NBER WORKING PAPER SERIES

EXPECTING THE UNEXPECTED:
EMISSIONS UNCERTAINTY AND ENVIRONMENTAL MARKET DESIGN

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Working Paper 20999
http://www.nber.org/papers/w20999

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
March 2015

This research was supported by a contract with the California Air Resources Board. Borenstein, Bushnell, and Wolak were members of the Market Simulation Group that advised ARB in 2012-2014. Zaragoza-Watkins worked with the MSG as a researcher. Bushnell's research was supported in part by the National Science Foundation under award 1229008. Zaragoza-Watkins' research was supported in part by the High Meadows Foundation, during a post-doctoral fellowship at the Environmental Defense Fund. We thank Elizabeth Bailey, David Kennedy, Ray Olsson, Billy Pizer, Rajinder Sahota, and Emily Wimberger for their input. We also thank participants in seminars and conferences at National Bureau of Economic Research, U.S. Environmental Protection Agency, University of Pittsburgh, UC Berkeley, and University of Minnesota for valuable comments. The opinions in this paper do not represent those of the California Air Resources Board, any of its employees, or the National Bureau of Economic Research.

Expecting the Unexpected: Emissions Uncertainty and Environmental Market Design
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NBER Working Paper No. 20999
March 2015, Revised August 2016
JEL No. Q5,Q52,Q54

ABSTRACT

We study potential equilibria in California's 2013-2020 cap-and-trade market for greenhouse gasses (GHGs) based on information available before the market started. We find large ex ante uncertainty in business-as-usual emissions, and in the abatement that might result from non-market policies, compared to the market-based variation than could plausibly result from changes in allowance prices within a politically acceptable price range. This implies that the market price is very likely to be determined by an administrative price floor or ceiling. Comparable analysis seems likely to reach similar conclusions in most cap-and-trade markets for GHGs, consistent with outcomes to date in such markets.

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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. A stable and predictable price of carbon into the distant future will more effectively incent firms and consumers to make long-lived investments in expensive lower-carbon technologies and stimulate innovation in the development of new low-carbon technologies, on which the ultimate success of any climate policy depends.

Existing cap-and-trade policies, however, have not been very successful in creating a stable, market-driven price of carbon.[1] Prices in existing cap-and-trade markets for greenhouse gasses (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 economically insignificant 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 emissions may come in under the caps, low or highly uncertain average emissions allowance prices do little to achieve the long-term climate policy goals of significant investments in low-carbon technologies.

In this paper, we argue that extreme price outcomes are very likely to occur in most real-world cap-and-trade markets for GHGs. We explore the relative importance of two aspects of GHG emissions that drive this conclusion. The first is the high level of exogenous GHG emissions volatility. GHG emissions are closely tied to economic activity and also vary with natural conditions such as temperature and rainfall. These uncertainties have long been recognized as an issue when forecasting both damages and mitigation cost.[3] The second factor is that the price elasticity of GHG abatement is likely to be relatively small over the range of prices generally deemed acceptable – at least over the timeframe of a decade – and very difficult to predict over a longer timeframe.

The inelasticity of the supply of GHG emissions abatement is exacerbated by other environmental policies that are commonly present in the same jurisdictions as cap-and-trade markets. These so-called "complementary policies" – such as

[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 and RGGI were both around $5 per metric 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."

fuel economy standards for cars and mandated renewable generation shares for electricity – may increase the political acceptance of cap-and-trade markets by requiring certain pathways to GHG reductions, but as we demonstrate below, these same mechanisms steepen the abatement supply curve by mandating mitigation that would otherwise be price responsive.

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 included price collars of a sort, as does California's program. The fact that California's market currently has the highest price among mandatory GHG cap-and-trade programs is largely due to its relatively high floor price.

California's cap-and-trade market undertook its first allowance auction on November 14, 2012 and compliance obligations began 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. There is an auction reserve price (ARP), managed through adjustments to the supply of allowances at 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 certain trigger levels at anytime during the program. This is a very soft price ceiling in that if all allowances in the APCR are used there would be no further mechanism to restrain allowance price increases.

Using data from prior to the commencement of California's market, we develop estimates of the distribution of allowance prices that account for uncertainty in GHG emissions, as well as the elasticity and uncertainty of the supply curve of abatement. Instead of estimating the full probability distribution of allowance prices, we focus on computing probabilities that allowance prices lie on four distinct segments of the abatement supply curve: (1) at or near the price floor (auction reserve price), (2) above the price floor and below the first step of the APCR (*i.e.,* on the upward sloping portion of the abatement supply curve), (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 uncertainties in "business-as-usual" (BAU) emissions and the quantity of abatement available from complementary policies create variation in the amount of abatement needed to meet a cap that is much larger than price-responsive abatement adjustment could plausibly provide.

One of the primary factors determining where in that distribution the market will equilibrate is the BAU emissions, which is substantially the result of economic activity driving electricity consumption and vehicle travel, as well as the emissions intensities of those activities, plus emissions from natural gas combustion in the residential, commercial and industrial sectors. We develop an econometric model of the drivers of GHG emissions using time-series methods, which we estimate with emissions and economic data starting in 1990, in order to estimate the distribution of future GHG emissions.

The steep supply of emissions abatement between the effective price floor and the APCR, along with substantial uncertainty we find in both business-as-usual emissions and abatement from complementary policies, implies a bimodal distribution of prices with most of the probability mass at either low or high price outcomes. We find that there is a very small probability of an "interior solution" in which supply and demand for emissions equilibrate at a level that is not driven primarily by administrative interventions that set a floor or ceiling.

In the case of California's market, we find that the emissions cap has been set at a level that implies a very high probability total GHG emissions will be below the cap and the allowance market price will be very close to or at the price floor.[4] 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.

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 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 a 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 price over the full 8-year course of the market.

Based on our empirical analysis, we believe that all GHG emissions allowance markets with a finite compliance period face a high probability that the market price will be determined by an administrative price floor or price ceiling. As we demonstrate below, many of the features of the market design that make a GHG emissions allowance market politically feasible also steepen the supply curve for abatement. Highly unpredictable BAU emmissions create a wide support of the demand for allowances while relatively inelastic abatement supply implies that only if allowance demand is in a narrow band will the market price not be determined by the administrative price floor or ceiling.

[4]Throughout this paper we refer to a single "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.

The remainder of the analysis proceeds as follows. Section II characterizes the set of 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."[5] These include a renewable portfolio standard (RPS) that mandates increased electricity generation from renewable sources, a fuel economy standard that reduces fuel use per vehicle mile traveled, a low-carbon fuel standard (LCFS) that lowers 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 will be largely independent of allowance prices, the effects of these programs 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 is emissions of GHGs from the covered entities, which are a function of the levels and intensities of their emissions-producing activities. Banking and (slightly 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 during the first year of the program,[7] under nearly any scenario,

[5] The terminology presents some irony, because in economic terms these programs are probably more aptly described as substitutes for a cap-and-trade program.

[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 possibilities 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 recently adopted changes, see

emissions during 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.

