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EXPECTING THE UNEXPECTED:
EMISSIONS UNCERTAINTY AND ENVIRONMENTAL MARKET DESIGN

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Expecting the Unexpected: Emissions Uncertainty and Environmental Market Design
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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. We use these estimates to forecast businss-as-usual (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 BAU emissions levels due to uncertainty in economic growth and other factors. Our analysis also suggests that 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 emissions uncertainty and inelastic abatement supply implies a high probability that the price of allowances in 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.

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I. INTRODUCTION

Among economists there is a general consensus that a carbon pricing mechanism, through either a tax or a cap-and-trade market for greenhouse gas (GHG) emissions allowances, 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, on which the ultimate success of any climate policy depends.

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.[1] 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 EU-ETS responded in 2014 by reducing the emissions cap. The Regional Greenhouse Gas Initiative (RGGI) in the Northeastern U.S. has gone through a similar experience.[2] Although they may meet short-term emissions caps, 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.[3]

The second reason is more subtle, but may be equally important. Market design features that make Cap and Trade 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. Climate policies implemented in parallel with cap-and-trade markets – including fuel economy standards for cars, mandated renewables shares for electricity generation, and output-based

[1]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 \$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. In 2013, the Liberal party, led by Tony Abbott, campaigned and formed a coalition government on a platform that included abolishing the CO_2 tax. On July 17, 2014 the Australian Senate voted to abolish the CO_2 tax.

[2]As of this writing, allowances in the EU-ETS were trading at 6.70 euros per metric tonne and in RGGI at 5.21 dollars per tonne.

[3]When discussing controversies about mitigation costs, Aldy, et. al. (2009) note that "[f]uture 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."

updating of allowance allocations (*i.e.,* refunding of allowance auction revenues to mitigate output price increases in allowance-consuming sectors of the economy) – may increase the political acceptance of cap-and-trade markets 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 never-enacted Waxman-Markey bill of 2010, as well as the California's operating 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.

California's cap-and-trade market undertook its first allowance auction on November 14, 2012 and compliance obligations commenced on January 1, 2013. The quantity of available allowances has been set for the first eight years, through 2020, after which the future of the program is uncertain. This market is a modified cap and trade system with a limited price-collar mechanism. There is an auction reserve price (ARP), managed through adjustments to the supply of allowances to the periodic auctions that sets a soft floor price for the market. This price floor rises each year. There is also an allowance price containment reserve (APCR) designed to have a restraining effect on prices on the high end by adding a pre-specified number of allowances to the pool when prices exceed pre-specified levels.

While the details of California's price-collars are described in regulations developed by the California Air Resources Board (ARB), recently approved regulatory changes would alter the exact manner in which the APCR would be applied and the degree to which it could mitigate uncertainty over prices.[4] 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 soft price floor or the APCR soft price ceiling.

In this paper we develop estimates of the distribution of allowance prices that accounts for uncertainty in both GHG emissions and 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

[4]The regulation is 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/ pricecontainment.pdf.

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 the 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 uncertainty in both "business-as-usual" (BAU) emissions and the supply curve of abatement, including the quantity of abatement available at the price floor, are key drivers of the probabilities of these four price outcomes.

This steep supply of emissions abatement between the effective price floor and the APCR, along with a substantial, but fairly exogenous, supply below the soft price floor implies a bi-modal distribution of prices with most of the probability mass at either low or high price outcomes. A primary factor determining where in that distribution the market will equilibrate is the BAU emissions level that would result if there were no GHG emissions reduction activities. 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 adapted from time-series econometrics, which we apply to emissions and economic data from 1990-2011, in order to forecast future emissions and the uncertainty of emissions.

Our empirical assessment of the potential demand for, and supply of, emissions allowances, as well as the offsets that augment this supply, suggests that the most likely 2020 market price will be very close to the auction reserve price floor.[5] In all of the scenarios we examine, we also find a low probability that the price will be in the intermediate range above the auction reserve price floor and below the containment reserve price. Thus, most of the remaining probability weight is on outcomes in which some or all of the allowances in the price containment reserve are needed. Moreover, we find that, absent further government policy change, there is a non-trivial probability that allowance prices will be above the highest price in the price containment reserve.

Throughout this analysis, 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 separate work – Borenstein, Bushnell, Wolak and Zaragoza-Watkins (2014) – we analyze the potential for market power and market manipulation given the characteristics of supply and demand in the market. While we find potential for short-term manipulation of the market, we do not find a plausible incentive to exercise market power in a way that would change the equilbrium

[5]Throughout this paper we refer to an "allowance market." The trading of allowances and their derivatives takes place 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.

price over the full 8-year course of 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 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 price projections 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. In Section V, we discuss other forms of abatement that will affect the supply-demand balance, including abatement responsive to the allowance price. We present results in Section VI under the baseline scenario for complementary policies and other abatement activities, and we also show how cap-and-trade might operate in the absence of complementary policies. Section VII concludes.

II. THE CALIFORNIA CAP-AND-TRADE MARKET

We focus on estimating the potential range and uncertainty in allowance prices over the entire 8-year span of the market.[6] 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 limited borrowing of allowances is permitted between 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 adopted in 2014,[7] under nearly any scenario, emissions during

[6]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. Consequently, the supply-demand balance of allowances for Quebec could alter the probabilities presented in this paper. Given the limited amount of emissions abatement possiibilities in Quebec versus California, including Quebec in our analysis is likely to increase the probability of higher price outcomes.

[7]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. For the

the first two compliance periods (ending December 31, 2014 and December 31, 2017) 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 of BAU emissions, we pay particular attention to establishing confidence intervals for the time path of annual emissions from 2013 to 2020.

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. 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. It features several elements that 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 market-driven effect in which firms or consumers reduce emissions in response to the level of allowance prices, and an independent effect in which emissions are reduced due to additional "complementary policies" outside the cap and trade program, regardless of the price of allowances.

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"[8]), and (c) offsets, which we discuss later (and which might be considered a form of lessening demand rather than increasing the supply of allowances, 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.[9]

In its revised scoping plan of 2010, ARB's preferred model projects that 63% of emissions abatement would arise from complementary policies rather than from

recently adopted changes, see
http://www.arb.ca.gov/regact/2013/capandtrade13/capandtrade15dayattach1.pdf. This rule change allows borrowing up to 10 percent of the available allowances three years in the future, which virtually eliminates the possibility that BAU emissions less the amount of abatement exceeds the amount of available allowances during the first two compliance periods.

[8]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.

[9]The potential levels of reshuffling and relabeling are examined in Bushnell, Chen, and Zaragoza-Watkins (2014). The offset market is discussed below. Some offset supply may be available at prices somewhat above the auction reserve price.

responses to the cap.[10] It is important to recognize that these reductions are not costless, indeed many are likely to 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 independent of the allowance price. 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 also limited by some of the allowance allocation policies that have been implemented with California's cap-and-trade market. The large amount of allowances allocated through mechanisms that are likely to reduce the price impact of allowance prices to consumers – output-based updating for many industrial emitters and allocations to utilities that will use them to limit the impact of allowance prices on consumer prices – will limit the amount of price-responsive emissions mitigation.[11] Most of the remaining emissions 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 these energy price effects are relatively small.[12] This is due in part to a feature of the program, described later, that will use revenues from the sale of allowances to limit the magnitude of potential retail electricity price increases. A similar policy applies to the retail natural gas sector.

[10] Four additional sensitivity models project between 30% and 63% of emissions abatement would arise from complementary policies. See http://www.arb.ca.gov/cc/scopingplan/economics-sp/updated-analysis/updated_sp_analysis.pdf at page 38 (Table 10).

[11] 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 output. 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.

