seems likely to be quite small.

f. Imported Electricity, Reshuffling, and Relabeling

The ARB has attempted to include all emissions from out-of-state generation of electricity delivered to and consumed in California under the cap and trade program's GHG accounting framework. ARB projects annual BAU emissions from imported electricity of 53.53 MMT, during the period 2013-2020.[56] However, due to the nature of the Western electricity market, it is generally impossible to identify the spescific generation resource supplying imported electricity. Electricity importers therefore have an incentive to engage in a variety of practices that lower the reported GHG content of their imports, a class of behaviors broadly labeled reshuffling. While reshuffling would not yield aggregate emissions reductions in the Western Interconnection, it could be a major source of measured emissions reductions under the cap and trade program.

Under one extreme, importers could reshuffle all imports to GHG free resources, resulting in no demand for allowances to cover imported electricity. ARB has tried to limit reshuffling by focusing on imports from coal plants partially owned by California utilities. Given the current information, we project emissions associated with imports from these plants to to account for 109 MMT during the eight-year period. We treat this as a lower bound on emissions from imports, assuming that all other imported energy is sourced from zero carbon generation.

In 2010 there were about 85 net TWh of electricity imported into California. If we assume imported electricity remains at this level during the 8 years, this implies 680 TWh over the 8 years of the cap.[57] Taking the 109 MMT, associated with roughly 109 TWh of electricity imports as a baseline, we consider two other possibilities for the remaining 571 TWh. The first is that all the remaining energy is imported at an emissions rate of 0.428 tons/MWh. This is the "default" emissions rate applied to any imports that do not claim a

[56] This comes from the ARB's 2012-2020 California GHG Emissions Forecast. http://www.arb.ca.gov/cc/inventory/data/tables/2020_ghg_emissions_forecast_2010-10-28.pdf

[57] California Energy Commission. http://energyalmanac.ca.gov/electricity/electricity_generation.html. The net total includes roughly 90 TWh of imports and 5 TWh of exports.

specific source for the power. Another scenario assumes roughly half the remaining energy is imported at zero emissions, while the other half is imported at 0.428 tonnes/MWh. The result is an average emissions rate of 0.214 tonnes/MWH for this remaining 571 TWh of energy.

Under the three scenarios for the residual (non utility-owned coal) energy, we have cumulative emissions of either 109.5, 232, or 354 MMT of GHG associated with power imports over the 8 years of the cap. Given that the 2013 cap was based upon emissions of 53.53 MMT from imports, we treat $53.53 \cdot 8 = 428.24$ as the BAU level from imports. The low, medium, and high "reductions" in carbon from power imports would therefore be **74**, **197**, or **319 MMT**.

g. Offsets

The cap and trade program permits a covered entity to meet its compliance obligation with offset credits for up to eight percent of its annual and triennial compliance obligations. This means that over the 8-year program up to 218 MMT of allowance obligations could be met with offsets.

Thus far, ARB has approved four categories of compliance offset projects that can be used to generate offsets: U.S. Forest and Urban Forest Project Resources Projects; Livestock Projects; Ozone Depleting Substances Projects; and Urban Forest Projects. Each individual offset program is subject to a rigorous verification, approval, and monitoring process. The ARB has approved two offset project registries – American Carbon Registry[58] and the Climate Action Reserve[59] – to facilitate the listing, reporting, and verification of specific offset projects. The Climate Action Reserve reports there are approximately 11.5 million existing offsets that were generated under a voluntary early action offset program overseen by the Climate Action Reserve that are eligible for conversion to cap and trade program compliance offsets.[60]

Offsets are expected to be a relatively low-cost (though not free) means for a covered entity to meet a portion of its compliance obligation.[61] The number of offsets expected to be

58 See http://americancarbonregistry.org/carbon-accounting/california-compliance-offsets.

59 See http://www.climateactionreserve.org/.

60 Data collected from the "listed projects" tab at http://www.climateactionreserve.org/.

61 http://www.arb.ca.gov/regact/2010/capandtrade10/capv3appf.pdf.

available in the cap and trade program is subject to a high degree of uncertainty and best guesses put the estimate substantially below the potential number of offsets that could be used (*i.e.,* 8% of compliance obligations). One third-party study from September 2012 estimates the number of offsets available under all four protocols between 2013 and 2020 at 66 MMT, only 30% of the 218 MMT of offsets that theoretically could be used to satisfy compliance obligations.[62] ARB, however, is considering adding at least two additional offset protocols – Rice Cultivation and Coal Mine Methane Capture and Destruction. The addition of these two protocols is estimated to make an additional 64 MMT of offsets available (for an estimated total of 130 MMT) between 2013 and 2020.[63]

For the purposes of our analysis, we consider three scenarios for offsets, one based on the existing protocols (**66 MMT**), one that adds in estimates for rice cultivation and coal mine methane (**130 MMT**), and one that assumes the full allowed **218 MMT** of offsets are approved and utilized for compliance.[64] These offsets enhance the effective supply of allowances. Most estimates of the price at which offsets would be available put their cost at below or just above the auction reserve price. For all three scenarios we assume that the offsets utilized are available below the auction reserve price. In reality, studies suggest that some may require a price slightly above the auction reserve price, but still likely below $20/tonne. We group these with the abatement available at or slightly above the auction reserve price.

h. Aggregating Scenarios for Emissions Abatement

Table 5 summarizes the analyses of emissions abatement. For each abatement source and scenario, the number shown represents the total abatement that would occur over the life of the program at an allowance price equal to the highest price of the APCR for each year.[65] For each source, we also highlight what seems to be the most likely abatement

[62] http://americancarbonregistry.org/acr-compliance-offset-supply-forecast-for-the-ca-cap-and-trade-program.

[63] http://americancarbonregistry.org/acr-compliance-offset-supply-forecast-for-the-ca-cap-and-trade-program.

[64] The analysis described in this document assumes a single eight-year compliance time horizon. As a result, the analysis does not address the fact that current rules do not allow a shortfall of offsets in an earlier compliance periods to be recaptured in later time periods, and thus results in a permanent shortfall in offsets from the theoretical potential.

[65] Table 6 shows figures at an allowance price equal to the auction reserve price, the lowest price of the APCR, and the highest price of the APCR.

Price-reponsive Allowance Demand Reduction							
	Elasticities		Range of Energy Price Changes At Different Levels of Allowance Price Over 8 years ($2012):			Abatement over 8 years at highest APCR step each year (MM tons)	
Sector	*Low*	*High*	*Auction Reserve*	*Lowest step of APCR*	*Highest step of APCR*	*Low*	*High*
Electricity most C&I ($/MWh)	-0.20	-0.50	$4.74/$6.66	$18.04/$25.38	$22.55/$31.73	19.3	47.2
Transportation ($/Gallon)	-0.10	-0.40	$0.10/$0.12	$0.37/$0.47	$0.46/$0.59	10.6	44.1
Natural Gas ($/MMBTU)	-0.20	-0.40	$0.60/$0.80	$2.39/$3.06	$2.99/$3.82	19.4	37.5

Notes: All energy price changes assume 100% passthrough.
Range of price changes shown are for first and last year covered by cap and trade program
Range of price changes for Transportation and Natural Gas are for 2015-2020 only, electricity for 2013-2020
Range of Transportation price changes based on weighted average of gasoline and diesel
Transportation abatement impact is for tailpipe emissions only, does not include associated upstream emissions
Low case considered for natural gas is zero abatement, like result if utilities awarded allowances to cover this liability
GHG intensities assumed are explained in the text

Other Abatement Not Responsive to Allowance Price	*Low*	*High*
Electricity - Exogenous Price Increases for all customers	13.9	34.1
Transport price increase due to Low Carbon Fuel Standard	0	10
Offsets	66	218
Reshuffling	74.6	318.7

All "other abatement" assumed available at auction reserve price except offsets
Two-thirds of Offsets assumed available at auction reserve price, remainder as just above auction reserve price

Table 5: Summary of Emissions Abatement Assumptions

scenario.

From Table 5 we then aggregate the scenarios for emissions. By summing the minimum, medium, and maximum abatement figures by for each source, we create the minimum, likely, and maximum estimated abatement. The minimum and maximum aggregates, however, would require extreme outcomes for each of these sources, which is extremely unlikely. So, we create low and high scenarios as the average between the medium and the extreme outcomes. This is obviously somewhat arbitrary, but it allows us to show the sensitivity of allowance prices to the abatement level that is attained. These scenarios are shown in Table 6.