We carry out the analysis based on estimates of the distribution of future emissions using data through 2010 and through 2012. Data through 2010 were available by mid-2012, less than a year before the market commenced. Presumably, a cap would have to be set by 6-12 months before any cap-and-trade market begins. This approach to the analysis addresses the question of what distribution of outcomes a regulator should be able to expect at the time the cap is set. Data through 2012 represent all information on activity prior to the opening of the market. Some of these data were not available until well after the market opened, but noisy estimates of these data may have been available at the beginning of 2013. Beyond considering two different information sets on which our distributions of future emissions are based, this approach also allows us to study how much uncertainty is resolved in the two intervening years.

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 Allowance Price Containment Reserve. 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 APCR 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 a very steep abatement supply curve, which we will demonstrate implies the potential for a very wide distribution of price outcomes. Abatement of capped emissions 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"[8]), and (c) offsets, which we discuss later (and which

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 minus the amount of abatement exceeds the amount of available allowances during the first two compliance periods.

[8]Also known an "resource shuffling." These terms include a practice known as "relabeling," which is reselling out-of-state power that comes from a high-emissions source so that the buyer can then import

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 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.

the power into California at the administratively determined default emissions rate.

[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.

[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 Fowlie (2012). If applied to a large enough set of industries or fraction of the allowances, Bushnell and Chen (2012) show that 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.

Compared to the aggregate level of reductions needed and expected under California GHG reduction legislation, known as "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.

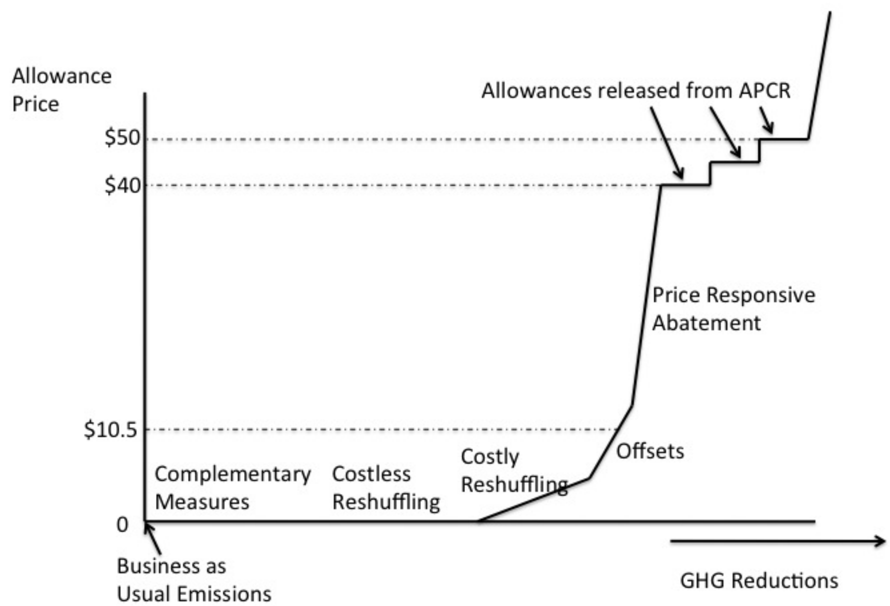

Figure 1. Supply of Abatement

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]

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

[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

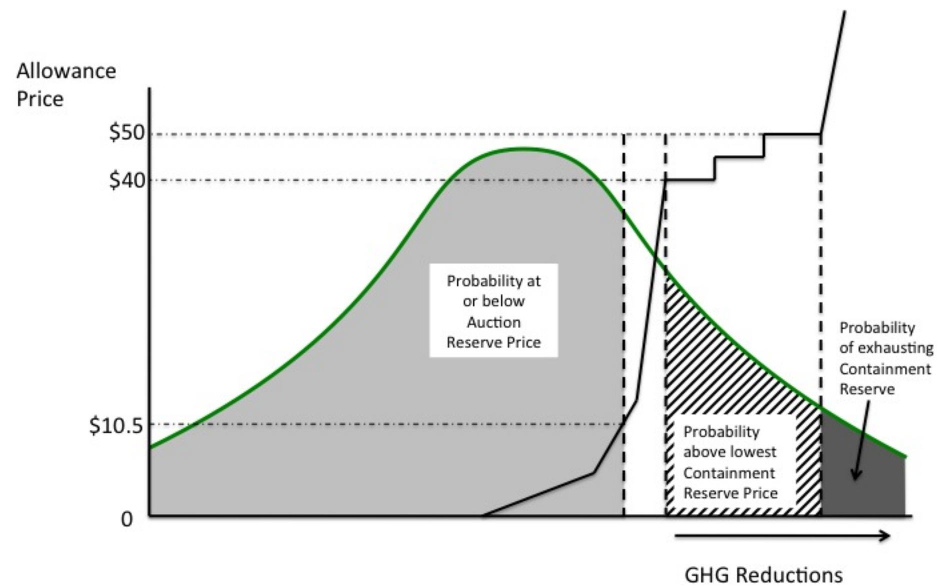

FIGURE 2. HYPOTHETICAL DISTRIBUTION OF ABATEMENT DEMAND (BAU MINUS ALLOWANCES OUTSIDE PRICE CONTAINMENT RESERVE) VERSUS ABATEMENT SUPPLY

One potential implication of this is that allowance prices may be 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 could constitute a large fraction of the overall distribution of potential emissions outcomes. This intuition is illustrated in Figure 2, which superimposes a hypothetical symmetric distribution of the amount of abatement needed (BAU emissions less the total amount of available allowances) onto the same horizontal axis as the abatement 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

Pathways Analysis available at: http://www.arb.ca.gov/regact/2010/capandtrade10/capv3appf.pdf.

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. When the market commenced, there was no clarity on how the program would evolve after 2020. That remains the case today.

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 allowances at different points in time are competitive and well integrated, then intertemporal arbitrage enabled by banking and borrowing (within and across 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, 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 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 previously 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

[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. Pizer and Prest (2016) suggest that intertemporal arbitrage may also may cap-and-trade preferred to a tax under some circumstances where either type of program may be subject to updating.

[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.

extremely high market price would probably not occur until the later years of the program.

Table 1—Emissions from Key California Sectors in 1990 and 2012 (in millions of metric tonnes (MMT)

Source	1990 Emissions	2012 Emissions
Electricity (domestic)	44.76	48.18
Electricity (imports)	29.61	43.09
Transportation (on road)	140.35	146.05
Industrial	74.86	65.62
Nat. Gas and Other	62.40	59.91

III. ESTIMATING THE BUSINESS AS USUAL EMISSIONS

Perhaps the largest factor driving the supply-demand balance in the GHG allowance 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 was 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 in California are referred 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 referred to as "Broad Scope Emissions." Table 1 summarizes the aggregate emissions from the key sectors in 1990 and 2012.

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 23-year period beginning in 1990. Predicting the level of economic activity from each of these sectors just one year in advance has the potential for significant uncertainty. Simulating the level of economic activity and GHG emissions eight or more years into the future involves even greater uncertainty, which implies a greater potential for very low or high allowance price realizations.