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

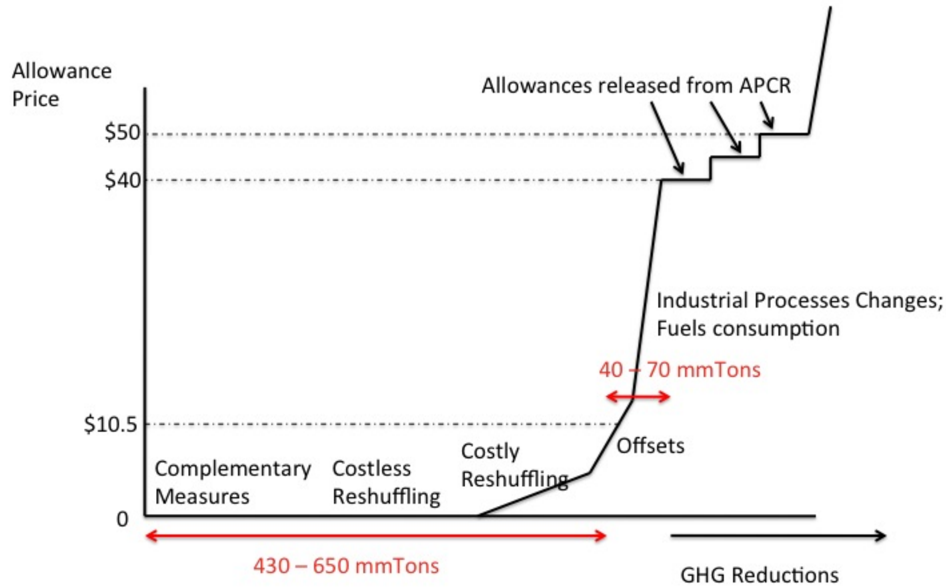

Figure 1. Supply of Abatement

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."[13]

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

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

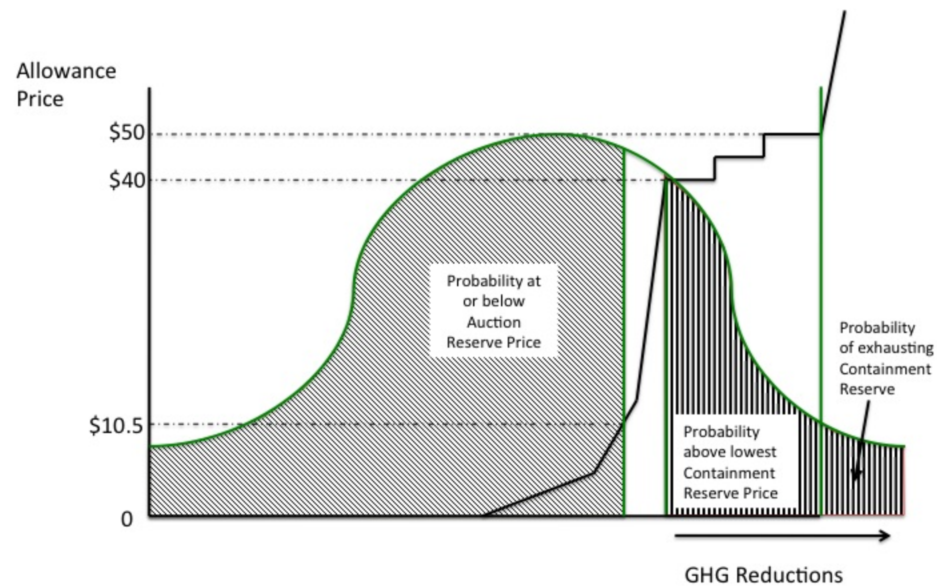

Figure 2. Hypothetical Distribution of Abatement Demand (BAU minus allowances outside price containment reserve) versus Abatement Supply

hypothetical symmetric distribution of the amount of abatement needed (BAU emissions less the total amount of available allowances) onto the same horizontal axis as our supply curve.

A. *Price Evolution and Estimated Equilibrium Price in the Market*

The analysis we present here models abatement supply and demand that evolves over time and is then 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 no clarity on 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 (within compliance periods) will cause the *expected* price change over time to be equal to the nominal interest rate (or cost of capital).[14] 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 for the entire program.[15]

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 Gross State Product (GSP) in California) 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. With risk neutral traders, the price at any point in time should be equal to the expected value of all the possible future prices that equilibrate the realized supply (less allowances and offsets) and realized demand for abatement.

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.

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 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. Emissions from these sources are typically re-

[14]This is the outcome envisioned when banking was first developed (Kling and Rubin, 1997). See also Holland and Moore (2013), for a detailed discussion of this issue.

[15]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 risk-neutral 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.

Table 1—Emissions from Key California Sectors in 2010 (in millions of metric tonnes (MMT)

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

ferred to as "Narrow Scope Emissions." The second phase, which began January 1, 2015, expands the cap to include emissions associated with the combustion of transportation fuels and natural gas at non-industrial facilities. The sum of these emissions and Narrow Scope Emissions are typically referred to as "Broad Scope Emissions." Table 1 summarizes the aggregate emissions from the key sectors from 1990 through 2011.

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 3 presents 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 uncertainty. Simulating the level of economic activity and GHG emissions eight or nine years into the future involves even greater uncertainty, which implies a greater potential for very low or high allowance price realizations.

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 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.[16] Due to the short time period for which the necessary disaggregated GHG emissions data have been collected, the model estimation is based on annual data from 1990 to 2011. Because data are available for 2012 on real GSP, in-state electricity production by

[16]VARs 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.

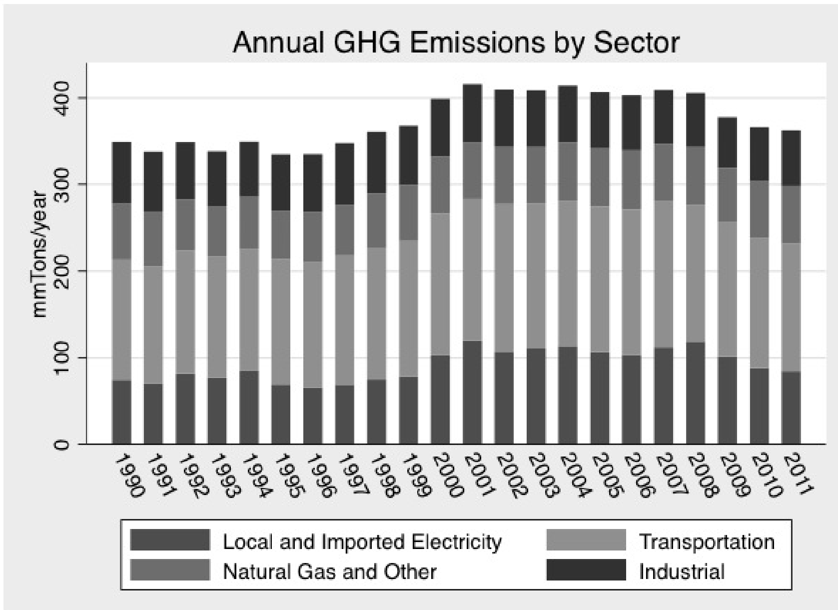

Figure 3. California Emissions Data 1990-2011

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 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 GSP 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 Appendix A 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 these 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 (TWh)
$X_{2t} =$ Total VMT (Thousands of Miles)
$X_{3t} =$ Industrial GHG & Other Natural Gas Emissions (MMT)
$X_{4t} =$ Real Retail Gasoline Price ($2011/Gallon)
$X_{5t} =$ Real Gross State Product ($2011)
$X_{6t} =$ Emissions Intensity of In-State Thermal Gen. (Metric Tonnes/MWh)
$X_{7t} =$ Emissions Intensity of VMT (Metric Tonnes/Thousand Miles)

The definitions of the units abbreviations used are: TWh = terawatt-hours, MMT = millions of metric tonnes, VMT = vehicle miles traveled, MWh = megawatt-hours.

All real dollar magnitudes are expressed in 2011 dollars. All GHG emissions are in metric tonnes of CO_2-equivalents. As noted above, we include real GSP in the model 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 simulated realizations 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 realization of the production of electricity in California net of hydroelectric generation in year t, we subtract the anticipated amount of renewable and nuclear energy produced in year t ,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 from 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 an administratively determined number. All that can actually be measured is the aggregate GHG emissions produced outside of California and those from the total electricity produced outside of California. Historically, the specific energy deemed to be "delivered" to California is the result of the financial contracting decisions of the importing firm, not the result of the actual flows of specific electrons into the state. Specifically, coal-fired electricity would be deemed to "delivered' to California because a coal-fired power plant outside of California contracted with a buyer in California to supply electricity. Because incentives for this contracting choice will change dramatically with the start of the cap-and-trade program, historical data on GHG emissions from electricity imports are not predictive of future values. We instead take the ARB's forecast for BAU 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 $\Delta Y_t = Y_t - Y_{t-1}$.

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 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 (Dickey and Fuller, 1979).[17] These hypothesis testing results are consistent with our decision to model the vector

[17] Results of the Dickey-Fuller tests are shown in Appendix A.

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. Time series processes that are 2nd-order stationary in first-differences (*i.e.,* ΔY_t is 2nd-order stationary) and have stationary linear combinations of the levels of their elements are said to be cointegrated.[18] 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:

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

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, 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 an $\alpha = 0.05$ significance level.[19] 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 an $\alpha = 0.05$ significance 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 Appendix A.