It is immediately clear from Table 6 that the greatest uncertainty in abatement supply to the market is in the use of offsets and the amount of reshuffling that will occur. Unfortunately, we currently have no way to narrow this uncertainty, which will be driven by

With more-stringent fuel economy standards	Very Low			Low			Medium			High			Very High		
	ARP	Low ACPR	HighACPR	ARP	Low ACPR	HighACPR	ARP	Low ACPR	HighACPR	ARP	Low ACPR	HighACPR	ARP	Low ACPR	HighACPR
Electricity elas	4.6	15.8	19.3	6.1	21.6	26.4	7.7	27.3	33.4	9.3	33.0	40.3	10.9	38.6	47.2
Transport elas	2.2	8.5	10.6	2.8	10.6	13.2	3.3	12.7	15.8	3.9	14.8	18.4	4.4	16.8	21.1
Nat Gas elas	0.0	0.0	0.0	2.0	7.8	9.7	4.1	15.5	19.4	6.0	22.8	28.5	7.9	30.0	37.5
Offsets	66.0	66.0	66.0	98.0	98.0	98.0	130.0	130.0	130.0	174.0	174.0	174.0	218.0	218.0	218.0
Electricity exog	13.9	13.9	13.9	19.0	19.0	19.0	24.1	24.1	24.1	29.1	29.1	29.1	34.1	34.1	34.1
Transport LCFS exog	0.0	0.0	0.0	2.5	2.5	2.5	5.0	5.0	5.0	7.5	7.5	7.5	10.0	10.0	10.0
Resource Shuffling exog	74.6	74.6	74.6	135.6	135.6	135.6	196.6	196.6	196.6	257.7	257.7	257.7	318.7	318.7	318.7
Total Specified Abatement	161.3	178.7	184.4	266.0	294.9	304.3	370.7	411.2	424.3	487.4	538.7	555.4	604.0	666.3	686.5
Changes with status quo fuel economy standards															
Transport elas	9.3	35.3	44.1	9.3	35.3	44.1	9.3	35.3	44.1	9.3	35.3	44.1	9.3	35.3	44.1
Total Specified Abatement	168.3	205.5	217.9	272.5	319.7	335.2	376.7	433.8	452.6	492.8	559.2	581.1	608.8	684.7	709.6

Table 6: Summary of Abatement Supply Scenarios

both unknown factors – such as the willingness of utilities out of California to sell cleaner power and buy coal-generated power – and by endogenous policy decisions – such as the speed of approval and stringency of new offset protocols and the degree of oversight and intervention to minimize reshuffling. Instead, we present results for a range of aggregate abatement figures and discuss scenarios that might result in those levels.

VI. SUPPLY/DEMAND BALANCE UNDER ALTERNATIVE SCENARIOS

In order to compute the probabilities of different price outcomes in California's GHG market, we combine the emissions simulations generated from the VAR models we estimated in Sections II and III with scenarios for abatement supply, offsets and reshuffling. We consider four mutually exclusive and exhaustive potential market clearing price ranges: (1) at or near the auction reserve price, with all abatement supply coming from low-cost abatement and offset supply, (2) noticeably above the auction reserve price, though without accessing any of the allowances in the allowance price containment reserve (APCR), with marginal supply coming from price-elastic sources, (3) above the lowest price at which allowances would be available from the APCR, but at or below the highest price of the APCR, and (4) above the highest price of the APCR.

We characterize price range (1) as "at or near" the auction reserve price for two reasons. First, the mechanism of the auction reserve price implies an uncertain economic price floor. The auction reserve price was set at \$10 per tonne for 2012 and then rising at 5% per year plus inflation. Setting aside the uncertainty of inflation, if investors' real cost of capital differs from 5%, then the effective economic price floor will not be the auction reserve price. If, for instance, investors' real cost of capital were 3% per year for an investment such as this, then the effective price floor today would be the present discounted value of the price floor in the last auction in which allowances are sold.[66] Thus, in any one year the effective economic price floor may differ somewhat from the auction reserve price. Second, we recognize that some offsets may require a price slightly above the auction reserve price.

As of this writing, the ARB is expected to implement new policies to address the possibility of the price containment reserve being exhausted. We do not address how high the price might go in case (4), which would be difficult to do even in the absence of this policy uncertainty, but in any case will be greatly influenced by the ARB's policy decisions scheduled to occur in the next year. We simply report the estimated probability of reaching this case.

Our analysis is in terms of real 2012 dollars, so there is no need to adjust for inflation, but the price trigger levels for the price containment reserve will, under current policy, increase at 5% in real terms every year. Thus, while the containment reserve is made available at prices from $40-$50 in 2013, the range escalates to $56.28-$70.35 in 2020 (in 2013 dollars). As we show below, the containment reserve prices are only likely to occur if BAU GHGs grow faster than anticipated over many years, so the most relevant containment reserve prices are those that will occur in the later years of market operations. Nonetheless, for the price-responsive abatement, we calculate response (for a given elasticity) as if the price is at the relevant step of the APCR in each year of the program.

We consider emissions forecasts from the VAR under the three different estimation approaches described in Section III: first with the VAR-forecasted transportation emissions intensity and then with two different adjustments that lower the assumed transport emissions intensity to reflect the impact of stricter fuel economy standards and greater biofuels share of retail fuel. We combine each scenario with the low, medium and high abatement scenarios that were described at the end of the last section.

We consider the medium availability scenario a good center of the possible outcomes. It is unlikely that all the low all the high cases for abatement and offset factors would occur, so we consider low cases and high cases as that for each source takes the average of the low and medium (for the low scenario) or the high and medium (for the high scenario).

[66] For example, if inflation were anticipated to be 2% per year, the nominal auction reserve price in 2020 would be $17.18. If investors anticipated some new sales of allowances in 2020 and their cost of capital was 3% per year, then the effective economic price floor in 2012 would be $17.18 discounted back to 2012 at 5% per year, or $11.63, rather than $10.