Imported electricity is a substantial category of emissions in the cap-and-trade program, likely to constitute more than 10% of total emissions. However, it is impossible to partitition aggregate GHG emissions from generation units outside California into those caused by electricity imports into California and those caused by serving electricity demand outside of California. Below we discuss

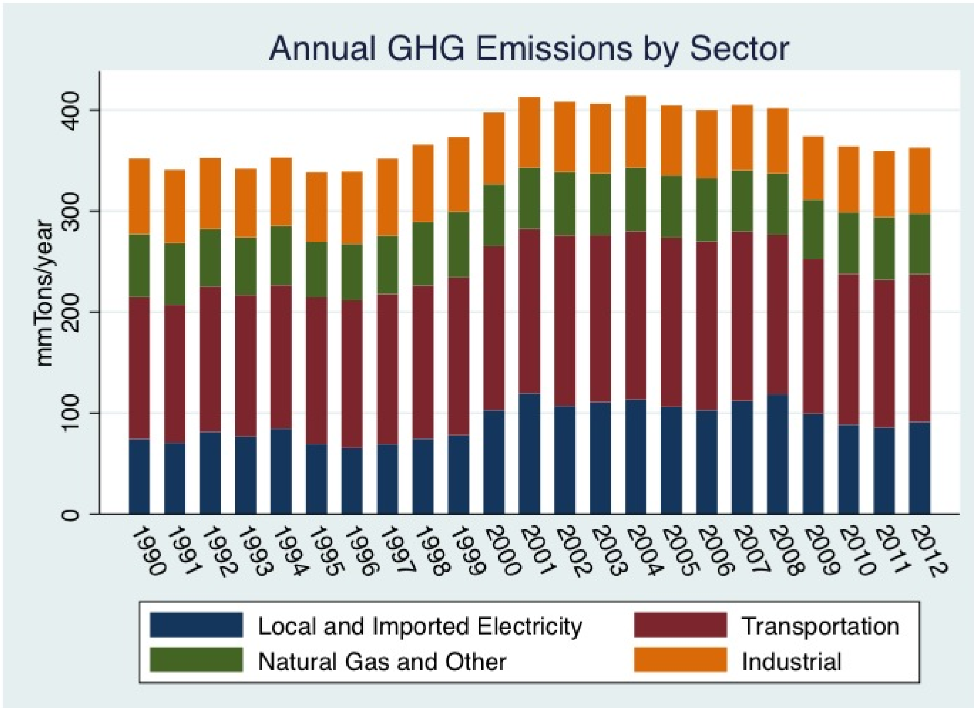

Figure 3. California Emissions Data 1990-2012

the challenges faced by the ARB in designing the adminstrative process used to incorporate emissions attributable to electricity imports. Because of this administrative process, electricity imports is the one area of BAU emissions in which we cannot estimate uncertainty. Using a point estimate for this component of aggregate GHG emissions is likely to lead to an understatement of the uncertainty in total BAU emissions.

To derive estimates of the expected future time path of in-state 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 either 2012 (up to the date of the market opening) or 2010 (the information that was available

[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.

at the time political consensus for the capped level of emissions was developed).

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 most 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, $t = 1990, 1991, ..., 2012$. 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 total vehicle miles traveled.

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. As discussed further below, 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. 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 be "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 changed 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. 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 were 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 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

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

(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_{2012} that takes into account both our uncertainty in the values of μ, Ω, γ, and α because of estimation error and uncertainty due to the fact that $(X'_{2013}, X'_{2014}, ..., X'_{2020})'$ depends on future realizations of ϵ_t for $t = 2013, ..., 2020$.[20]

We employ a two-stage smoothed bootstrap approach to compute an estimate of this distribution.[21] 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 2012. Note that we can only compute values of $\hat{\epsilon}_t$ for t =1991 to 2012, 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.

[20]We describe the estimate for the approach that uses data through 2012. The approach is comparable using data only through 2010, but results for 2011 and 2012 are simulated as part of the procedure to create simulated values for 2013 through 2020.

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

We then draw $T = 22$ values from (3.4) and use the parameter estimates and these draws to compute re-sampled values of Y_t for $t = 1, 2, ..., T = 22$. Let $(\hat{\epsilon}_1^m, \hat{\epsilon}_2^m, ..., \hat{\epsilon}_{22}^m)'$ denote the mth draw of the 22 values of $\hat{\epsilon}_t$ from $\hat{f}(t)$. We compute the Y_t^m, the 22 resampled values of Y_t for t =1991 to 2012, by applying the following equation starting with the value of Y_t in 1990 ($Y_{1990}^m = Y_{1900}$ for all m)

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

We then estimate the values of μ, Ω, and Θ_1 by applying Johansen's (1988) ML procedure using the Y_t^m and imposing the cointegration rank restriction that $(1 - \Theta_1) \;=\; -\gamma\alpha'$. 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 $(\hat{\epsilon}_{T+1}^m, \hat{\epsilon}_{T+2}^m, ...\hat{\epsilon}_{T+8}^m)'$. Using these draws and $\hat{\mu}^m$, $\hat{\Omega}^m$, and $\hat{\Theta}_1^m$ we compute future values Y_{T+k} for $k = 1, 2, ..., 8$ given Y_T using the following equation:

$$Y_{T+k|T}^m = \hat{\mu}^m + \hat{\Theta}_1^m Y_{T+k-1|T,T-1}^m + \hat{\epsilon}_{T+k}^m \quad \text{for} \quad k = 1, 2, ..., 8 \tag{3.6}$$

This yields one realization of the future sample path of Y_t for t =2013, 2014,..., 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 $Y_{T+k|T}^m$ for $k = 1, 2, ..., 8$ replicated $m = 1$ to $M = 1000$ times produces 1,000 realizations from the simulated distribution of $X_{2013}', ..., X_{2020}')'$.

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.

B. Data

To compute the GHG emissions intensities of the in-state electricity sector and transportation sector from 1990 to 2012 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 2012 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 2012.

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 2000-2012 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 2008-2012 MRR and Inventory industrial emissions data series shows annual 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 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.

[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/reported-data/ghg-reports.htm.

Table 2—Summary Statistics of Data for Vector Autoregression

	mean	S.D.	min	max	year min.	year max.
California Elec. Generation (TWh)	195.3	14.2	166.1	220.1	1991	2006
California Hydro. Gen (TWh)	34.9	9.4	22.4	51.7	1992	1998
Vehicle Miles Traveled (Billions)	302.9	26.7	258.0	330.0	1991	2005
Industry, Natural Gas & Other Emissions (MMT CO2e)	129.6	4.8	121.6	139.4	1995	1998
Gross State Product (Nominal $Trillion)	1.44	0.49	0.77	2.20	1990	2012
Gasoline Price (Nominal $/gallon)	2.10	1.01	1.09	4.03	1990	2012
In-state Electric Thermal Intensity (tons/MWh)	0.483	0.065	0.390	0.624	2012	1993
Vehicle Emissions. Intensity (tons/1000 VMT)	0.508	0.030	0.444	0.546	2012	1992

Note: Data are for 1990-2012

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.

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,

[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.

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. The top panel of Figure 4 shows actual GSP data through 2010 and forecasts from the VAR for 2011-2020, with 95% confidence intervals for the forecast, while the bottom panel displays actual data through 2012 and forecasts for 2013-2020. The vertical dots show the distribution of simulation outcomes. The uncertainty in GSP suggest how difficult it would be to forecast business as usual emissions, which are the product of GSP and the emissions intensity of economic activity. The two years of growth experienced in 2011 and 2012 increased the mean 2020 forecast from to 2.44 to 2.49 trillion dollars. Table 3 lists the means and standard deviations of simulated values of each element of X_t for each year from 2013 to 2020, based on estimates using data through 2010, as well as the annual and cumulative emissions resulting from those values. Table 4 shows forecasts based on data through 2012. Section IV 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.