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

[18] See Engle and Granger (1987) for a complete discussion of this concept and its implications.
[19] Results of these tests are shown in Appendix A.

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 in-state electricity production net of hydroelectric generation (X_1), the real price of gasoline in California (X_4), and real 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.[20] The first step computes an estimate of the joint distribution of the elements 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 (ML) 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 $(1 - \Theta_1) \ = \ -\gamma\alpha'$. 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)

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

ML procedure using the Y_t^m and imposing the cointegration rank restriction that $(1-\Theta_1) = -\gamma\alpha'$. 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), calling these values $(\hat{\epsilon}^m_{T+1}, \hat{\epsilon}^m_{T+2}, ...\hat{\epsilon}^m_{T+9})'$. Using these draws and $\hat{\mu}^m$, $\hat{\Omega}^m$, and $\hat{\Theta}_1^m$ we compute future values Y_{T+k} for $k = 1, 2, ..., 9$ given Y_T using the following equation:

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

This yields one realization of the future sample path of Y_t for t =2012, 2013,..., 2020. The elements of Y_t are then 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 $Y^m_{T+k|T}$ for $k = 1, 2, ..., 9$ replicated $m = 1$ to $M = 1000$ times produces 1,000 realizations from the simulated distribution of $(X'_{2012}, X'_{2013}, ..., X'_{2020})'$.[21]

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 emissions from in-state and imported 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.

[21] 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 in-state electricity production net of hydroelectric generation (X_1), the real gasoline price in California (X_4), and real 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 in-state electricity production net of hydroelectric generation (X_1), the real price of gasoline in California (X_4), and real 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 in-state electricity production net of hydroelectric generation, the real price of gasoline, and real GSP 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.

B. Data

To compute the GHG emissions intensities of the in-state 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.[22] 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:

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).[23] This is 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 dataset 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), which is the methodology used to calculate an entity's compliance obligation under the cap-and-trade program.[24]

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 of uncertainty in the future time path. Because

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

[23] The Inventory is available at: http://www.arb.ca.gov/cc/inventory/inventory.htm.

[24] Information on the MRR is available at: http://www.arb.ca.gov/cc/reporting/ghg-rep/ghg-rep.htm.

Table 2—Summary Statistics of Data for Vector Autoregression

	mean	S.D.	min	max	year min.	year max.
California Elec. Generation (TWh)	191.20	15.80	158.90	216.80	1991	2006
California Hydro. Gen (TWh)	34.60	9.30	20.20	49.50	1992	1998
Vehicle Miles Traveled (Billions)	300.60	26.84	257.98	329.27	1991	2005
Industry, Natural Gas & Other Emissions (MMT CO2e)	141.90	4.83	131.98	145.60	1995	1998
Gross State Prod.t (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 Elec. Thermal 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

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).[25] Gasoline prices are collected from the Energy Information Administration (EIA).[26] In-state electric generation is collected from the California Energy Commission (CEC).[27]

Our primary measure of 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 Inventory. The emissions levels reported in Table 1 reflect this partition of on-road and off-road emissions. The details of this partitioning are further described in Appendix B.

[25]Gross Domestic Product by State is available at: http://www.bea.gov/regional/index.htm#data.
[26]Retail fuel price by State is available at: http://www.eia.gov/dnav/pet/pet_pri_gnd_dcus_sca_w.htm.
[27]In-state California electric generation and consumption are available from the CEC at http://energyalmanac.ca.gov/electricity/index.html.

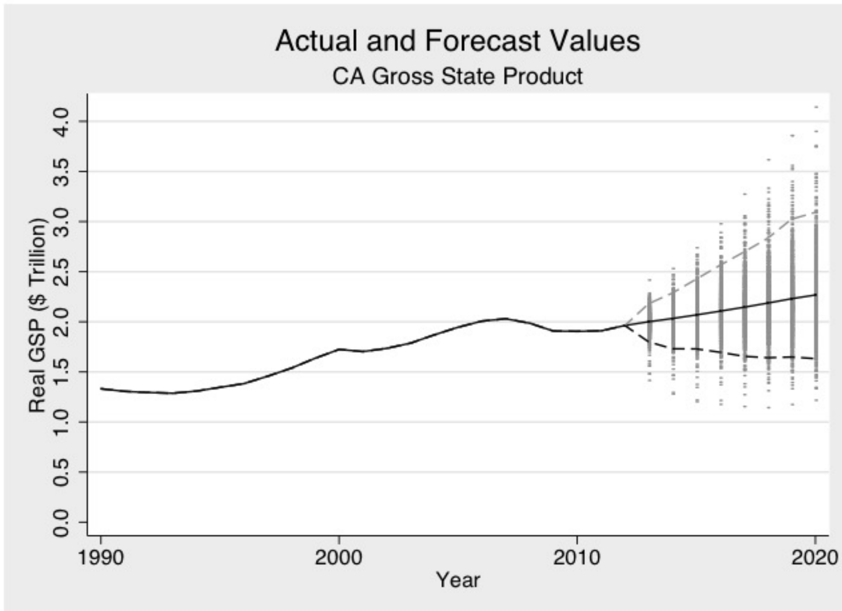

FIGURE 4. FORECAST RESULTS – GROSS STATE PRODUCT

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. We have undertaken a number of sensitivity analyses of our allowance price distribution modeling results to these assumptions and found them to be largely invariant to reasonable changes.

C. Results

The parameter estimates for the 7-variable VAR are shown in Appendix A. Table 3 lists the means and standard deviations of simulated values of each element of X_t for each year from 2013 to 2020, as well as the annual and cumulative emissions resulting from those values. Figure 4 shows actual data (up to 2012) and forecasts from the 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 using these results to simulate 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 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 the ARB 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}, in-state electricity production minus hydroelectric energy production and VMT respectively, into GHG emissions.

In the case of electricity, the main complementary policies are energy efficiency (EE) investments and the RPS. 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 California's imposition of a 33% RPS target by 2020 and the recent unexpected retirement of the San Onofre Nuclear Generation Station in Southern California. To get from a simulation of X_{1t} for 2013-2020 to a simulation of GHG emissions from in-state thermal 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 in-state 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.

Table 3—Summary Statistics of Simulated VAR Variables and Emission

Year	California Electricity net of Hydro Twh	Vehicle Miles Traveled Million Miles	Nat. Gas, Ind. & Other MMT	Gasoline Price $2011	Gross St. Product $2011 Trillion	Therm. Intensity tons/ MWh	Trans. Intensity tons/1000 Miles	Broad Scope Emis. MMT	Cum. Emis. MMT
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 the standard deviations of 1000 draws.

For the RPS, we apply a California Public Utilities Commission forecast of new renewable generation (MWh) taken from the 2012 Long-term Procurement Planning (LTPP) process.[28] 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.[29]

Table 4—Assumed Zero-Carbon Electricity Output and Vehicle Emissions Intensities

Year	Zero-Carbon Power RPS GWh	Zero-Carbon Power Nuclear GWh	Low VMT Intensity tons/1000 miles	Medium VMT Intensity tons/1000 miles	BAU Forecast VMT Intensity tons/1000 miles
2013	32316	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

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 17,530 GWh 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-fueled generation sources.

We then multiply this simulated value of in-state, fossil-fueled electricity generation by X_{6t}, the emissions intensity factor produced by the simulation of future values from the VAR, to translate the simulation of in-state, fossil-fueled electricity generation into GHG emissions. Mathematically, we calculate electricity emissions from in-state, fossil-fueled electricity generation 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 in-

[28]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.

[29]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.

state production of electricity net of hydro production. The variables RPS_TWH and $Nuke\_TWH$ 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 EE, there is a strong preexisting 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 EE improvements would double count the reductions that are already part of the forecast. Indeed, as table 3 indicates, emissions per unit of GSP decline under our BAU forecast by about 1.74% per year from 2013 to 2020. We therefore make no further adjustments in addition to EE effects already integrated into our forecasts.

To incorporate the impact of complementary 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 BAU 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 economic activity in the transportation sector. Our derivations are summarized here but described in more detail in the Appendix B.

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 having zero GHG emissions for the purposes of the cap-and-trade program, 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%.[30] 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 sets of 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

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

standards as the passenger vehicle fleet.