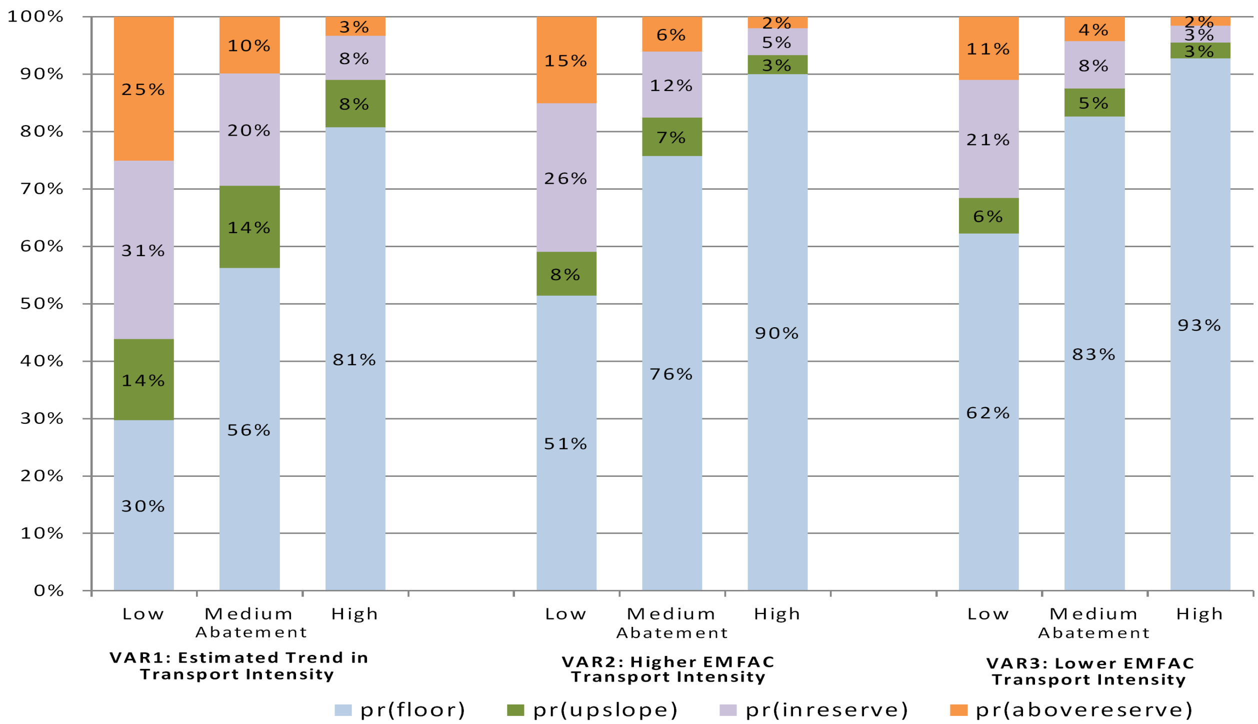

Figure 9: Allowance Price Probabilities By Scenario

We put these together with the predetermined allowance supply available (not counting allowances in the price containment reserve) to determine the supply through 2020 at prices below the lower trigger price for the containment reserve. At prices between the lower and upper trigger price for the containment reserve, we also added in the available supply from the containment reserve. We then combine the supply scenarios with the distribution of demand for greenhouse gas allowances under the three VAR estimation approaches discussed in Section III to determine the probabilities that the market outcome will fall in each of the four price ranges discussed above. Figure 9 shows these probabilities using each of the three demand estimation methods and each of the three supply scenarios.

Focusing on the middle bar of the graph – using the VAR with adjustment to the higher transport intensity from the EMFAC model and with medium abatement – the bar suggests that by 2020 there is a 76% probability that the allowance price will be at or near the auction reserve price, a 7% probability that it will be substantially above the auction reserve price, but still below the lowest price at which the containment reserve allowances can be sold, a 12% probability that the price will be within the range of the containment reserve, and an 6% probability that the containment reserve will be exhausted.

In contrast, if low, but plausible, abatement outcomes occur, then even with the assumed moderate improvements in transport emissions intensity of the VAR2 case, we estimate a 15% probability that the APCR will be exhausted and, absent other government intervention, the price would climb to above the levels of the APCR. The probability of triggering the APCR is 41% in that case. If the state is very successful in reducing transport emissions intensity, the VAR3 case, then the low abatement scenario still leaves an 11% probability of exhausting the APCR and a 32% probability of triggering the APCR.

The results make clear the importance of accomplishing high levels of what we have termed abatement, but the previous section and Table 6 make clear that the greatest variation in that category will come from offsets and reshuffling. Both of these reduce the need for abatement by covered entities. Over the range of prices from the auction reserve to the top of the APCR, price-responsive abatement, while not inconsequential, is likely to play a smaller role.

The three different VAR scenarios with different transport emission intensity paths also demonstrate that the effectiveness of the state in lowering transport emissions intensities will play a major role in determining the ultimate supply/demand balance in the market. If the state achieves the full range of planned policies in improving transport emissions intensities (the VAR3 cases in figure 9), then the probability of exhausting the APCR is below 10% under nearly all scenarios of other abatement methods. But if the state were to just maintain the existing trend in transport intensities, as estimated in the VAR1 case, then other abatement will need to be successful in order to keep the probability of exhausting the APCR in a low range.

Finally, the results demonstrate that the relationship between these scenarios of transport emissions intensities and abatement on the one hand and the allowance market outcome on the other hand is not at all deterministic. There is quite a bit of variation in the business as usual emissions, as shown in figure 9, resulting from uncertainty in GSP, fuel prices, and related factors. Without accounting for this BAU uncertainty, it is not possible to recognize the range of possible outcomes and how other policies change the probabilities out those outcomes.

VII. IMPLICATIONS FOR CURRENT POLICY PROPOSALS

In this paper, we have attempted to analyze the impact on the cap and trade market of

California's greenhouse gas policies as they are currently written. A number of proposals, however, are under consideration to modify the policies. In this section, we consider the potential impact of a few of those proposals.

a. Price Containment Reserve

As described above, the allowance price containment reserve was established to help to mitigate undue volatility in allowance prices. It is accompanied by an associated floor price that will be enforced in the allowance auctions. As currently configured the reserve has a finite number of allowances available. The ARB has considered changes that would permit allowances from later years (of the 2013 to 2020 program) to be shifted to earlier years if the price rises to a sufficiently high level. This is a useful response to the concern that the first compliance period (2013-14) could have a shortage of supply. The Board's action, however, doesn't address the more significant threat, examined here, that there could be a supply/demand mismatch for the entire 8-year program.

Left unchanged, current regulations suggest that if demand for allowances exceeds supply at the highest price of the APCR, the allowance price would be allowed to rise to any level that is necessary to ratchet down allowance demand to meet the capped supply. However, we believe that it is highly unlikely that the political and regulatory process would allow the market to continue to operate freely at unduly high allowance prices, such as above the highest tier of the APCR. Such an intervention in the California GHG market is currently not well defined in the regulation and would almost certainly be more disruptive when taken under duress.

Recent developments appear to increase the prospects for a practical implementation of this option. Board Resolution 13-44 of October 25, 2013, directs the Executive Officer to develop a plan for a post-2020 Cap-and-Trade Program, including cost containment, before the beginning of its third compliance period to provide market certainty and address a potential 2030 emissions target. This resolution provides a starting point for a policy that enforces a credible maximum price for the pre-2020 period by borrowing allowances from the post-2020 compliance period.

b. Expanding Renewable Portfolio Standard

Our analysis assumed complete attainment of a 33% Renewable Portfolio Standard by 2020. Proposals are now being widely discussed in California to raise that standard, possibly to 50% by 2030. If all of the incremental renewables increase occurred after 2020, then our analysis of the program only through 2020 would be unchanged. This, however, highlights the importance of any post-2020 policy that would maintain the value of allowances banked past 2020 or would allow borrowing from post-2020 allowance supply.

To the extent that a change in the RPS accelerates the supply of energy from renewable sources in the period up to and including 2020, this would have the effect of widening the flat portion of the supply curve that is at or near the price floor. Even though such renewables might not be economic with an allowance price at the floor, if they are mandated by a complementary environmental policy, then this would still have the effect of increasing the supply of abatement independent of the price of allowances, that is, even at a price of zero. Thus, to the extent that expanding the RPS policy increases low-price supply of abatement, it raises the probability of an equilibrium allowance price at or near the floor and lowers the probability of high allowance prices.

c. Free Allowances for Emissions from Transportation Fuels and Natural Gas

Some reports and policy discussions at ARB stakeholder meetings suggest that state policy might be altered to distribute free allowances to cover emissions from some or all burning of transportation fuels or end-use natural gas consumption. The impact of such policies would depend in large part on how the allowances are distributed and how, if at all, the free distribution would affect retail prices. We assume that such free distribution of allowances would not change the total supply of allowances, but instead would be taken from the supply in allowance auctions.

Virtually all analyses agree that distributing an exogenously-determined fixed quantity of allowances for free to refiners (and other fuel distributors) in the unregulated fuels sector would have no effect on the price of fuels. That is, fuel prices would still fully incorporate the market price of the associated greenhouse gas emissions. This is simply because a refiner would face the opportunity cost of using an allowance to sell more fuel, and that opportunity cost is the price at which the allowance could be resold in the allowance market. Thus, such a policy would not change incentives for abatement and would not change the supply/demand analysis above. It would transfer significant wealth from the state budget accounts that receive auction revenues to the refining companies that would be given the free allowances.

Some proposals suggest that the free allocations to refiners (and other fuel distributors) should be based on sales using output-based updating. If the allocation were for 100% of sales, then the free allocations would exactly match sales and the cap and trade system would not impact fuel prices at all. The price would not rise to reflect any of the cost of emissions and the companies distributing fuels would see no impact on their profits. In addition, there would be no fuel and greenhouse gas savings from a price-elastic response to incorporating greenhouse gases. So, the abatement from reduced fuel usage discussed in section V.a would not occur, reducing the price responsiveness of abatement supply and increasing the probability of a high-price outcome for allowances.

To the extent that the output-based updating is less than 100%, some share of the allowance price would be incorporated into the price of fuels. If, for instance, the free allocation covered 80% of the emissions for which a distributor was responsible, then the effective cost of selling fuel would include the cost of covering 20% of emissions through purchases of allowances. This cost would be passed along in the retail price, resulting in 80% less elasticity than would be the case with no output-based updating (as in section V.a).