D. *Robustness to an alternative GHG forecast method*

The VAR approach to forecasting GHG emissions may be seen by some as imposing excessive structure on such a short time series of data.[28] To examine the robustness of this approach, we also explored a bare bones bootstrap GHG forecast method that draws GHG growth rates for each year from the distribution of GHG growth rates over the 23-year sample, 1990-2012. We created 1000 bootstrap GHG paths, all starting at the observed 2012 (or 2010, to examine the potential forecast when the cap was set) GHG emissions and then for each successive year drawing from the 22 annual growth rates from 1990-2012 (or 20 annual growth rates through 2010) with replacement. This will likely tend to understate the forecast uncertainty, both because it ignores positive serial correlation in growth rates and because it fails to capture the potential for a confluence

[28]There is also a broader concern that this is a very short time series on which to forecast up to a decade of future emissions. We agree wholeheartedly, but the fact is that it is representative of the information on which policy makers must make decisions on GHG caps.

of outlier events of the components of GHG growth that isn't present in the 22 years of annual change. Using this approach and data through 2012, the mean forecast BAU GHG emissions for the 2013-2020 period is 2571.4 with a standard deviation of 108.4, about 14% lower than the standard deviation from the VAR forecast. Using data through 2010, the mean forecast BAU GHG emissions for the 2013-2020 period is 2579.5 with a standard deviation of 129.7, about 33% lower than from the VAR forecast using data through 2010. Thus, the uncertainty in BAU forecasts with this bare bones forecasting approach is smaller, but largely consistent with the VAR approach.

IV. ACCOUNTING FOR COMPLEMENTARY POLICIES IN FORECASTS

While the ARB 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.

Much of California's greenhouse gas policy was in flux during the 2010-2012 time period, making it difficult to identify exactly when aspects of the complementary programs became expected policies. Rather than attempting to parse exact dates or believed probabilities, we assume that the major programs set in law by 2013 were anticipated at the times we simulate distributions of outcomes. Also, in order to avoid confusing the VAR forecast errors with speculation about when a complementary policy was set, we assume the same anticipated complementary policies for the 2010 forecast as for the 2012 forecast.

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, we include California's adoption in April 2011 of a 33% RPS target by 2020.[29]

For three decades prior to the opening of California's cap-and-trade program, nuclear power was the largest contributor of zero-emissions electricity generation, coming from Diablo Canyon Nuclear Power Plant and San Onofre Nuclear Generation Stations (SONGS). In January 2012, SONGS was shut down due to faulty

[29]In 2015, California adopted a new target of 50% by 2030, but this did not change the target for 2020. The state now seems likely to exceed the 33% level by 2020, but we do not make further adjustments as it was not clear in 2010-2012 how difficult attaining the 2020 standard would be.

upgrades that had been made in 2009 and 2010, and there was widespread speculation about when it would reopen. In June 2013, Southern California Edison announced that the SONGS closure would be permanent. In the simulations, we assume that SONGS does not produce electricity. Diablo Canyon was widely assumed to operate through 2020, though PG&E announced in 2016 that it would close permanently in 2025. In the simulations, we assume annual output from Diablo Canyon equal to its annual average over the period 2003-2012.

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.

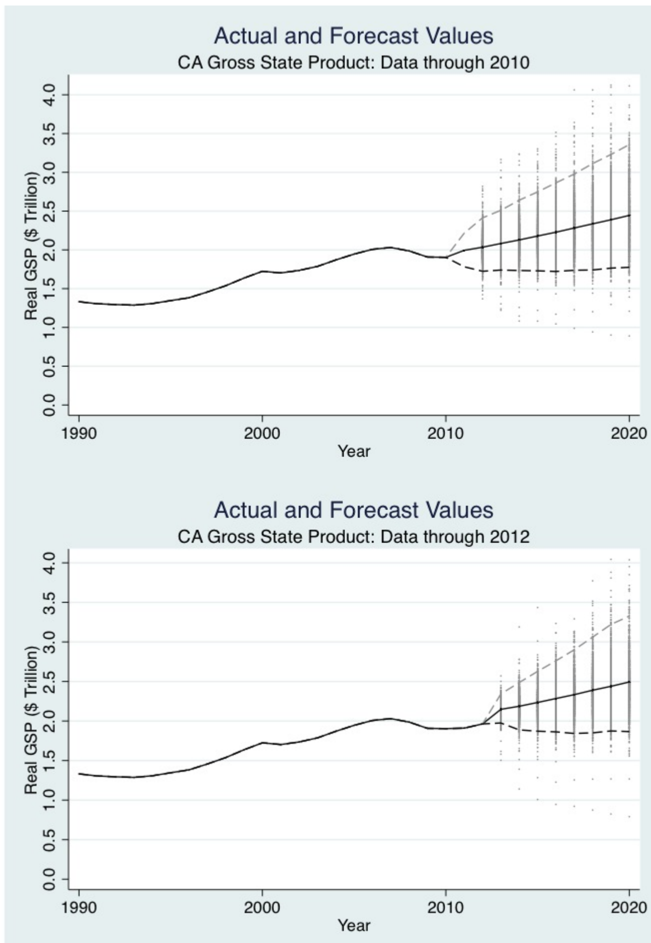

Figure 4. Forecast Results – Gross State Product

Table 3—Summary Statistics of Simulated VAR Variables and Emission: Data through 2010

Year	California Electricity net of Hydro Twh	Vehicle Miles Traveled Million Miles	Nat. Gas, Ind. & Other MMT	Gasoline Price $2012	Gross St. Product $2012 Trillion	Therm. Intensity tons/ MWh	Trans. Intensity tons/1000 Miles	Broad Scope Emis. MMT	Cum. Emis. MMT
2013	182.0	332.9	124.4	3.36	2.08	0.383	0.453	380.4	161.1
	(21.2)	(10.8)	(10.6)	(0.77)	(0.20)	(0.047)	(0.020)	(17.8)	(10.7)
2014	184.2	336.6	124.1	3.48	2.13	0.378	0.449	380.5	322.3
	(24.8)	(12.5)	(11.6)	(0.89)	(0.23)	(0.062)	(0.023)	(20.1)	(22.0)
2015	186.5	340.3	123.6	3.61	2.18	0.373	0.445	380.8	703.1
	(25.7)	(14.2)	(12.3)	(1.03)	(0.26)	(0.085)	(0.025)	(22.5)	(40.6)
2016	189.0	344.4	123.3	3.70	2.23	0.370	0.442	381.7	1084.8
	(27.1)	(15.8)	(13.4)	(1.14)	(0.30)	(0.111)	(0.027)	(24.8)	(63.2)
2017	190.5	348.4	123.0	3.83	2.28	0.366	0.439	382.2	1467.0
	(29.4)	(17.1)	(14.4)	(1.29)	(0.33)	(0.137)	(0.029)	(29.0)	(90.1)
2018	193.6	352.3	122.6	3.95	2.34	0.363	0.436	383.4	1850.4
	(31.8)	(18.9)	(15.3)	(1.41)	(0.37)	(0.165)	(0.031)	(32.8)	(120.6)
2019	195.6	356.3	122.4	4.05	2.39	0.360	0.433	384.2	2234.6
	(33.4)	(20.7)	(16.0)	(1.55)	(0.40)	(0.197)	(0.033)	(37.6)	(155.8)
2020	197.2	360.6	122.4	4.17	2.44	0.358	0.430	385.0	2619.6
	(34.8)	(22.2)	(17.1)	(1.70)	(0.43)	(0.253)	(0.034)	(40.4)	(194.0)

Note: Estimates are mean values of 1000 draws, values in parenthesis are the standard deviations of 1000 draws.