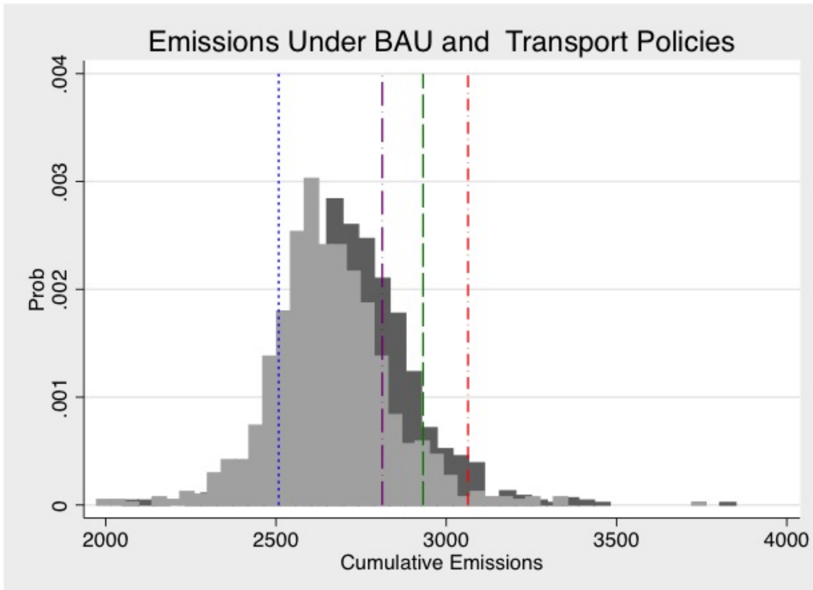

Figure 5. Targeted Transportation Policies Shift Emissions Distribution

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 2011 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 VMT 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 5, which shows the distribution of cumulative total emissions from 2013 to 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 four vertical lines are, from left to right, the total allowance budget, followed by the allowance budget plus the total abatement available at a price at the top of the APCR under low, medium, and high abatement scenarios, which we discuss in the next section.[31]

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.

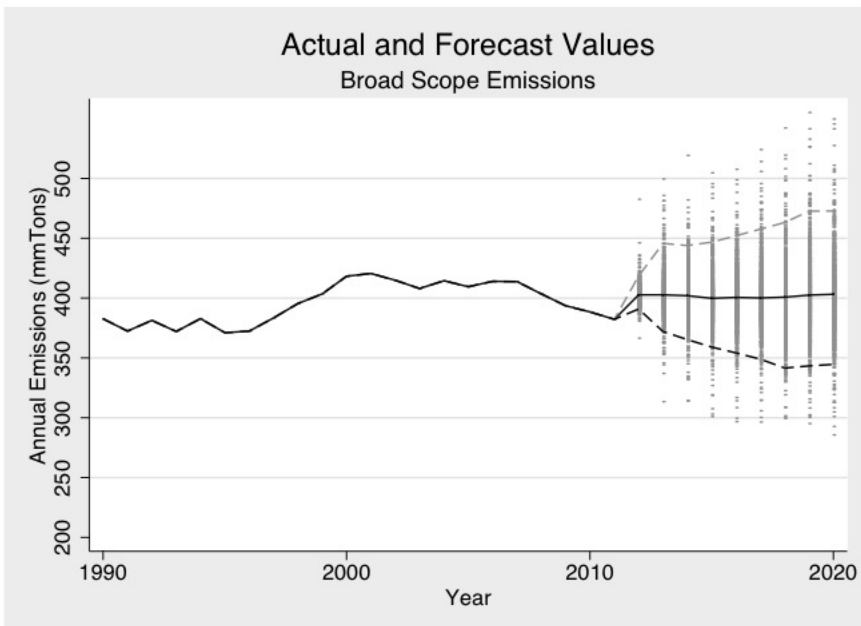

Figure 6. Forecast Results – Broad Scope Emissions

Figure 6 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 7 shows the forecast cumulative covered emissions – Narrow Scope Emissions for 2013-2014, Broad Scope Emissions for later years – along with pointwise 95% confidence intervals for the value for each year from 2013 to 2020.

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

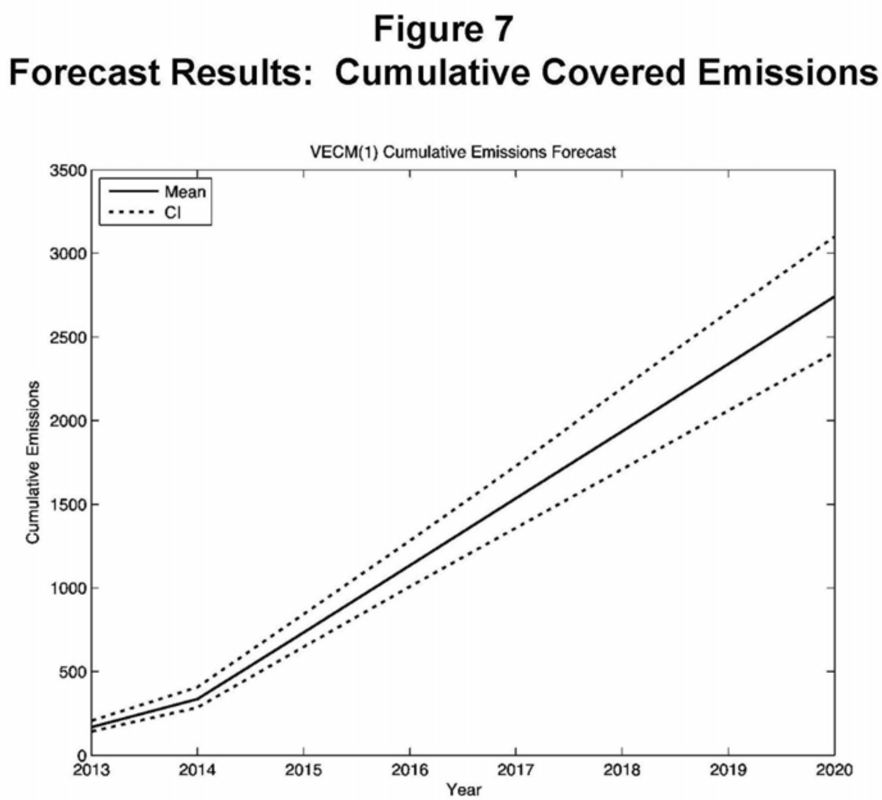

Figure 7. Forecast Results: Cumulative Covered Emissions

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.

V. ADDITIONAL SOURCES OF EMISSIONS ABATEMENT

While the VAR estimation and simulations described in the previous section account for the changes in BAU emissions levels, transport emissions intensities, and zero-carbon electricity generation, the price of allowances will also affect total emissions by changing the cost of emitting GHGs. In addition the use of offsets and electricity contract reshuffling will reduce the total amount of emissions that sources must cover by submitting allowances. Thus, informed assumptions about the size of these additional will be important to estimating the supply-demand balance in the allowance market.

In appendix C, we assess in detail the potential abatement from higher allowance prices and higher energy prices that result from separate policies, citing regulatory decisions that affect how allowance prices will be passed through as well as previous literature on elasticities. Here, we summarize the range of potential impacts we consider and discuss them briefly. Table 6 shows these ranges as well as the possible impact of offsets and reshuffling. It is immediately clear that the size and uncertainty of the offsets and reshuffling impact is much larger than the potential impact from demand response to higher energy prices. We discuss offsets and reshuffling in more detail.

A. Price-elastic Response of Demand

It is important to recognize that the actual allowance price path will evolve over time as more information arrives about 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 very 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 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 – will reduce the total responses to those prices.

For gasoline and diesel price response, we assume 100% allowance price pass-through based on many papers that study pass-through of tax and crude oil price changes. We use a relatively low elasticity assumption – below most long-run elasticity estimates – because improved fuel economy is a large part of the difference between long-run and short-run elasticity estimate, but complementary policies are already requiring higher fuel economy than consumers would choose. For natural gas, elasticities are taken from the literature, but for political reasons discussed in Appendix C, passthrough is likely to be far less than 100% and possibly close to zero. For electricity, elasticities are also taken from the literature, but passthrough is likely to be zero for residential customers and slightly more than 100%, on average, for commercial and industrial customers, again for political reasons.

In Appendix C, we also discuss possible changes in industrial emissions and explain why – due to a combination of low elasticities and policies designed to lower the cost of Cap and Trade for industrial emiters – these changes are likely to be very small.