Free allowances for emissions have a somewhat different impact in natural gas because the entity responsible for compliance would be an investor-owned or government-owned public utility. In that case, the degree to which the free allowances impact retail rates would depend very much on the policy decision of the regulator or government of how to use the gains from the free allowances. With either fixed-quantity distribution or output-based updating, the utility would receive valuable allowances, and in either case they could redistribute that value to customers by lowering retail prices or through some lump-sum transfer. Experience suggests lump-sum transfers are fairly rare. Using the free allowances to suppress retail prices would again reduce the price responsiveness of abatement supply and increase the probability of allowance prices ending up in the high-price range.

While free allowances that result in suppressed prices for fuels and natural gas are obviously inconsistent with the basic concept of cap and trade, our analysis suggests that the expected impact on allowances prices might not be large. If an effective price ceiling is imposed at the highest tier of the price containment reserve, then our analysis suggests that the impact of the allowance price responsiveness of abatement is modest to begin with. While eliminating much of that elasticity from transportation fuels and natural gas consumption with output-based updating – or other free allowance programs that suppress the passthrough of allowance costs to retail price – is not helpful in incenting abatement, it's impact is likely to be limited. This is because as allowance prices increase from the auction price floor to highest price step in the APCR, our allowance price elasticity assumptions imply limited emissions reductions.

d. Auction Frequency and Emissions Information Disclosure

Our conclusion that the abatement supply curve is likely to be flat over a wide range and then fairly steeply upward sloping has potentially important implications for the impact that new information might have on the market. If at some point in the program the supply demand balance is thought to be close to exhausting the supply of cheap (or required by complementary policies) abatement and offsets, then small changes in beliefs about abatement demand or supply could cause very large price movements. Some parties have suggested that more frequent auctions be held and/or that market or sector level emissions information be released more often. Both of these changes could potentially reduce large information shocks to the market and thus help to mitigate the price volatility that could result from a steep abatement supply curve.

Frequent public auctions would result in timely and transparent allowance prices available to all market participants at no cost. Current policy is for quarterly auctions. Whether more frequent auctions would reduce volatility is in part a function of how quickly new information about the supply/demand balance becomes available. One potential concern about frequent auctions is liquidity. To increase participation, as well as reduce transaction costs for market participants, it could be helpful to conduct two-sided auctions in which participants are permitted to submit sell offers as well as purchase bids.

Even with frequent auctions that result in transparent prices, there is concern that some confidential information may become available only intermittently and could cause volatility. Measures of industry activity may allow analysts to predict emissions fairly well from many sectors. One area, however, where this is less certainty is electricity imports. Emissions from electricity imports will depend on the declared source of the power, and could vary from zero for renewable sources, to the default emissions rate for unspecified sources, to more than twice the default rate for power from a coal-fired plant. There seems to be a real potential for the annual ARB GHG emissions inventory reports to have substantial impact on prices.

This problem is exacerbated by the timing of such reports, generally planned to cover a calendar and be released in November of the following year. This means, for instance, that the first ARB report on emissions during the program period will be in November 2014, covering 2013. No more information will be released before December 31, 2014 when the first compliance period ends. At that point, all demand elasticity and virtually all supply elasticity for the first compliance period disappears with the exception of elasticity from allowances that were to be banked for future compliance periods. More frequent information releases would seem to have substantial value, particularly if there were done with a shorter lag from the time period covered.

There are, of course, very real administrative costs of more frequent auctions and more frequent and timely information releases. These must be weighed against the potential benefits. The benefits, however, may be substantial, particularly in light of the steep abatement supply curve once low-cost offsets, complimentary policies, and other exogenous emissions reductions are exhausted.

VIII. CONCLUSION

Economists have for decades advocated using market mechanisms to reduce pollution externalities. California has now embarked on a plan to reduce greenhouse gas emissions through such a market mechanism, a cap and trade program. The price that comes out of that market will have important distributional and political impacts. That possible distribution of the California allowance price will depend on the demand for the emissions allowances, resulting from firms and individuals who wish to engage in GHG-emitting activities, and the supply of both emissions allowances and the ability to reduce emissions.

We have shown that there is significant uncertainty in both the demand and supply in this market. Furthermore, it seems likely that the great majority of available abatement supply will occur independently of the allowance price or at prices near the price floor. As a proportion of the market, our analysis indicates that fairly little additional supply will be forthcoming at prices substantially above the floor, but still below the price that will trigger "safety valve" releases of additional allowances from the auction price containment reserve (APCR). Combined with the uncertainty in the demand for allowances, this suggests that the market price is unlikely to fall in an intermediate range substantially above the auction reserve price, but still below the level at which allowances from the price containment reserve would be made available. A significant driver of this outcome is the fact that several program design features that enhance the political viability of the program also steepen the supply curve of abatement at prices between the auction floor and first step of the APCR.

Our analysis also suggests that there is a small, but not insignificant, chance that the demand for emissions allowances could exceed the available supply after accounting for abatement activity and the supply of emissions offsets. This possibility supports the view expressed by ARB in October 2013 that it is prudent to pursue further policies that would prevent the price from skyrocketing if demand for emissions allowances turned out to be much stronger than expected.

It is important to note that the scenarios under which the price for emissions could climb very high by 2020 may not produce high prices in 2013. High prices towards the end of the program would result from unexpectedly strong demand and/or low abatement/offset supply over the years 2013-2020. Our analysis suggests that such outcomes are plausible, but are not the most likely outcome. The price of allowances in 2013 reflects the full distribution of potential supply/demand outcomes that could occur over the life of the program. If demand for allowances turned out to be higher than expected over the subsequent years (owing most likely to stronger than expected economic growth in the state) or the supply of abatement/offsets were lower than expected (owing to smaller effects of complementary policies than anticipated, smaller offset supply than anticipated, or other factors) then we would expect that the market price would gradually increase over these years to reflect the increased probability that a shortage of allowances could occur by the end of the program.

The potential for there being a range of outcomes in which the supply of abatement/offsets is very price inelastic (*i.e.,* a steep supply curve) also raises concerns that small changes in the demand for allowances might have substantial effects on the allowance price. Such a situation is at least a warning that there might be the potential for non-competitive activities by some market participants that could artificially inflate or depress the price. In ongoing work, we are examining these possibilities in more detail.

These estimates for the California market have broad implications for the design of cap and trade markets to address climate change. The counterfactual emissions levels from which reductions will occur are often taken as known quantities. There is, in fact, a great deal of uncertainty in such BAU emissions forecasts and, thus, uncertainty in the demand for allowances and abatement. At the same time, many of the policies that are being instituted in areas where cap and trade programs are in place or anticipated will reduce the price-responsiveness of abatement. Some such policies *require* certain emissions-reducing actions be taken regardless of the allowance price, while others buffer stakeholders from allowance prices in a way that reduces their incentive to respond when those prices rise. The combination of uncertain allowance demand and price-inelastic allowance/abatement supply increases the probability of price volatility and of very high or low equilibrium prices. After one year of operation, California's outcome has been consistent with this analysis, as allowance prices have remained very close to the price floor. Price histories in the EU-ETS and the Northeastern U.S. RGGI markets also lend support to this conclusion.

References

Aldy, Joseph E., Alan J. Krupnick, Richard G. Newell, Ian W.H. Parry, and William A. Pizer. "Designing climate mitigation policy," National Bureau of Economic Research Working Paper #15022, June 2009.

Burtraw, Dallas, Karen Palmer, and Danny Kahn. "A Symmetric Safety Valve." Discussion Paper 09-06. Washington D.C.: Resources for the Future.

Bushnell, James, and Yihsu Chen. "Allocation and leakage in regional cap-and-trade markets for CO2." *Resource and Energy Economics* **34**(4), (2012): 647-668.

Bushnell, James, Yihsu Chen, and Matthew Zaragoza-Watkins. "Downstream regulation of CO2 emissions in California's electricity sector." *Energy Policy* **64**, (2014): 313-323.

California Air Resources Board, "Appendix F to the California Cap on Greenhouse Gas Emissions and Market Based Compliance Mechanisms: Compliance Pathways Analysis." (2010).