Table 4—Summary Statistics of Simulated VAR Variables and Emission: Data through 2012

Year	California Electricity net of Hydro Twh	Vehicle Miles Traveled Million Miles	Nat. Gas, Ind. & Other MMT	Gasoline Price $2012	Gross St. Product $2012 Trillion	Therm. Intensity tons/ MWh	Trans. Intensity tons/1000 Miles	Broad Scope Emis. MMT	Cum. Emis. MMT
2013	172.1	329.5	124.3	4.18	2.15	0.389	0.444	372.1	157.4
	(25.7)	(8.1)	(6.8)	(0.73)	(0.09)	(0.038)	(0.014)	(10.0)	(6.5)
2014	170.8	332.3	123.9	4.38	2.19	0.384	0.440	370.7	313.9
	(22.3)	(9.6)	(9.2)	(0.92)	(0.16)	(0.038)	(0.017)	(14.3)	(12.7)
2015	171.9	336.1	123.7	4.58	2.23	0.379	0.436	370.9	684.8
	(22.9)	(11.3)	(10.4)	(1.11)	(0.20)	(0.042)	(0.019)	(16.6)	(25.3)
2016	174.3	339.6	123.3	4.79	2.28	0.373	0.432	370.9	1055.7
	(24.6)	(12.7)	(10.8)	(1.30)	(0.23)	(0.044)	(0.021)	(18.1)	(41.3)
2017	175.3	343.3	122.8	4.99	2.33	0.370	0.429	370.9	1426.6
	(27.7)	(14.6)	(11.5)	(1.51)	(0.26)	(0.048)	(0.024)	(20.3)	(59.7)
2018	177.5	347.1	122.7	5.24	2.39	0.364	0.425	371.2	1797.8
	(29.3)	(16.3)	(12.4)	(1.75)	(0.30)	(0.051)	(0.026)	(22.5)	(80.3)
2019	178.9	350.6	122.3	5.47	2.44	0.358	0.421	370.8	2168.7
	(30.9)	(17.7)	(13.1)	(1.96)	(0.33)	(0.053)	(0.027)	(24.0)	(102.2)
2020	180.1	354.6	121.9	5.68	2.49	0.354	0.418	370.9	2539.5
	(32.9)	(19.2)	(13.7)	(2.15)	(0.37)	(0.056)	(0.030)	(26.0)	(126.1)

Note: Estimates are mean values of 1000 draws, values in parenthesis are the standard deviations of 1000 draws.

Data for renewable generation come from the California Energy Almanac for actual generation levels and from the Statewide Annual Planning Renewable Net Short (RNS) Update for future renewable generation levels. Both reports are produced by the California Energy Commission. The RNS update provides forecasts of renewable energy needs, which includes adjustments for exempted sales, energy efficiency, and imported renewable energy. For the years 2013-2018 we assume that the State will exactly meet RPS targets quantified in these reports.

Table 5—Assumed Zero-Carbon Electricity Output and Vehicle Emissions Intensities

Year	Zero-Carbon Power RPS GWh	Zero-Carbon Power Nuclear GWh	EMFAC VMT Intensity tons/1000 miles	BAU Forecast VMT Intensity tons/1000 miles
2013	35893	17530	0.477	0.444
2014	41807	17530	0.468	0.440
2015	49297	17530	0.456	0.436
2016	49297	17530	0.440	0.432
2017	52397	17530	0.423	0.429
2018	54997	17530	0.406	0.425
2019	62797	17530	0.390	0.421
2020	67797	17530	0.374	0.418

These values for carbon-free electricity are summarized in the second and third columns of Table 4. The remaining in-state generation, net of hydro, 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

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

where $Nhydro\_TWH_{m,T+k}$ is the realization of $X_{1,T+k}$ for simulation draw m of the in-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 energy efficiency, there is a strong pre-existing trend of efficiency improvements already present in the time-series data we used to forecast the BAU emissions. Total emissions per unit of GSP declined at an average rate of about 1.8% per year from 1990 to 2012. 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 two different 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 value we use is 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. We summarize it here and described in more detail in the Appendix B.

Using EMFAC, we derive anticipated emissions intensities (essentially fleet average miles per gallon) assuming 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.[31]

Column 4 of table 4 presents the the point estimate of fleet average emissions intensity from the EMFAC model assuming fuels economy standards are met, but biofuels remain at 10% of the fuel mix. Column 5 presents the mean transport intensity value forecast by the VAR. However, even though the standards may be fully complied with, considerable uncertainty remains as to the emissions intensity of the full transportation emissions. Among other factors, a substantial minority of transport emissions come from commercial trucking and other heavy-duty vehicles that will not be subject to the same kind of binding fuel economy standards as the passenger vehicle fleet.

In order to reflect the underlying random aspects of vehicle emissions, even with successfully implemented complementary policies, we model the effect of these policies as a shift in the distribution of emissions intensity from a BAU level to a level achieved, on average, by the policies. This is accomplished by shifting each VMT emissions 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

[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 pre-2012 level of biofuels was already about 10%.

[31]In a third scenario, we assumed 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. Even before the market commenced in 2013, this scenario seemed quite unlikely due to debates about the ability of most cars to use fuel with more than 10% biofuels without damaging engines. This approach results in substantially lower transport emissions intensity and would yield an even higher predicted probability of a price at or near the floor than we present below.

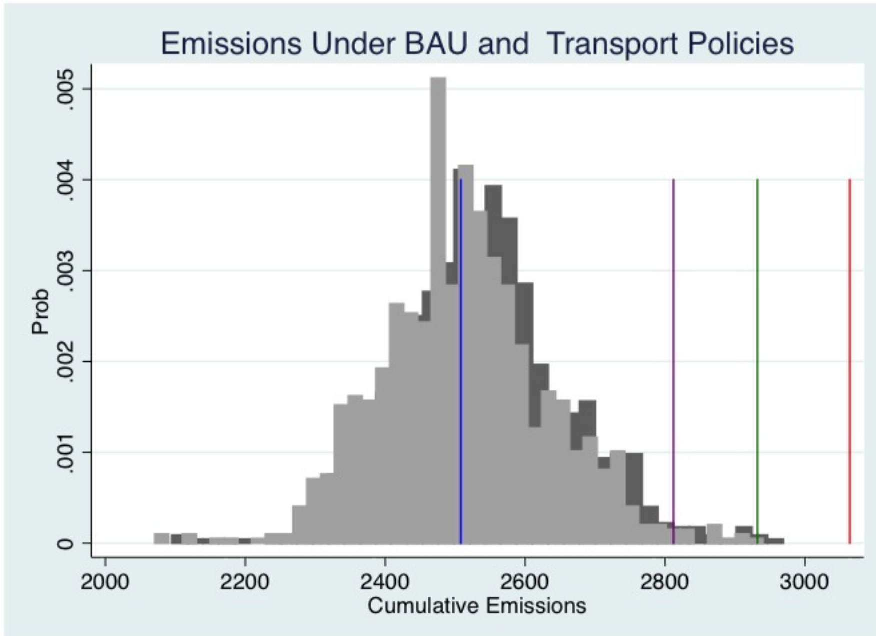

FIGURE 5. TARGETED TRANSPORTATION POLICIES SHIFT EMISSIONS DISTRIBUTION

to calculate total transport sector emissions for year t. More formally, transport emissions can be expressed as

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

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 $T+k$, respectively, and TI^{policy}_{T+k} is the transport emissions intensity derived by EMFAC 2011 in year $T+k$.