We also account for two other possible price changes not attributable to the cap-

Table 5—Summary of Potential for Price-Responsive Emissions Abatement

Price-responsive Allowance Demand Reduction	Elasticities		Range of Energy Price Changes At Different Levels of Allowance Price Over years in program ($2012):			Abatement over years in program at highest APCR step each year (MM tons)	
Sector	Low	High	Auction Reserve	Lowest step of APCR	Highest step of APCR	Low	High
Electricity most C&I ($/MWh)	-0.20	-0.50	$3.68/$5.17	$13.74/$19.34	$17.18/$24.17	21.3	52.4
Transportation ($/Gallon)	-0.10	-0.20	$0.10/$0.12	$0.36/$0.46	$0.45/$0.58	10.6	21.0
Natural Gas ($/MMBTU)	-0.30	-0.50	$0.57/$0.80	$2.13/$3.00	$2.66/$3.75	28.1	45.4

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
GHG intensities assumed are explained in the Appendix C

and-trade program. Real prices of electricity in California are likely to rise over the 2013-2020 period due to increased use and integration of renewable energy and other factors. We take a recent estimate of those increases and apply a range of elasticity assumptions. The real price of transportation fuels may also rise due to the cost of using more renewable fuels mandated under the LCFS. We take a range of possible estimates of this effect.

B. *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[32] and the Climate Action Reserve[33] – to facilitate the listing, reporting, and verification of specific offset projects. The ARB reports that approximately 5.3 million offsets have been listed with ARB under a voluntary early action offset program that are eligible for conversion to cap-and-trade program compliance offsets.

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.[34] The number

[32]See http://americancarbonregistry.org/carbon-accounting/california-compliance-offsets.
[33]See http://www.climateactionreserve.org/.
[34]http://www.arb.ca.gov/regact/2010/capandtrade10/capv3appf.pdf.

of offsets expected to be 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.[35] ARB, however, is considering adding at least two additional offset protocols – Rice Cultivation and Mine Methane Capture and Destruction. The addition of these two protocols is estimated to make an additional 100 MMT of offsets available (for an estimated total of 130 MMT) between 2013 and 2020.[36]

For the purposes of our analysis, we consider the low scenario based on the existing protocols (66 MMT), a medium scenario that adds in estimates for rice cultivation and coal mine methane (130 MMT), and the highest scenario under which the full allowed 218 MMT of offsets are approved and utilized for compliance.[37] 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.

C. 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.[38] However, due to the nature of the Western electricity market, it is generally not possible to identify the specific 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 California cap-and-trade program.

Under one extreme, California importers could reshuffle all imports to be GHG-

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

[36]Ibid.

[37]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. It seems quite likely that this rule would be adjusted if allowance price increased and the limit on offsets were constraining.

[38]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

free resources, resulting in no demand for allowances to cover imported electricity. ARB has tried to limit reshuffling, 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 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-GHG 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.[39] Taking the 109 MMT, associated with roughly 109 TWh of electricity imports from coal-fired plants as a baseline, we consider three possibilities for the remaining 571 TWh. The highest is that all the remaining energy is imported at an emissions rate of 0.428 tons/MWh. This is the California cap-and-trade market's administratively set "default" emissions rate applied to any imports that do not claim a specific source for the power. We consider this to be the highest plausible average emissions rate that would be claimed for non-coal imports. We then consider two other scenarios in which the emissions rate are set, somewhat arbitrarily to one-third (lowest) and two-thirds (medium) of the 0.428 rate. The resulting abatement levels are shown in table 6.

[39] 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.

Table 6—Summary of Abatement Supply Scenarios

Baseline Abatement Scenarios in MMTs of CO_2

	Low			Medium			High		
	ARP	Low APCR	High APCR	ARP	Low APCR	High APCR	ARP	Low APCR	High APCR
Electricity Elasticity	4.6	15.5	19.0	7.7	26.9	32.9	10.9	38.0	46.4
Transport Elasticity	2.4	8.6	10.6	3.6	12.8	15.8	4.8	17.0	21.0
Natural Gas Elasticity	0.0	0.0	0.0	1.5	5.3	6.5	3.0	10.5	13.0
Exogenous Elec. rate effects	13.9	13.9	13.9	24.1	24.1	24.1	34.1	34.1	34.1
Transport LCFS	0.0	0.0	0.0	6.6	6.6	6.6	13.2	13.2	13.2
Offsets	66.0	66.0	66.0	130.0	130.0	130.0	218.0	218.0	218.0
Resource Shuffling	74.6	74.6	74.6	157.6	157.6	157.6	238.3	238.3	238.3
Total Abatement	161.5	178.6	184.1	330.8	362.7	372.8	522.0	568.2	582.8

Abatement Scenarios with No Complementary Policies in MMTs of CO_2

	Low			Medium			High		
	ARP	Low APCR	High APCR	ARP	Low APCR	High APCR	ARP	Low APCR	High APCR
Electricity Elasticity	5.1	17.3	21.3	8.4	30.1	37.0	12.0	42.7	52.4
Transport Elasticity	6.7	24.1	29.6	9.0	31.9	39.3	11.2	39.7	48.8
Natural Gas Elasticity	7.1	23.4	28.1	9.5	30.8	36.9	11.8	38.0	45.4
Exogenous Elec. rate effects	13.9	13.9	13.9	24.1	24.1	24.1	34.1	34.1	34.1
Transport LCFS	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Offsets	66.0	66.0	66.0	130.0	130.0	130.0	218.0	218.0	218.0
Resource Shuffling	74.6	74.6	74.6	157.6	157.6	157.6	238.3	238.3	238.3
Total Abatement	173.4	219.3	233.6	338.5	404.4	424.8	525.4	610.7	637.0

VI. ESTIMATED MARKET CLEARING IN THE CAP-AND-TRADE MARKET

To estimate the possible outcomes in the allowance market, we combine the 1000 simulations of BAU emissions (adjusted for complementary policies) with 1000 simulated outcomes from the additional sources of abatement that have been discussed in this section. Each source of abatement is drawn independently and all draws are independent of the BAU emissions draws. Given the very short data series and outside sources for much of the abatement assumptions, incorporating estimated or assumed correlations of these draws from empirical analysis isn't very credible. Nor, unfortunately, are even the signs of these correlations obvious.[40] Thus, we simply append a simulated draw of additional abatement sources to each draw of BAU emissions adjusted for complementary policies.

To produce the simulated abatement, we assume that the distribution of possible abatement from each source in table 6 is a $\beta(2,2)$ distribution with support from the low to the high scenario abatement level from each.[41] Combined with the simulated BAU plus complementary policies outcomes, this produces 1000 simulations of total covered emissions at various allowance market prices.

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 (some of which may require a price slightly above the auction reserve), (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.

As of this writing, California is considering implementing 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). This would be difficult to do even in the absence of this policy uncertainty, because it will be greatly influenced by the state's policy decisions. We simply report the estimated probability of reaching this case and note that prices could be extremely high.

Based on the 1000 simulations, we report in table 7 the distribution of estimated demand for allowances at each of the three break-points between the four price regions. The supply quantity at which the market will ultimately clear will depend on the price interval: below 2386.8 at the price floor, 2386.8 MMT from the price floor to just below the lowest price of the APCR, then increasing in three equal-

[40]For instance, lax offset policy could be positively correlated with lax policy towards reshuffling, or an inability to control reshuffling could lead to a looser allowance market and put less pressure of regulators to approve questionable offset applications.

[41]A $\beta(2,2)$ distribution looks like an inverted U with endpoints, in this case, at the low and high scenario abatement levels. The $\beta(2,2)$ is symmetric between the endpoints which doesn't correspond exactly to the distribution suggested by table 5 in all cases, but the implied asymmetry in table 5 would have no noticeable impact on the results.

sized additions of 40.6 MMT from the allowance reserve to be 2508.6 MMT at or above the highest price of the APCR. Combining demand and supply, the bottom panel of table 7 shows the probabilities that the equilibrium price will fall into each price range.

Table 7—Net Allowance Demand and Price Probabilities

Net Allowance Demand (MMT)	Allowance Price Level			
	at floor price	at low-APCR price	at high-APCR price	
	2318 (182)	2286 (182)	2276 (182)	
Probability Distribution of Equilibrium Price	near ARP	above ARP below APCR	in APCR	above APCR
	69%	6%	16%	9%

Assuming the moderate scenario for transportation emissions intensity, we find a 69% chance of the market clearing at or very close to the price floor and a 6% probability of the market clearing on the upward-sloping part of the abatement supply curve that is above the auction reserve price and below the APCR. The remainder of the distribution is in price ranges that would likely be very problematic politically, with 16% probability of settling in the APCR, and a 9% probability of exhausting the APCR.