California Air Resources Board, "Board Resolution 12-51." (2012).

California Air Resources Board, "California Cap on Greenhouse Gas Emissions and Market Based Compliance Mechanisms." (2013).

California Air Resources Board, "Greenhouse Gas Emissions Inventory Technical Support Document." (2010).

California Air Resources Board, "Initial Statement of Reasons: Amendments to the California Cap on Greenhouse Gas Emissions and Market Based Compliance Mechanisms." (2013).

California Air Resources Board, "Regulation for the Mandatory Reporting of Greenhouse Gas Emissions." (2011).

California Air Resources Board, "Updated Economic Analysis of California's Climate Change Scoping Plan." (2010).

California Energy Commission, "California Installed Capacity and Generation." (2012).

California Energy Commission, "Energy Consumption Database." (2013).

California Public Utilities Commission, "Renewable Portfolio Standard Calculator for the Transmission Planning Process." (2013).

California Public Utilities Commission, "Decision Adopting a Cap and Trade Greenhouse Gas Allowance Revenue Allocation Methodology for the Investor-Owned Electric Utilities." (2012).

Dahl, Carol A., " Measuring global gasoline and diesel price and income elasticities." *Energy Policy* **41**, (2012): 2-13.

Dickey, David A., and Wayne A. Fuller. "Distribution of the estimators for autoregressive time series with a unit root." *Journal of the American Statistical Association* **74**(366a), (1979): 427-431.

Efron, Bradley, and Robert Tibshirani. *An introduction to the bootstrap.* Vol. 57. CRC press, 1993.

Ellerman, A. Denny, and Barbara K. Buchner. "Over-allocation or abatement? A preliminary analysis of the EU ETS based on the 2005-06 emissions data." *Environmental and Resource Economics* **41**(2), (2008): 267-287.

Engle, Robert F., and Granger, Clive W., "Co-integration error correction: Representation, estimation and testing." *Econometrica* **55**(2), (1987): 251-276.

Engle, Robert F., and Byung Sam Yoo. "Forecasting and testing in co-integrated systems." *Journal of Econometrics* **35**(1), (1987): 143-159.

Fowlie, Meredith. "Updating the allocation of greenhouse gas emissions permits in a federal cap-and-trade program." in *The design and implementation of US climate policy*, Don Fullerton and Catherine Wolfram, editors (2011).

Holland, Stephen and Moore, Michael R. "Market design in cap and trade programs: Permit validity and compliance timing," *Journal of Environmental Economics and Management*, **66**(3), (2013): 671-687.

Hughes, Jonathan E., Christopher R. Knittel and Daniel Sperling, "Evidence of a shift in the short-run price elasticity of gasoline." *The Energy Journal*, **29**(1), (2008): 113-34.

Ito, Koichiro. "Do consumers respond to marginal or average price? Evidence from nonlinear electricity pricing." *American Economic Review*, (Forthcoming).

Johansen, Sren. "Statistical analysis of cointegration vectors." *Journal of Economic Dynamics and Control*, **12**, (1988): 231-254

Johansen, Sren. *Likelihood-based inference in cointegrated vector autoregressive models.* New York: Oxford University Press, (1995).

Kamerschen, David R., and David V. Porter. "The demand for residential, industrial and total electricity, 1973-1998." *Energy Economics*, **26**(1), (2004): 87-100.

Kling, Catherine L., and Jonathan Rubin. "Bankable Permits for the Control of Environmental Pollution." *Journal of Public Economics* 64(1), (1997): 101115.

Pizer, William A. "Combining price and quantity controls to mitigate global climate change." *Journal of Public Economics*, **85**(3), (2002): 409-434.

Stock, James H., and Mark W. Watson. "Vector autoregressions." *The Journal of Economic Perspectives*, **15**(4), (2001): 101-115.

U.S. Bureau of Economic Analysis, "Real Gross Domestic Product by State." (2012).

U.S. Energy Information Administration, "California Average Retail Price of Electricity to Ultimate Customers by End-Use Sector." (2013).

U.S. Energy Information Administration, "California Natural Gas Prices." (2013).

U.S. Energy Information Administration, "California Weekly Retail Gasoline and Diesel Prices." (2012).

APPENDIX

Parameter Estimates and Unit Root/Cointegration Tests for VAR

This appendix describes the results of the unit root tests for each of the individual elements of the vector Y_t, the results of the cointegrating rank tests for the vector autoregressive model for Y_t, and presents the parameter estimates of the error correction vector autogressive model that is used to perform our simulations.

The following variable definitions are used throughout this appendix.

ln_twh_p_hydro = Natural logarithm of instate electricity production net of hydroelectric generation (terawatt-hours (TWh))]

ln_vmt = Natural logarithm of total vehicle-miles travelled (thousands of miles)

ln_ngother_industrial = Natural logarithm of emissions from non-electricity-generation natural gas combustion and other industrial processes (millions of metric tons (MMT) of GHGs)]

ln_real_gas_price = Natural logarithm of Real Retail Gasoline price ($2011/gallon)

ln_real_gsp = Natural logarithm of Real Gross State Product ($2011)

ln_thermal_intensity = Natural logarithm of Emissions Intensity of In-State Thermal Generation (metric tons/MWh)

ln_transport_intensity = Natural logarithm of Emissions Intensity of Vehicle Miles Travelled (metric tons/thousand miles)

We perform three versions of the unit root test for each element of Y_t and report two test statistics for each hypothesis test. Let Y_{it} equal the ith element of Y_t. The first version of the unit root test, the zero mean version, assumes Y_{it} follows the model,

$$Y_{it} = \alpha Y_{it-1} + \eta_{it} \qquad (ZeroMean)$$

meaning that Y_{it} is assumed to have a zero mean under both the null and alternative hypothesis. The hypothesis test for this model is H: $\alpha = 1$ versus K: $\alpha < 1$. We report two test statistics for this null hypothesis

$$\hat{\rho} = T(\hat{\alpha} - 1) \qquad \text{and} \qquad \hat{\tau} = \frac{\hat{\alpha} - 1}{SE(\hat{\alpha})}$$

where $\hat{\alpha}$ is the ordinary least squares (OLS) estimate of α and $SE(\hat{\alpha})$ is OLS standard error estimate for $\hat{\alpha}$ from a regression without a constant term and T is the number of

Variable	Type	$\hat{\rho}$	$Pr < \hat{\rho}$	$\hat{\tau}$	$Pr < \hat{\tau}$
ln_twh_p_hydro	Zero Mean	0.01	0.67	0.44	0.80
	Single Mean	-6.77	0.24	-1.86	0.34
	Trend	-15.04	0.08	-2.26	0.43
ln_vmt	Zero Mean	0.01	0.67	1.45	0.96
	Single Mean	-2.37	0.72	-2.36	0.16
	Trend	0.26	0.99	0.09	0.99
ln_ngother_industrial	Zero Mean	0.00	0.67	-0.07	0.65
	Single Mean	-19.04	0.00	-3.00	0.05
	Trend	-18.56	0.02	-2.87	0.19
ln_real_gas_price	Zero Mean	0.79	0.86	1.27	0.94
	Single Mean	0.01	0.95	0.00	0.95
	Trend	-10.60	0.29	-2.30	0.42
ln_real_gsp	Zero Mean	0.03	0.68	1.30	0.95
	Single Mean	-2.73	0.67	-1.72	0.41
	Trend	-18.46	0.02	-2.01	0.56
ln_thermal_intensity	Zero Mean	0.35	0.76	1.84	0.98
	Single Mean	0.44	0.97	0.27	0.97
	Trend	-5.15	0.77	-1.55	0.78
ln_transport_intensity	Zero Mean	0.01	0.67	1.02	0.91
	Single Mean	1.01	0.98	0.28	0.97
	Trend	-2.35	0.95	-0.62	0.97

Table A-1: Unit Root Test Statistics

observations in the regression. The column labeled "$Pr < \hat{\rho}$" is the probability that a random variable with the asymptotic distribution of the $\hat{\rho}$ under the null hypothesis is less than the value of the statistic in the column labeled "$\hat{\rho}$". The column labeled "$Pr < \hat{\tau}$" is the probability that a random variable with the asymptotic distribution of the $\hat{\tau}$ under the null hypothesis is less than the value of the statistic in the column labeled "$\hat{\tau}$".