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 shows actual data (up to 2010 or 2012) and forecast from VAR for Broad Scope Emissions, with 95% confidence intervals for the forecast. The vertical dots show the distribution of simulation outcomes. The upper panel shows the forecast circa 2010 and the lower panel the forecast using data through 2012. Using the additional two years of data, 2011 and 2012, the mean BAU forecast for 8 years of cumulative emissions declines by about 10 MMT in 2020 and 80 MMT cumulative (about 3.5%) over the 8 years of the program. It is important

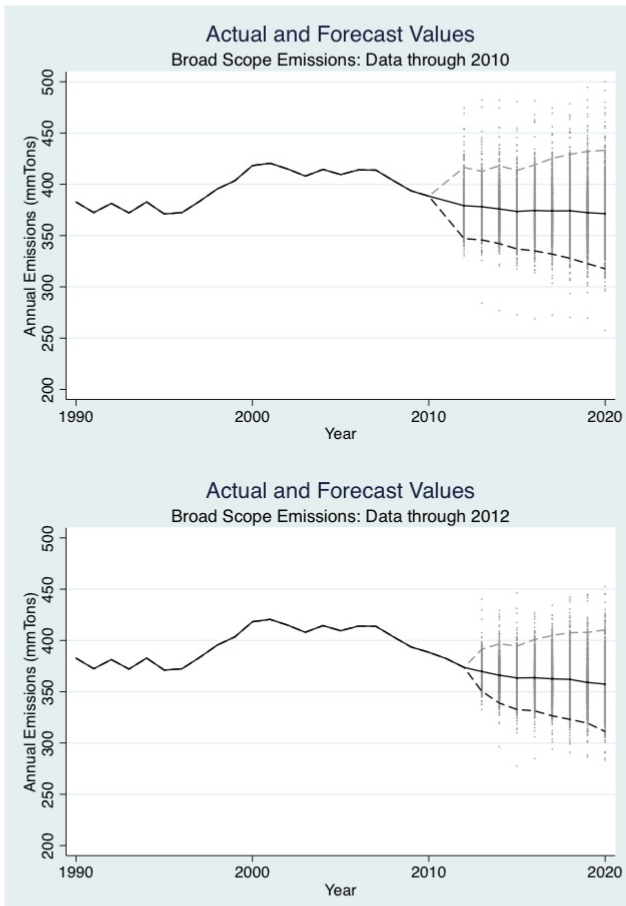

Figure 6. Forecast Results – Broad Scope Emissions

to note that at the time California finalized its regulation, the ARB's forecast of 2020 BAU emissions from capped sources was around 400 MMT per year, and the cap is scheduled to decline from that level to about 375 per year by 2020. As can be seen from figure 6, many forecast draws (which include complementary policies) fall below this level of emissions by 2020. Indeed even the mean 2012 vintage forecast (again with other policies) falls below the 2020 target. As we shall see, this is a large contributing factor to the expectation of low allowance prices.

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 sources of abatement 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. We also incorporate the effect of exogenous energy price increases were forecast at the time the market commenced. These assessments rely in part on regulatory decisions that affect how allowance prices will be passed through, as well as on previous estimates of demand elasticities. Here, we summarize the range of potential impacts we consider and discuss them briefly. Table 7 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*

To evaluate the impact of allowance prices on the demand for GHG-producing products, 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. Even if very high prices were to eventually occur, they 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 could 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.[32] For these reasons, while we use the APCR price levels to calculate potential responses to high prices in every year of the program, 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 (see, for example, Marion and Muehleggar (2011)). We use an elasticity assumption that is below most long-run elasticity estimates, because improved vehicle fuel economy is a large part of the difference between long-run and short-run elasticity estimate. Complementary policies, however, 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.

Table 6—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 ($2012):			Abatement in program at highest APCR step each year (MM tons)	
Sector	Low	High	Auction Reserve	Lowest step of APCR	Highest step of APCR	Low	High
Electricity							
most C&I ($/MWh)	-0.2	-0.5	$3.68/$5.17	$13.74/$19.34	$17.18/$24.17	21.3	52.4
Transportation ($/Gallon)	-0.1	-0.2	$0.10/$0.12	$0.36/$0.46	$0.45/$0.58	10.6	21
Natural Gas ($/MMBTU)	-0.3	-0.5	$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

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

[32]In addition, considerable policy uncertainty continues even into 2016 due to a lawsuit opposing the way in which the program was established by the legislature.

to be very small.

We also account for two other possible price changes not attributable to the cap-and-trade program. Real prices of electricity in California were likely to rise over the 2013-2020 period due to increased use and integration of renewable energy and other factors. We take a 2012 estimate of those increases and apply a range of elasticity assumptions. The real price of transportation fuels could 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. Our estimates do not explicitly anticipate the 2014-15 collapse of oil prices and the associated decline in transport fuel prices, though the VAR estimate includes a wide range of possible gasoline prices, as shown in tables 3 and 4.

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.

As of the start of the program, ARB had approved four categories of compliance offset projects that could 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 approved two offset project registries – American Carbon Registry[33] and the Climate Action Reserve[34] – to facilitate the listing, reporting, and verification of specific offset projects. The ARB reports that approximately 5.3 million offsets were listed with ARB under a voluntary early action offset program that are eligible for conversion to cap-and-trade program compliance offsets.

Offsets were expected to be a relatively low-cost (though not free) means for a covered entity to meet a portion of its compliance obligation.[35] The number 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.[36] ARB, however, was considering adding at least additional offset protocols, such as rice cultivation and mine methane capture and destruction, both of which were approved after the program began. The addition

[33]See http://americancarbonregistry.org/carbon-accounting/california-compliance-offsets.
[34]See http://www.climateactionreserve.org/.
[35]http://www.arb.ca.gov/regact/2010/capandtrade10/capv3appf.pdf.
[36]http://americancarbonregistry.org/acr-compliance-offset-supply-forecast-for-the-ca-cap-and-trade-program.

of these two protocols it was estimated would more than double the number of offsets available between 2013 and 2020.[37]

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.[38] 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

California's cap-and-trade program attempts to include all emissions from out-of-state generation of electricity delivered to and consumed in the state. Prior to the market commencing, ARB projected annual BAU emissions from imported electricity of 53.53 MMT, during the period 2013-2020.[39] 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-free resources, resulting in no demand for allowances to cover imported electricity. ARB has tried to limit reshuffling, focusing on avoiding reshuffling of imports from coal plants partially owned by California utilities. Based on the information available when the market opened, 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

[37]Ibid.

[38]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.

[39]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

implies 680 TWh over the 8 years of the cap.[40] Assuming as a baseline that the roughly 109 TWh of electricity imports from coal-fired plants generate about 109 MMT of emissions, we consider three possibilities for the remaining 571 TWh of imports. 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 7.