From speaking to stakeholders from all sides of the issue in California, it seems very likely that state intervention would take place before this last, and most extreme, outcome occurred. One possible response would be an inexhaustible reserve or other form of "hard" price cap while another would be suspension of the entire market. Thus, while the idea of the cap and trade market is to allow price to fluctuate in order to balance supply and demand for emissions abatement, the reality is that price is far more likely to be at an administratively-determined price floor (at which quantity of abatement then fluctuates) or at some sort of price ceiling in which government intervention is again a primary determinant of the market price.

A. How much difference do complementary policies make?

As sections IV and V discussed, we make a number of assumptions about complementary policies in order to adjust the BAU estimates to reflect changes that are likely to occur during 2013-2020. Some of these adjustments are directly associated with state policies outside cap and trade that are also likely to reduce GHGs. In this subsection, we re-estimate the distribution of possible outcomes under a counter-factual in which complementary policies are not pursued and cap and trade is the single mechanism for reaching GHG reduction goals. To do this, we make assumptions about the alternative path of regulatory rules – such as the RPS mandate and light-duty fuel economy standards. We also make assumptions about consumption changes that would result if complementary policies were not pursued and the full cost of allowances were passed through to consumers of transport fuels, natural gas and electricity. Thus, we are assessing a more idealized implementation of cap and trade in which no other programs pursue GHG reduction, but all sectors are assumed to be fully exposed to the price of allowances.

To implement this approach, we make the following changes in abatement assumptions:
1) Renewable electricity output is frozen at its 2012 level (32316 TWh per year);
2) Baseline transportation emissions intensity (*i.e.,* with zero price of GHG emissions) follows the BAU path forecast in the VAR (shown in table 3) rather than the lower emissions intensity associated with fuel economy standards;
3) A higher transportation fuels elasticity range is assumed, -0.3 to -0.5, because of the absence of stricter fuel economy standards;
4) Natural gas elasticity range of -0.3 to -0.5, as before, but now assuming 100% passthrough;
5) Electricity elasticity range of -0.2 to -0.5, as before, but now applied to 100% passthrough of emissions from electricity generation;
6) No LCFS, so no impact of the LCFS on the price of fuels.

Table 8—Net Allowance Demand and Price Probabilities: No Complimentary Policies

Net Allowance Demand (MMT)	Allowance Price Level			
	at floor price	at low-APCR price	at high-APCR price	
	2442 (184)	2377 (184)	2356 (184)	
Probability Distribution of Equilibrium Price	near ARP	above ARP below APCR	in APCR	above APCR
	39%	16%	28%	17%

The effects of the assumptions 1 and 2 are indicated in table 4. The effects of assumptions 3-6 are shown in the bottom panel of table 6.

As we did before, we generated 1000 simulations of BAU emissions adjusted for zero-carbon generation and transportation emission intensity, though now incorporating assumptions 1 and 2 in the list above, and we combine that with 1000 simulations of the price-sensitive and other abatement activities, though now incorporating assumptions 3 through 6 in the list above. We report in table 8 the distribution of estimated demand for allowances at each of the three break-point between the four price regions. Combining demand and supply, the bottom panel of table 8 shows the probabilities that the equilibrium price will fall into each price range.

Figure 8 contrasts the probabilities with and without complimentary policies. Under this scenario with no complementary policies, we find a much smaller chance, 39%, of the market clearing at or very close to the price floor and a much larger probability, 16%, of the market clearing on the upward-sloping part of the abatement supply curve but still below the APCR. The probability of very high prices nearly doubles, however, with a 28% probability of settling in the APCR, and a 17% probability of exhausting the APCR. Eliminating complementary policies would more than double the probability that price adjustment would clear the market on the upward sloping part of the abatement supply curve, but it would also greatly increase the probability that the price would increase into the region in which price ceiling policies determine the outcome.

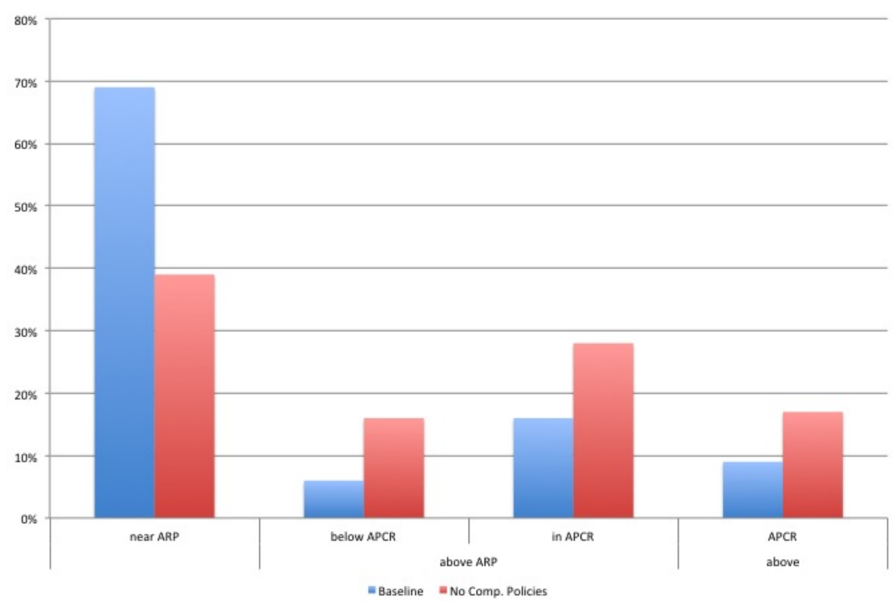

Figure 8. Distributions of Price Outcomes with and without Complimentary Policies

VII. CONCLUSION

For California's cap and trade program to succeed and be a model for the rest of the world, it is important that the outcomes of the market are reasonable and understandable. We have modeled supply and demand in the market in order to forecast the range of possible outcomes and the factors that could drive those outcomes.

Our analysis has demonstrated two aspects of using cap and trade mechanisms for addressing GHG emissions that do not seem to have been widely appreciated. First, there is very considerable uncertainty in the BAU emissions from which any assessment of needed abatement must start. Many policy analyses of the California program have taken BAU emissions as a known quantity. Our analysis suggests that BAU uncertainty is likely to be at least as large as uncertainty about the effect of abatement measures. Second, over the range of prices that have been considered politically acceptable, at least in California, there is likely to be relatively little price elasticity of emissions. This is in part intrinsic to the demand for emitting GHGs, but exacerbated by the complementary policies that have been adopted by California. The complementary policies force many of the changes that consumers and producers might otherwise have made in response to an emissions price.

Together these two conclusions suggest that equilibrium price in cap-and-trade markets for GHGs may be much more volatile than is generally recognized. The "hockey stick" shape of the abatement supply curve – driven by the large quantity of abatement required by complementary policies and then the inelasticity of additional supply beyond that – combined with significant uncertainty in the demand for abatement – drive by uncertainty in BAU emissions – implies that extreme prices (both high and low) are most likely. In the case of California, we find the most probability weight on outcomes that would result in excess allowances and leave price at or very close to the administrative floor, but about a 25% chance that the price would rise to the point of triggering regulatory intervention to contain further increases.

Our findings are consistent with the results in the California market through 2013 and 2014. In 2012, the program some allowances traded for nearly $20 when the price floor was $10.50, but by early 2013 the price had fallen to within one dollar of the price floor and has remained in that range ever since. The analysis is also consistent with the outcomes in the EU-ETS and RGGI, both of which have substantial complementary policies and both of which have seen prices drop to very low levels.

It is important to note that the scenarios under which the price for emissions could climb very high by 2020 in our analysis would not necessarily 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 and 2014 has reflected 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.

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Online Appendix A: 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 In-State Electricity Production Net of In-State Hydroelectric Generation (TWh)
ln_vmt	=	Natural Logarithm of Total VMT (Thousands of Miles)
ln_ngother_industrial	=	Natural Logarithm of Emissions from Non-Electricity Natural Gas Combustion and Other Industrial Processes (MMT)
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 (MT/MWh)
ln_transport_intensity	=	Natural Logarithm of Emissions Intensity of VMT (MT/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 zero mean version of the unit root test assumes Y_{it} follows the model,

$$Y_{it} = \alpha Y_{it-1} + \eta_{it}$$

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 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 "$\hat{\tau}$".