The second version of the unit root test is the single mean. In this case the assumed model is:

$$Y_{it} = \mu + \alpha Y_{it-1} + \eta_{it} \qquad (SingleMean)$$

where $\mu \neq 0$. The hypothesis test is still H: $\alpha = 1$ versus K: $\alpha < 1$. The two test statistics for this null hypothesis are

$$\hat{\rho} = T(\hat{\alpha} - 1) \qquad \text{and} \qquad \hat{\tau} = \frac{\hat{\alpha} - 1}{SE(\hat{\alpha})}$$

where $\hat{\alpha}$ is the ordinary least squares (OLS) estimate of α and $SE(\hat{\alpha})$ is OLS standard error estimate for $\hat{\alpha}$ from a regression that includes a constant term and T is the number of observations in the regression. The test statistics and probability values are reported in the same manner as for the zero mean version of the test statistic.

The third version of the test assumes that the mean of Y_{it} contains a time trend so that the assumed model is:

$$Y_{it} = \mu + \nu t + \alpha Y_{it-1} + \eta_{it} \qquad (Trend)$$

Table A-2: Cointegration Rank Test Using Trace				
H0:	H1:	Eigenvalue	LR(r)	5% Critical Value
Rank=r	Rank>r			
0	0	0.9095	155.59	123.04
1	1	0.8448	105.15	93.92
2	2	0.6599	66.02	68.68
3	3	0.6077	43.37	47.21
4	4	0.4727	23.72	29.38
5	5	0.2937	10.28	15.34
6	6	0.1323	2.98	3.84

Table A-2: Cointegration Rank Test Using Trace

where $\mu \neq 0$ and $\nu \neq 0$. The hypothesis test is still H: $\alpha = 1$ versus K: $\alpha < 1$. The two test statistics for this null hypothesis are again

$$\hat{\rho} = T(\hat{\alpha} - 1) \qquad \text{and} \qquad \hat{\tau} = \frac{\hat{\alpha} - 1}{SE(\hat{\alpha})}$$

where $\hat{\alpha}$ is the ordinary least squares (OLS) estimate of α and $SE(\hat{\alpha})$ is OLS standard error estimate for $\hat{\alpha}$ from a regression that includes a constant term and a time trend, and T is the number of observations in the regression. The test statistics and probability values are reported in the same manner as for the zero mean version of the test statistic.

For all three versions of the unit root test and two test statistics, there is little evidence against the null hypothesis in all seven elements of the Y_t. In all but a few cases, the probability value is greater than 0.05, which implies no evidence against the null hypothesis for a size 0.05 test of the null hypothesis. Although there are a few instances of probability values less than 0.05, this to be expected even if the null hypothesis is true for all of the series, because the probability of rejecting the null given it is true for a 0.05 size test is 0.05.

Table A-2 presents the results of our cointegrating matrix rank tests. In terms of the notation of our error correction model

$$\Delta Y_t = \mu + \Lambda Y_{t-1} + \epsilon_t \qquad (A-1)$$

where Λ is (7x7) matrix that satisfies the restriction $\Lambda = -\gamma\alpha'$ and γ and α are (7 x r) matrices of rank r. Hypothesis test is H: $Rank(\Lambda) = r$ versus K: $Rank(\Lambda) > r$, where r is less than or equal to 7, the dimension of Y_t. Each row of the table presents the results of Johansen's (1988) likelihood ratio test of the null hypothesis that $Rank(\Lambda) = r$ against the alternative that $Rank(\Lambda) > r$, for a given value of r. Johansen (1995) recommends a multi-step procedure starting from the null hypothesis that $Rank(\Lambda) = r = 0$ and then proceeding with increasing values of r until the null hypothesis is not rejected or all null hypotheses are rejected in order to determine the rank of Λ. Rejecting the null hypothesis for all values of r would imply that the elements of Y_t are not cointegrated.

The column labelled "LR(r) " is Johansen's (1988) likelihood ratio statistic for the cointegrating rank hypothesis test for the value of r on that row of the table. The column labelled "5% Critical Value" is the upper 5th percentile of the asymptotic distribution of the LR statistic under the null hypothesis. The column labelled "Eigenvalue" contains the second largest to smallest eigenvalue of the estimated value of Λ. Let $1 > \hat{\lambda}_1 > \hat{\lambda}_2, ... > \hat{\lambda}_K$ equal the eigenvalues of the maximum likelihood estimate of Λ ordered from largest to smallest. The LR(r) statistic for test H: $Rank(\Lambda) = r$ versus K: $Rank(\Lambda) > r$ is equal to

$$LR(r) = -T \sum_{j=r+1}^{K} ln(1 - \hat{\lambda}_j)$$

Following Johansen's procedure, we find that the null hypothesis is rejected for r = 0 and r = 1, but we do not reject the null hypothesis at a 0.05 level for r = 2 or for any value larger than 2. For this reason, we impose the restriction that rank of Λ is equal to 2 in estimating and simulating from our error correction vector autoregressive model.

Table A-3 presents the results of estimating our error correction vector autoregressive model in the notation in equation (A-1). The prefix "Δ" is equal to $(1 - L)$, which means that the dependent variable in each equation is the first difference of variable that follows. The variable Λ_i_j is the (i,j) element of Λ and μ_j is the jth element of μ.

Transportation Emissions

The California data were reportedly constructed by the California Department of Transportation (CalTrans) from a mix of in-road traffic monitors (*e.g.,* from the California Performance Measurement System (PeMS)) and traffic counts conducted by CalTrans. Figure A-1 displays the series of annual California on-road VMT as reported in these surveys.

While these data measure on-road VMT, the cap and trade program caps emissions from all diesel and gasoline combusted as transportation fuel in California, regardless of whether the fuel is combusted on-road or off-road. Therefore, this measure of on-road VMT understates the total VMT covered under the cap and (when carried through our calculations) overstates average emissions factors for on-road VMT. Critically, because certain complementary policies target vehicle emissions factors, an overstated measure of "business-as-usual" emissions factors could lead us to conclude that complementary policies should be expected to achieve a larger impact than might realistically be feasible.

To address this potential source of bias we deviate from ARB's emissions categorization by excluding GHG emissions from off-road vehicle activities from the transportation sector, in favor of categorizing them into "Natural Gas and Other". Therefore, beginning with total transportation sector combustion emissions, we partition emissions into on-road and