[40] 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 7—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 discussed in section V. 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 likely to be credible. Nor, unfortunately, are even the signs of these correlations obvious.[41] 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 7 is a $\beta(2,2)$ distribution with support from the low to the high scenario abatement level from each.[42] 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.

California has considered program modifications to address the possibility of the price containment reserve being exhausted, but as of this writing none has been adopted. 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 VI the distribution of estimated demand for allowances at each of the three break-points between the four

[41] 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.

[42] 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. We also estimated possible outcomes assuming that the abatement followed a triangular distribution with the low and high ends of the support from the low and high abatement scenarios and the mode at the medium scenario. The results differed very little from using the $\beta(2,2)$ distribution.

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-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 VI shows the probabilities that the equilibrium price will fall into each price range.

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

	Allowance Price Level			
Net Allowance Demand (MMT)	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
(2010 data)	91.8 %	2.6 %	4.0 %	1.6 %
(2012 data)	97.2 %	1.3 %	1.4 %	0.1 %

Assuming the moderate scenario for transportation emissions intensity and using the forecast as of 2010, we find a 92% chance of the market clearing at or very close to the price floor and a 3% 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 4% probability of settling in the APCR, and a 2% probability of exhausting the APCR. These results reflect the best information at the time the regulations were effectively codified in 2010. With just two more years of data, the price distribution shifts downward noticeably. Using data through 2012, the probability of prices falling into the price-floor region rises to over 97%.

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 9—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	
	2318 (182)	2286 (182)	2276 (182)	
Probability Distribution of Equilibrium Price	near ARP	above ARP below APCR	in APCR	above APCR
(2010 data)	79.6 %	8.5 %	8.8 %	3.1 %
(2012 data)	92.3 %	4.6 %	2.9 %	0.2 %

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 9 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 9 shows the probabilities that the equilibrium price will fall into each price range.

Under this scenario with no complementary policies, the 2010 vintage forecast yields a much smaller chance of the market clearing at or very close to the price floor, 79.6% vs. 91.8%, and a significantly larger (but still modest) probability, 8.5% vs. 2.6%, 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 about doubles, however, with a 8.8% probability of settling in the APCR, and a 3.1% probability of exhausting the APCR. Using the 2012 vintage forecast, the impacts of complementary policies are less pronounced, reflecting the fact that the cap was less likely to be binding in any event when analyzed with data through 2012.

VII. IS CALIFORNIA DIFFERENT?

Our findings are consistent with the results in the California market through mid-2016. In 2012, 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 two quarterly auctions auctions in 2016 produced prices at the floor, in the second auction selling only about 10% of the available allowances.

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. Of course, low prices could simply result from setting a very high GHG cap ex ante. However, in the EU-ETS, RGGI and California, the cap was set to reduce emissions relative to a higher historical level and there was an upward trend in emissions before the cap-and-trade program was put in place.

Still, one might ask how applicable the particular analysis of California's BAU emissions uncertainty, complimentary policies and price-responsive abatement is to other locations. While a similar analysis of the EU-ETS or RGGI markets is beyond the scope of this paper, a few important similarities are worth noting.

One might think that California's future BAU emissions are more uncertain than would be the case in a larger market. BAU emissions are a function of economic activity and larger economies are likely to be less volatile due to diversification. While there is some sign of this in comparing California and the U.S., the effect is not large. The standard deviation of GHG annual growth rate over

1990-2012 is 2.46% for California and 2.18% for the entire U.S.[43] For the EU-ETS, the corresponding number for covered CO_2 emissions for the period 1990 to 2004, the period before the start of Phase II of the EU-ETS, is 2.34%. Consequently, even for large regions like the U.S. and EU, BAU emissions uncertainty is comparable to that in California. For smaller states or countries that are considering cap-and-trade markets, this uncertainty could be even greater.

Although, California has pursued complementary policies more aggressively than most of the rest of the U.S. or many other parts of the world, regions with cap-and-trade markets typically have significant complementary policies. While complementary policies do reduce the elasticity of abatement supply, the previous subsection shows that drastically reducing complementary policies – to below levels that are likely to be in place in other areas that adopt cap-and-trade – still leaves a very inelastic abatement supply and a very high probability that the market equilibrium price will be driven by an administratively determined floor or ceiling.

California does differ from other parts of the U.S. and many other regions outside the U.S. in that it implemented a cap-and-trade market starting with fewer opportunities for market-driven abatement from its electricity sector. California's share of coal-fired generation in 2012 (all under contracts for imported electricity), was less than one-quarter of the U.S. average in 2012, so California's electricity generation sector had less opportunity to substitute natural gas for coal as the price of GHG rises.

In our analysis, the only substitution of gas for coal shows up in reshuffling opportunities, and takes place entirely at prices at or near the floor, so is not attributed to price-responsive abatement. In other markets, a higher GHG price would trigger market-driven coal-to-gas substitution. Even in those cases, however, Cullen and Mansur (2015) show that the GHG price at which significant substitution occurs, which is very sensitive to natural gas prices, would be extremely difficult to predict at the time a market opens, and could be very high. In their baseline 2025 fuel cost scenario ($2.25/MMBTU for coal and $5.75/MMBTU for natural gas), they estimate (table 7.2) that a $60/tonne GHG price would reduce emissions as a result of coal-to-gas switching by only about 10% of U.S. electricity emissions (or 4% of U.S. non-agricultural GHG emissions).

Even taking the extreme assumption that the entire U.S. coal fleet, responsible for about 1500 MMT of emissions in 2014, converts to natural gas generation, this would yield approximately 750 MMT/yr of GHG reductions, or about 12% of the U.S. 2014 total of about 6300 MMT of non-agricultural CO2 emissions.[44] By comparison, our estimates for the 8-year standard deviation of BAU emissions in California (Table 3) is about 200 MMT out of 2700. Four standard deviations, the approximate size of a 95% confidence interval on BAU emissions, would constitute almost 30% of the expected BAU amount. Therefore even if California had

[43] U.S. figure is based on the USEPA Emissions Inventory sum of CO_2, CH_4, and N_2O.
[44] See USEPA, 2016.

proportinally as much coal-to-gas switching opportunity as the U.S. as a whole had in 2012, the price-responsive abatement available in California would still be far less than a reasonable range of uncertainty in BAU emissions.[45] This "best-case" calculation supports the view that our results are relevant for cap-and-trade markets in other parts of the U.S. and other regions of the world.

VIII. CONCLUSION

If cap-and-trade programs for greenhouse gasses are to succeed and be expanded around the the world, it is important that the outcomes of these markets are reasonable and understandable. We have analyzed supply and demand in the California cap-and-trade market over the 2013-2020 period for which it has been authorized in order to forecast the range of possible outcomes and the factors that could drive those outcomes. We find that great uncertainty associated with BAU emissions creates a wide range of possible allowance demand while a steep supply curve of abatement creates quite inflexible allowance supply. As a result, we conclude that absent administrative restrictions, the price of allowances in the market would likely be extremely low or high.

Our analysis has demonstrated two implications 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 abatement. This is in part intrinsic to the demand for emitting GHGs, but exacerbated by the complementary policies – such as the renewable portfolio standard and auto fuel economy standards – 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. Inelastic abatement supply is also driven by output-based free allowances to most industrial emitters, which reduces the passthrough of allowances prices to final consumers.