Variable	Type	$\hat{\rho}$	Pr $< \hat{\rho}$	$\hat{\tau}$	Pr $< \hat{\tau}$
ln_twh_p_hydro	Zero Mean	0.01	0.6719	0.44	0.8002
	Single Mean	-6.77	0.2386	-1.86	0.3429
	Trend	-15.04	0.0843	-2.26	0.4348
ln_vmt	Zero Mean	0.01	0.6716	1.45	0.9585
	Single Mean	-2.37	0.715	-2.36	0.1642
	Trend	0.26	0.9945	0.09	0.9945
ln_ngother_industrial	Zero Mean	0	0.6684	-0.07	0.6475
	Single Mean	-19.04	0.0023	-3	0.0516
	Trend	-18.56	0.024	-2.87	0.1904
ln_real_gas_price	Zero Mean	0.79	0.8569	1.27	0.9426
	Single Mean	0.01	0.9474	0	0.9484
	Trend	-10.6	0.2894	-2.3	0.4154
ln_real_gsp	Zero Mean	0.03	0.6761	1.3	0.9458
	Single Mean	-2.73	0.6686	-1.72	0.4071
	Trend	-18.46	0.0249	-2.01	0.5601
ln_thermal_intensity	Zero Mean	0.35	0.755	1.84	0.9799
	Single Mean	0.44	0.967	0.27	0.9704
	Trend	-5.15	0.774	-1.55	0.7765
ln_transport_intensity	Zero Mean	0.01	0.6707	1.02	0.9124
	Single Mean	1.01	0.9832	0.28	0.9711
	Trend	-2.35	0.9504	-0.62	0.9654

Table A1—Unit Root Test Statistics

The second version of the unit root test assumes a non-zero mean. In this case the assumed model is:

$$Y_{it} = \mu + \alpha Y_{it-1} + \eta_{it}$$

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 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:

$$Y_{it} = \mu + \nu t + \alpha Y_{it-1} + \eta_{it}$$

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 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 for 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.

H0: Rank=r	H1: Rank > r	Eigenvalue	LR(r)	5% Critical Value
0	0	0.9095	155.5929	123.04
1	1	0.8448	105.1496	93.92
2	2	0.6599	66.0195	68.68
3	3	0.6077	43.3706	47.21
4	4	0.4727	23.7197	29.38
5	5	0.2937	10.282	15.34
6	6	0.1323	2.9812	3.84

TABLE A2—COINTEGRATION RANK TEST USING TRACE

Table A2 presents the results of our cointegrating matrix rank tests. In terms of the notation of our error correction model

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

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 A3 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_{ij} is the (i,j) element of Λ and μ_j is the jth element of μ.

Appendix B: Transportation Emissions

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:

$$GHG_t = VMT_t \cdot \bar{E}I_t.$$

As described in the main text, our primary measure of VMT is compiled from a series of state-level transportation surveys administered by the National Highway Transportation Safety Administration (NHTSA) Office of Highway Information (OHI). 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 B1 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. Because certain complementary policies target on-road-vehicle emissions factors (*e.g.,* CAFE), an overstated measure of BAU' emissions factors could lead us to conclude that complementary policies should be expected to achieve a greater 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 off-road activities using the more granular activity-based emissions values reported in the Inventory. Table B1 reports the results of this partitioning, revealing the contribution of off-road emissions to be

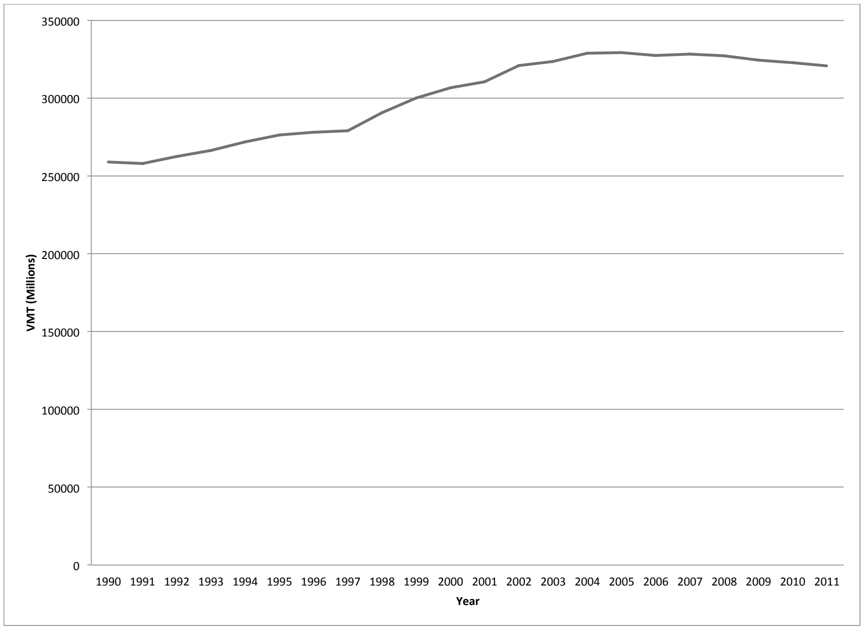

Figure B1. Annual California On-road VMT 1990-2011

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%.

To decompose transportation sector GHG emissions into VMT (miles) and an average emissions factor per mile (grams/mile), we divide our adapted series of on-road GHG emissions by our measure of on-road VMT, the ratio of which is our implied average emissions factor per mile of travel. Table B2 reports our adjusted transportation sector emissions, VMT, and the calculated average annual emissions factors for on-road activity over the period 1990-2011.

B1. 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. EMFAC 2011 uses historical data on fleet composition, emissions factors, VMT, and turnover to forecast future motor vehicle emissions inventories in tons-per-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.

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 EMFAC 2011 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 EMFAC 2011 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 B3 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 only provides point estimates for the emissions intensity of VMT. 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.

Online Appendix C: Abatement in Response to the Market Price of Allowances

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 APCR, and at the price to access the third (highest) tier of the APCR.[42] We also consider responses of industrial emissions to allowance prices.

C1. 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 binding 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.[43] Long-run elasticities are generally between -0.3 and -0.5.[44] 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.[45]

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

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

[44] See Dahl, 2012

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

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.[46] 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 would not 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 $49.06 in 2013 going up to $69.03 in 2020),[47] the result using a -0.1 elasticity is a reduction of 10.6 MMT over the life of the program from reduced use of gasoline and diesel. Assuming an elasticity of -0.2 about doubles the reduction to 21.0 MMT. As part of the later analysis without complementary policies, we also consider the potentially more-elastic response if vehicle fuel economy standards are not separately increased. Assuming elasticities of -0.3, -0.4, and -0.5 yields reductions of 29.6 MMT, 39.3 MMT, and 48.8 MMT, respectively.[48] (Note the fuels will be under the cap only in 2015-2020, so we calculate reductions for only these six years.) When we examine the market with no complementary policies, 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 had not been effectively implemented.

In the primary scenario with complementary policies, we also consider the potential cap-and-trade market impact of the state's low-carbon fuel standard, which could end up significantly raising gasoline prices. Discussions with market participants and regulators suggest that the impact is likely to be capped at $0.40 per gallon, and could be much smaller if regulations are relaxed. We consider scenarios in which the LCFS raises gasoline prices by zero, $0.20 and $0.40 per gallon, using an elasticity of -0.15.

[46]We also assume that the allowance cost of tailpipe CO2 emissions is passed through 100% to the retail price. Many studies on passthrough of fuel taxes and crude oil price changes, including Borenstein, Cameron and Gilbert (1997), Lewis (2011), and Marion and Muehlegger (2011), have found passthrough to retail price equal or very close to 100%.

[47]These allowance prices translate to an increase of about $0.39 to $0.55 per gallon of gasoline at the pump in 2012 dollars (after accounting for 10% biofuels. For diesel, it implies and increase of $0.50 to $0.70 per gallon.

[48]Each of these estimates assumes that biofuels share of retail gasoline is 10%.

C2. 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, three large regulated investor-owned utilities (IOUs) that serve the vast majority of load in California 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 for their GHG emissions. 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,[49] 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 customers will see the full pass-through of energy price increases due to allowance costs.[50]

The CPUC estimates that 85% of revenues will go to residential customers, who make up about 34% of demand.[51] 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.

[49]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.

[50]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 on equilibrium wholesale electricity prices.

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

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.[52] 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 calculate the elasticity based on same-year average price.[53] 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, 26.9 MMT when price is at the lowest step of the containment reserve, and 32.9 MMT when price is at the highest step of the containment reserve.[54]

Electricity prices, however, are likely to rise for all customers over the years of the

[52]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 long-term supply contracts with prices set prior to or independent of the impact of GHG costs on market price.

[53]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.

[54]We also calculate a low elasticity case of -0.2 and a high elasticity case of -0.5, the results for which are shown in table. 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.