Equation	Parameter	Estimate	Std Err	Variable
Δ_ln_twh_p_hydro	μ_1	-1.6518	2.0290	1
	Λ_1_1	-0.7333	0.2648	ln_twh_p_hydro(t-1)
	Λ_1_2	0.7430	0.2762	ln_vmt(t-1)
	Λ_1_3	-0.2489	0.0995	ln_ngother_industrial(t-1)
	Λ_1_4	0.4276	0.2695	ln_real_gas_price(t-1)
	Λ_1_5	-0.2619	0.0962	ln_real_gsp(t-1)
	Λ_1_6	0.6383	0.5114	ln_thermal_intensity(t-1)
	Λ_1_7	-0.0706	0.0405	ln_transport_intensity(t-1)
Δ_ln_vmt	μ_2	-0.3245	0.3854	1
	Λ_2_1	0.0481	0.0503	ln_twh_p_hydro(t-1)
	Λ_2_2	-0.0265	0.0525	ln_vmt(t-1)
	Λ_2_3	0.0239	0.0189	ln_ngother_industrial(t-1)
	Λ_2_4	-0.0733	0.0512	ln_real_gas_price(t-1)
	Λ_2_5	0.0194	0.0183	ln_real_gsp(t-1)
	Λ_2_6	-0.1375	0.0971	ln_thermal_intensity(t-1)
	Λ_2_7	0.0110	0.0077	ln_transport_intensity(t-1)
Δ_ln_ngother_industrial	μ_3	-1.3596	0.7855	1
	Λ_3_1	-0.1799	0.1025	ln_twh_p_hydro(t-1)
	Λ_3_2	0.2300	0.1069	ln_vmt(t-1)
	Λ_3_3	-0.0449	0.0385	ln_ngother_industrial(t-1)
	Λ_3_4	0.0078	0.1043	ln_real_gas_price(t-1)
	Λ_3_5	-0.0595	0.0372	ln_real_gsp(t-1)
	Λ_3_6	-0.0485	0.1980	ln_thermal_intensity(t-1)
	Λ_3_7	-0.0036	0.0157	ln_transport_intensity(t-1)
Δ_ln_real_gas_price	μ_4	-9.2245	2.5068	1
	Λ_4_1	0.3356	0.3272	ln_twh_p_hydro(t-1)
	Λ_4_2	0.1628	0.3412	ln_vmt(t-1)
	Λ_4_3	0.2840	0.1229	ln_ngother_industrial(t-1)
	Λ_4_4	-1.2189	0.3329	ln_real_gas_price(t-1)
	Λ_4_5	0.1695	0.1188	ln_real_gsp(t-1)
	Λ_4_6	-2.4524	0.6318	ln_thermal_intensity(t-1)
	Λ_4_7	0.1766	0.0501	ln_transport_intensity(t-1)
Δ_ln_real_gsp	μ_5	-2.9867	0.4974	1
	Λ_5_1	-0.1127	0.0649	ln_twh_p_hydro(t-1)
	Λ_5_2	0.2522	0.0677	ln_vmt(t-1)
	Λ_5_3	0.0084	0.0244	ln_ngother_industrial(t-1)
	Λ_5_4	-0.2151	0.0661	ln_real_gas_price(t-1)
	Λ_5_5	-0.0266	0.0236	ln_real_gsp(t-1)
	Λ_5_6	-0.4948	0.1254	ln_thermal_intensity(t-1)
	Λ_5_7	0.0288	0.0099	ln_transport_intensity(t-1)
Δ_ln_thermal_intensity	μ_6	0.9922	1.0852	1
	Λ_6_1	-0.0808	0.1416	ln_twh_p_hydro(t-1)
	Λ_6_2	0.0223	0.1477	ln_vmt(t-1)
	Λ_6_3	-0.0476	0.0532	ln_ngother_industrial(t-1)
	Λ_6_4	0.1683	0.1441	ln_real_gas_price(t-1)
	Λ_6_5	-0.0348	0.0514	ln_real_gsp(t-1)
	Λ_6_6	0.3263	0.2735	ln_thermal_intensity(t-1)
	Λ_6_7	-0.0249	0.0217	ln_transport_intensity(t-1)
Δ_ln_transport_intensity	μ_7	-0.5789	0.6728	1
	Λ_7_1	-0.0813	0.0878	ln_twh_p_hydro(t-1)
	Λ_7_2	0.1019	0.0916	ln_vmt(t-1)
	Λ_7_3	-0.0210	0.0330	ln_ngother_industrial(t-1)
	Λ_7_4	0.0077	0.0894	ln_real_gas_price(t-1)
	Λ_7_5	-0.0271	0.0319	ln_real_gsp(t-1)
	Λ_7_6	-0.0131	0.1696	ln_thermal_intensity(t-1)
	Λ_7_7	-0.0022	0.0134	ln_transport_intensity(t-1)

Table A-3: Error Correction Vector Autoregression Parameter Estimates

off-road activities using the more granular activity-based emissions values reported in the combined 1990-2004 and 2000-2011 Emissions Inventories. Table A-4 reports the results of this partition, revealing the contribution of off-road emissions to be small and somewhat weakly correlated with total transportation sector emissions, ranging from a low of 2.57% in 1993 to a high of 4.52% in 2006, around a mean of 3.55%.

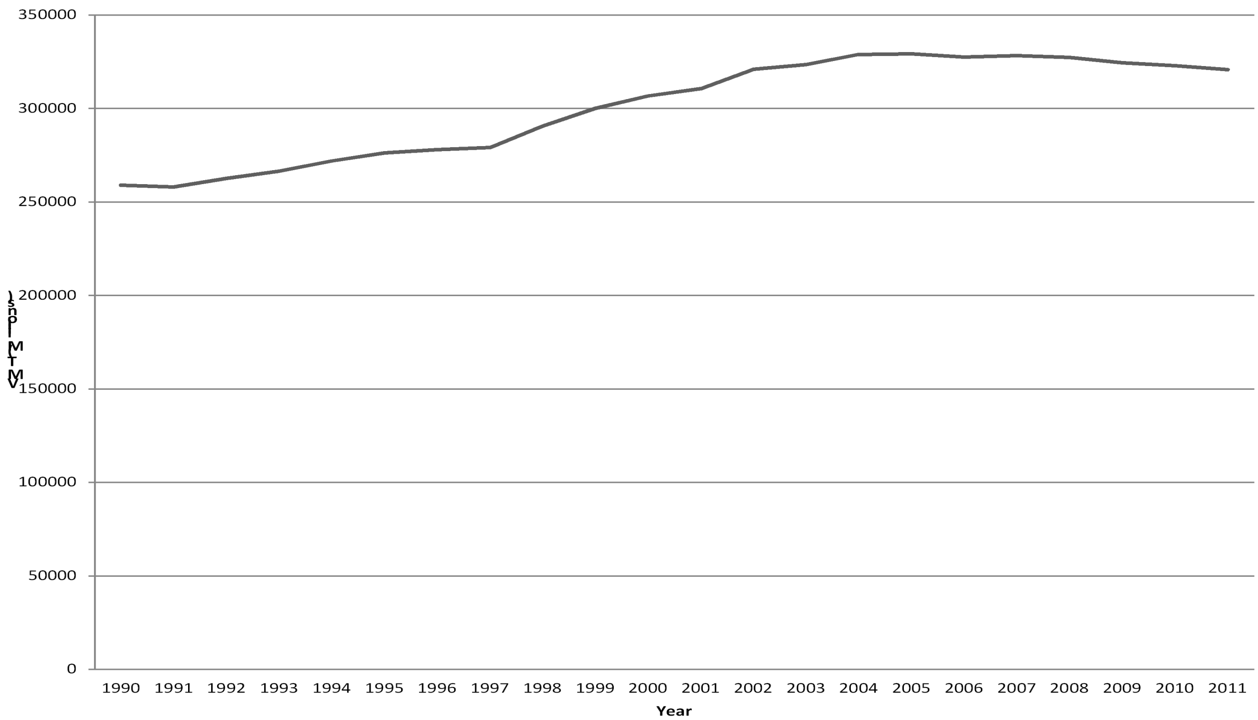

Figure A-1: Annual California On-road VMT 1990-2011

As described above, our approach to forecasting emissions from the transportation sector is to decompose GHG emissions into its VMT component and an average emissions factor per mile of travel. Separating emissions into VMT and an average emissions factor allows us to more accurately capture the underlying drivers of GHG emissions trends and to better model the effects of complementary policies that may cause these emissions drivers to deviate from their preexisting trends. Essentially, our data are derived from the basic identity relating annual GHG emissions to annual VMT and an annual average emissions factor per mile:

$$GHG_t = VMT_t \cdot \bar{EI}_t.$$

To decompose transportation sector GHG emissions into VMT (miles) and an average emissions factor per mile (grams/mile), we take our adapted series of transportation sector GHG emissions (described above) as given, and divide annual GHG emissions by our measure of VMT, the ratio of which is our implied average emissions factor per mile of travel. Table A-5 reports our adjusted transportation sector emissions, OHI VMT, and the calculated average annual emissions factors for on-road activity over the period 1990-2011.

Year	Off-road (MMT)	On-road (MMT)	Share On-road
1990	6.09	137.96	95.77%
1991	6.18	134.45	95.61%
1992	5.15	141.73	96.49%
1993	3.68	139.40	97.43%
1994	4.77	140.42	96.71%
1995	4.97	143.53	96.65%
1996	4.78	145.00	96.81%
1997	4.54	148.31	97.03%
1998	4.23	151.25	97.28%
1999	4.30	155.80	97.31%
2000	5.33	163.48	96.84%
2001	5.54	163.58	96.72%
2002	6.17	169.88	96.49%
2003	6.50	166.35	96.24%
2004	6.95	167.45	96.02%
2005	7.62	167.69	95.66%
2006	7.94	167.65	95.48%
2007	7.40	167.56	95.77%
2008	6.23	157.04	96.18%
2009	5.22	153.28	96.71%
2010	5.40	149.19	96.51%
2011	5.67	146.08	96.26%

Table A-4: On-road and Off-road Transportation Emissions 1990-2011

Transportation Complimentary Policies

To incorporate the impact of complimentary policies targeting the transportation sector, we use EMFAC 2011, the ARB's tool for forecasting fleet composition and activity in the transportation sector. The advantage of explicitly modeling on-road vehicle fleet composition and activity is that we can more precisely simulate the impact of complimentary policies that are designed to directly target specific segments of the vehicle fleet. Moreover, because vehicles are long-lived durable goods, it is advantageous for a model to be capable of carrying forward the effects of earlier policies as the composition of the vehicle fleet evolves through time.

EMFAC 2011 is an engineering-based model that can be used to estimate emissions factors for on-road vehicles operating and projected to be operating in California for calendar years 1990-2035. EMFAC2011 uses historical data on fleet composition, emissions factors, VMT, and turnover to forecast future motor vehicle emissions inventories in tons/day for a specific year, month, or season, and as a function of ambient temperature, relative humidity, vehicle population, mileage accrual, miles of travel and speeds. Emissions are calculated for forty-two different vehicle classes composed of passenger cars, various types of trucks and buses, motorcycles, and motor homes. The model outputs pollutant emissions for hydrocarbons, carbon monoxide, nitrogen oxides, particulate matter, lead, sulfur oxides, and carbon dioxide. EMFAC 2011 is used to calculate current and future inventories of motor vehicle emissions at the state, air district, air basin, or county level. Accordingly, the model can be used to forecast the effects of air pollution policies and programs at the local or state level.

Year	Emissions (MMT)	EF (kg/mi)	VMT (1,000)
1990	137.96	0.53	258,926,000
1991	134.45	0.52	257,976,000
1992	141.73	0.54	262,548,000
1993	139.40	0.52	266,408,000
1994	140.42	0.52	271,943,000
1995	143.53	0.52	276,371,000
1996	145.00	0.52	278,043,000
1997	148.31	0.53	279,096,000
1998	151.25	0.52	290,630,000
1999	155.80	0.52	300,066,000
2000	163.48	0.53	306,649,000
2001	163.58	0.53	310,575,000
2002	169.88	0.53	320,942,000
2003	166.35	0.51	323,592,000
2004	167.45	0.51	328,917,000
2005	167.69	0.51	329,267,000
2006	167.65	0.51	327,478,000
2007	167.56	0.51	328,312,000
2008	157.04	0.48	327,286,000
2009	153.28	0.47	324,486,000
2010	149.19	0.46	322,849,000
2011	146.08	0.46	320,784,000

Table A-5: On-road Emissions, Emissions Factors, and VMT 1990-2011

For our purposes, EMFAC 2011 generates adjusted estimates of average VMT and annual GHG emissions for each on-road vehicle-class by model-year. From the EMFAC2011 outputs, we calculate annual average emissions factors for on-road VMT by taking the ratio of the sum of GHG emissions over the sum of VMT across vehicle-classes and model-years within each calendar year. A known weakness of the EMFAC 2011 model is that it does not accurately reflect the effects of the Great Recession on new light-duty vehicle sales, emissions factors or fleet VMT for the years 2009-present. In terms of new vehicle sales, EMFAC 2011 figures there to have been approximately 30% more new vehicle sales in California in 2009 than were actually recorded by the California Board of Equalization. This difference has declined, approximately linearly, over time as sales of new vehicles have slowly rebounded, and are on track to return to pre-recession levels in 2015. Additionally, EMFAC 2011 has VMT growing steadily through the recession, while in reality VMT sharply declined in 2009 and has declined modestly ever since.

To account for these differences we adjust new vehicle sales and total (not per-capita) VMT for model-years 2009-2014. Beginning with a 30% reduction in sales and VMT for model-year 2009, we reduce the adjustments to sales and VMT in each subsequent model-year by five percentage points, so that 2014 is the last model-year impacted by our adjustment. Importantly, as the impact of the Great Recession on the size of each model-year fleet can reasonably be expected to persist over time, these adjustments are imposed across all calendar years 2009-2020. That is, because fewer model-year 2009 vehicles were sold in 2009, there will accordingly be fewer model-year 2009 vehicles in the fleet in future years. While the decline in VMT was almost certainly not purely driven by the decline in new vehicles sales, the reduction in VMT resulting from the sales adjustment causes EMFAC

2011's measure of VMT to closely mimic the actual path of VMT over the same time period. In the absence of better information about the distribution of changes to VMT across model-years, we make this simplifying assumption, noting the goodness of fit.

To account for the impact of complementary policies, we calibrate average emissions factors and emissions intensities of transportation fuel over the period 2012-2020 using our adjusted EMFAC 2011 model.

To account for CAFE, a policy that proposes to drive the average emissions intensity of new light-duty cars and trucks from 26.5 in 2011 to 54.5 in 2020, we calculate average emissions factors by model-year and vehicle class from the adjusted EMFAC2011 forecasts and force new light-duty vehicles in model-years 2012-2020 to match the fuel-economy standards established by CAFE. We then calculate annual average emissions factors for calendar years 2012-2020, by taking the VMT weighted sum over the set of all model-year by vehicle-class emissions factors.

To account for the LCFS, a policy that proposes to reduce the average carbon content of all on-road vehicle transportation fuel sold in California by an additional 10% between now and 2020, we adjust the emissions intensity of gasoline and diesel according to the incremental share of zero-GHG fuel that must be sold in order to achieve the LCFS. Here it is worth noting an important difference between the cap and trade program and EMFAC 2011 methods of accounting for GHG emissions from biofuels. While the cap and trade program does not assign a compliance obligation to emissions from ethanol, EMFAC 2011 includes combustion emissions from fossil and bio-fuels in the measure of GHG emissions. Therefore, our adjustment of emissions intensity of gasoline and diesel must take into account not only the incremental contribution of the LCFS, but also the preexisting levels of biofuels in California transportation fuel.

We model the full implementation of the LCFS as a linear decline in GHG emissions intensity of on-road gasoline VMT as beginning at 89% in 2012 and falling to 81% in 2020. For diesel, the share of preexisting biofuels is quite small, so we model the decline in GHG emissions intensity of on-road diesel VMT as beginning at 98% in 2012 and falling to 90% in 2020. These declines are taken after the implementation of CAFE, so in practice they are implemented as reductions in the annual average emissions factors calculated above. In light of recent court challenges, we also consider an alternative implementation of LCFS where the regulation is not fully implemented. In this scenario GHG emissions intensity of on-road gasoline VMT is held steady at 89% through 2020 and no penetration of biodiesel is modeled. Table A-6 reports annual average emissions factors and implied average MPG under the combinations of full implementation of CAFE with full and partial implementations of the LCFS. The combined impact of the full implementation of these policies and the preexisting trend in VMT emissions intensity takes average emissions factors from 0.49kg/mi in 2012 down to 0.36kg/mi in 2020.

Unlike our VAR, EMFAC 2011 does not provide errors on the emissions intensity of VMT.

Year	CAFE & Partial LCFS EF (kg/mi)	CAFE & Partial LCFS MPG (mi/gal)	CAFE & Full LCFS EF (kg/mi)	CAFE & Full LCFS MPG (mi/gal)
2012	0.48	18.36	0.48	18.60
2013	0.48	18.68	0.47	19.04
2014	0.47	19.02	0.46	19.52
2015	0.46	19.51	0.44	20.16
2016	0.44	20.24	0.42	21.07
2017	0.42	21.06	0.40	22.07
2018	0.41	21.91	0.38	23.13
2019	0.39	22.80	0.37	24.25
2020	0.37	23.80	0.35	25.50

Table A-6: Adjusted EMFAC 2011 Average Emissions Factors and MPG 2012-2020

We believe that taking the point estimates of VMT intensity from EMFAC 2011 could eliminate an important source of variance in our VAR. To account for the uncertainty in VMT intensity we incorporate the EMFAC 2011 point estimates for each of the adjusted EMFAC 2011 cases into the VAR framework. We treat the impact of complimentary policies as varying with the realization of VMT coming from our VAR. Here, we calculate the annual emission reduction of the complimentary policies targeting the transportation sector as the product of the realized random draw of VMT from our VAR and the difference between mean VTM emission intensity from the VAR and the relevant EMFAC 2011 annual point estimate of VMT emission intensity.