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,[55] we assume that this price will increase by 2.15% (real) per year due to exogenous (to Cap and Trade) factors.[56] Again assuming a long-run demand elasticity of -0.35 and a marginal CO_2e intensity of 0.428 tonne/MWh, yields a reduction of 24.1 MMT (if the allowance price is at the highest price in the price containment reserve) over the life of the program. Table 6 also shows the low and high elasticity results for -0.2 and -0.5 elasticities.[57]

Thus, at the highest level of the price containment reserve we estimate total abatement from electricity demand reduction of 57.0 MMT over the life of the program. Using an elasticity of -0.2 reduces the impact of electricity demand reduction to 31.8 MMT at the highest price of the containment reserve. The marginal GHG intensity of 0.428 is based on a combined-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.

C3. Demand for Natural Gas

ARB policy will give free allowances to natural gas suppliers (who are nearly all investor-owned regulated utilities in California) equal to their 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). CPUC Decision 12-12-033 suggests that the most likely outcome through 2020 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.[58] That outcome is not certain, however, so we also explore the impact of emissions prices being partially passed through to consumers. "Consumers" in this case include all emissions sources not covered in the industrial categories.

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

[56] This increase is based on a projected real increase from $144/MWh in 2012 to $211/MWh in 2030, an average increase of 2.15% per year. See Energy & Environmental Economics (2014).

[57] Ito (2014) estimates a medium-long run price elasticity for residential electricity demand of -0.1, suggesting that a lower elasticity might be more relevant under the no complementary policies case when we assume 100% passthrough to all types of customers.

[58] See http://docs.cpuc.ca.gov/PublishedDocs/Published/G000/M040/K631/40631611.PDF.

(Large industrial customers, which are in the program beginning with the first compliance period, are discussed in subsection *C5*.)

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[59] before allowance costs, and examine 0%, 15% and 30% passthrough of the allowance cost to retail. It's difficult to know the elasticity of retail demand for natural gas. We take an estimate of -0.4 over the 6-year time frame of natural gas in the program.[60] 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, 30% passthrough would be associated with 13.0 MMT of abatement over the life of the program. For analysis with no complementary policies, we assume 100% pass-through and consider low, medium and high cases with elasticities of -0.3, -0.4, and -0.5 respectively.

C4. 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 current 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.

[59]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.

[60]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.

C5. 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.[61] 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. 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.

[61] 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.

Equation	Parameter	Estimate	Standard Error	Variable
$\Delta ln\_twh_p\_hydro$	μ_1	-1.65177	2.02895	1
	Λ_{11}	-0.73325	0.26481	$ln\_twh\_p_hydro_{(t-1)}$
	Λ_{12}	0.74296	0.27618	$ln\_vmt_{(t-1)}$
	Λ_{13}	-0.24889	0.09949	$ln\_ngother\_industrial_{(t-1)}$
	Λ_{14}	0.42764	0.26946	$ln\_real\_gas\_price_{(t-1)}$
	Λ_{15}	-0.26193	0.09617	$ln\_real\_gsp_{(t-1)}$
	Λ_{16}	0.63832	0.51141	$ln\_thermal\_intensity_{(t-1)}$
	Λ_{17}	-0.07056	0.04052	$ln\_transport\_intensity_{(t-1)}$
Δln_vmt	μ_2	-0.32453	0.38536	1
	Λ_{21}	0.04808	0.05029	$ln\_twh\_p_hydro_{(t-1)}$
	Λ_{22}	-0.02646	0.05246	$ln\_vmt_{(t-1)}$
	Λ_{23}	0.02385	0.0189	$ln\_ngother\_industrial_{(t-1)}$
	Λ_{24}	-0.07333	0.05118	$ln\_real\_gas\_price_{(t-1)}$
	Λ_{25}	0.01937	0.01827	$ln\_real\_gsp_{(t-1)}$
	Λ_{26}	-0.13747	0.09713	$ln\_thermal\_intensity_{(t-1)}$
	Λ_{27}	0.01101	0.0077	$ln\_transport\_intensity_{(t-1)}$
$\Delta ln\_ngother\_industrial$	μ_3	-1.35962	0.7855	1
	Λ_{31}	-0.17986	0.10252	$ln\_twh\_p_hydro_{(t-1)}$
	Λ_{32}	0.22999	0.10692	$ln\_vmt_{(t-1)}$
	Λ_{33}	-0.0449	0.03852	$ln\_ngother\_industrial_{(t-1)}$
	Λ_{34}	0.00775	0.10432	$ln\_real\_gas\_price_{(t-1)}$
	Λ_{35}	-0.05954	0.03723	$ln\_real\_gsp_{(t-1)}$
	Λ_{36}	-0.04853	0.19799	$ln\_thermal\_intensity_{(t-1)}$
	Λ_{37}	-0.00361	0.01569	$ln\_transport\_intensity_{(t-1)}$
$\Delta ln\_real\_gas\_price$	μ_4	-9.22454	2.50676	1
	Λ_{41}	0.33562	0.32717	$ln\_twh\_p_hydro_{(t-1)}$
	Λ_{42}	0.16277	0.34122	$ln\_vmt_{(t-1)}$
	Λ_{43}	0.28399	0.12292	$ln\_ngother\_industrial_{(t-1)}$
	Λ_{44}	-1.21894	0.33291	$ln\_real\_gas\_price_{(t-1)}$
	Λ_{45}	0.16946	0.11882	$ln\_real\_gsp_{(t-1)}$
	Λ_{46}	-2.45244	0.63184	$ln\_thermal\_intensity_{(t-1)}$
	Λ_{47}	0.17656	0.05006	$ln\_transport\_intensity_{(t-1)}$
Δln_real_gsp	μ_5	-2.98668	0.49738	1
	Λ_{51}	-0.11266	0.06492	$ln\_twh\_p_hydro_{(t-1)}$
	Λ_{52}	0.25216	0.0677	$ln\_vmt_{(t-1)}$
	Λ_{53}	0.00843	0.02439	$ln\_ngother\_industrial_{(t-1)}$
	Λ_{54}	-0.21511	0.06606	$ln\_real\_gas\_price_{(t-1)}$
	Λ_{55}	-0.02664	0.02358	$ln\_real\_gsp_{(t-1)}$
	Λ_{56}	-0.49481	0.12537	$ln\_thermal\_intensity_{(t-1)}$
	Λ_{57}	0.02875	0.00993	$ln\_transport\_intensity_{(t-1)}$
$\Delta ln\_thermal\_intensity$	μ_6	0.99216	1.08524	1
	Λ_{61}	-0.08083	0.14164	$ln\_twh\_p_hydro_{(t-1)}$
	Λ_{62}	0.02234	0.14773	$ln\_vmt_{(t-1)}$
	Λ_{63}	-0.04758	0.05322	$ln\_ngother\_industrial_{(t-1)}$
	Λ_{64}	0.16834	0.14413	$ln\_real\_gas\_price_{(t-1)}$
	Λ_{65}	-0.03475	0.05144	$ln\_real\_gsp_{(t-1)}$
	Λ_{66}	0.32625	0.27354	$ln\_thermal\_intensity_{(t-1)}$
	Λ_{67}	-0.02487	0.02167	$ln\_transport\_intensity_{(t-1)}$
$\Delta ln\_transport\_intensity$	μ_7	-0.57887	0.67276	1
	Λ_{71}	-0.08132	0.0878	$ln\_twh\_p_hydro_{(t-1)}$
	Λ_{72}	0.10193	0.09158	$ln\_vmt_{(t-1)}$
	Λ_{73}	-0.021	0.03299	$ln\_ngother\_industrial_{(t-1)}$
	Λ_{74}	0.00768	0.08935	$ln\_real\_gas\_price_{(t-1)}$
	Λ_{75}	-0.02712	0.03189	$ln\_real\_gsp_{(t-1)}$
	Λ_{76}	-0.01313	0.16957	$ln\_thermal\_intensity_{(t-1)}$
	Λ_{77}	-0.00222	0.01344	$ln\_transport\_intensity_{(t-1)}$

Table A3—Error Correction Vector Autoregression Parameter Estimates

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 B1—On-road and Off-road Transportation Emissions 1990-2011

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

Table B2—On-road Emissions, Emissions Factors, and VMT 1990-2011

Year	CAFE & 10% Biofuels		CAFE & LCFS	
	EF (kg/mi)	MPG (mi/gal)	EF (kg/mi)	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 B3—Adjusted EMFAC 2011 Average Emissions Factors and MPG 2012-2020