Together these two conclusions suggest that equilibrium prices 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

[45] As coal is phased out in the U.S. in response to low gas prices and other environmental policies, this is becoming an even smaller potential source of abatement. On the other hand, if the cost of renewable electricity continues to fall, it is possible that more substitution to renewables could occur as a GHG price rises (within a politically acceptable range), even without the complementary tax credit policies that currently exist.

demand for abatement – driven by uncertainty in BAU emissions – implies that extreme prices (both high and low) are most likely. Based on data through 2010 – by which time most features of the market were determined – we find an over 90% probability that the market would have excess allowances, leaving the price at or very close to the administrative floor. But we also find about a 6% chance that the price would rise to the point of triggering regulatory intervention to contain further increases. We estimate less than a 3% probability of the market clearing in an intermediate region that is not primarily determined by the price containment policies. Using data through 2012, some of which were not available until well after the market began, we find an even higher probability of the price being driven primarily by the administrative floor.

While California may be somewhat of an outlier in factors that make the abatement supply curve inelastic, our analysis of the program in the absence of complementary policies, a comparison of California BAU uncertainty with other areas, and work by others on the potential for coal-to-gas switching in electricity generation suggests that any cap-and-trade program for greenhouse gasses is likely to face the same problem of volatility, if not to exactly the same magnitude. Thus, credible price ceilings and floors will likely play an important role in successful implementation of these programs.

One reaction to our findings has been that the likelihood of extreme-price outcomes would be greatly reduced if the cap-and-trade market were established for a much longer period, such as many decades, because the elasticity of abatement supply is likely to be larger over a longer period of time. While this view of abatement supply elasticity is almost surely correct, two factors suggest that prices in a longer cap-and-trade market may not be less extreme. First, a cap-and-trade market established for a longer period of time is likely to create greater uncertainty about whether politicians will be willing to stick with a given capped quantity throughout the market period. Second, though abatement supply elasticity would likely be greater over a longer period, so would the uncertainty of BAU emissions. There is no empirical evidence of which would increase faster as the established market period lenghtens.[46] In addition, the endpoint problem we have described would still arise in a longer program when the remaining uncertainty in BAU emissions is sufficiently small that market participants can determine that there will either be excess or too few allowances to achieve compliance given the maximum amount of abatement possible until the end of the program.

Another reaction to our findings has been to conclude that pricing greenhouse gases is an ineffective policy. Our work does not support this inference. Pricing GHGs creates incentives for technological advance, and in the future might create large incentives for switching from high-GHG to low-GHG technologies as their

[46]Even longer run markets with substantial abatement supply elasticity would be likely to exhibit price volatility if borrowing and banking were restricted. Existing markets have generally permitted nearly unlimited banking, but have placed tight restrictions on borrowing.

relative costs change. The magnitudes of these effects could be quite large, but they are extremely uncertain, consistent with our conclusion that the probability of an interior solution in a cap-and-trade market – one not driven primarily by an administrative price floor or ceiling – is quite low. To the extent that a stable and predictable price of carbon into the distant future creates an economic signal more conducive to producing low-carbon investments and innovations, this suggests that a greenhouse gas tax or cap-and-trade with a narrow price collar (floor and ceiling) is likely preferred.

References

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

Borenstein, Severin, Colin Cameron, and Richard Gilbert. "Do Gasoline Prices Respond Asymmetrically to Crude Oil Price Changes?" *Quarterly Journal of Economics* **112**(February 1997).

Borenstein, Severin, James B. Bushnell, Frank A. Wolak and Matthew Zaragoza-Watkins. " "Report of the Market Simulation Group on Competitive Supply/Demand Balance in the California Allowance Market and the Potential for Market Manipulation." Energy Institute at Haas Working Paper #251 (July 2014).

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Cullen, Joseph A., and Erin T. Mansur. "Inferring Carbon Abatement Costs in Electricity Markets: A Revealed Preference Approach using the Shale Revolution." National Bureau of Economic Research Working Paper #20795, May 2015.

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

Dickey, David A., and Wayne A. Fuller. "Distribution of the estimators for autoregressive time series with a unit root." *Journal of the American Statistical*

Association **74**(366a), (1979): 427-431.

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

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

Energy & Environmental Economics. *Investigating a Higher Renewables Portfolio Standard in California*, January 2014.

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

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

Fell, Harrison, Dallas Burtraw, Richard Morgenstern, and Karen Palmer. "Climate Policy Design with Correlated Uncertainties in Offset Supply and Abatement Cost." *Land Economics* **88**, no. 3 (2012).

Fowlie, Meredith. "Updating the allocation of greenhouse gas emissions permits in a federal cap-and-trade program." in *The design and implementation of U.S. climate policy*, Don Fullerton and Catherine Wolfram, editors (2012).

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

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

Ito, Koichiro. "Do consumers respond to marginal or average price? Evidence from nonlinear electricity pricing." *American Economic Review*, 2014.

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

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

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

Kling, Catherine L., and Jonathan Rubin. "Bankable Permits for the Control of Environmental Pollution." *Journal of Public Economics* 64(1), (1997): 101-115.

Lewis, Matthew S. "Asymmetric Price Adjustment and Consumer Search: An Examination of the Retail Gasoline Market." *Journal of Economics and Management Strategy*, **20** (2), Summer 2011: 409-449.

Marion, Justin and Erich Muehlegger. "Tax Incidence and Supply Conditions." *Journal of Public Economics*, **95**(9-10), 1202-1212, October 2011.

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

Pizer, William A. and Brian Prest. "Price versus Quantities with Policy Updating." National Bureau of Economic Research Working Paper #22379, June 2016.

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

Taylor, Lester D. "The Demand for Electricity: A Survey." *The Bell Journal of Economics*, **6**(1), (1975): 74-110.

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

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

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

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

U.S. Environmental Protection Agency. "U.S. Greenhouse Gas Inventory Report: 1990-2014." (2016).

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	0.02	0.6720	0.63	0.8439
	Single Mean	-5.18	0.3718	-1.49	0.5148
	Trend	-17.14	0.0370	-2.59	0.2873
ln_vmt	Zero Mean	0.01	0.6710	1.61	0.9688
	Single Mean	-2.09	0.7496	-2.22	0.2071
	Trend	0.05	0.9920	0.01	0.9931
ln_ngother_industrial	Zero Mean	-0.01	0.6660	-0.29	0.5682
	Single Mean	-15.52	0.0102	-2.51	0.1288
	Trend	-15.77	0.0604	-2.45	0.3458
ln_real_gas_price	Zero Mean	0.52	0.7959	0.92	0.8979
	Single Mean	-0.99	0.8726	-0.47	0.8769
	Trend	-10.80	0.2678	-2.35	0.3903
ln_real_gsp	Zero Mean	0.03	0.6759	1.50	0.9614
	Single Mean	-2.12	0.7453	-1.55	0.4865
	Trend	-12.68	0.1622	-1.64	0.7372
ln_thermal_intensity	Zero Mean	0.38	0.7619	1.24	0.9387
	Single Mean	-0.26	0.9312	-0.13	0.9329
	Trend	-17.49	0.0325	-3.62	0.0551
ln_transport_intensity	Zero Mean	0.01	0.6705	1.65	0.9711
	Single Mean	2.93	0.9986	1.22	0.9970
	Trend	-3.27	0.9075	-0.61	0.9656

Table A1—Unit Root Test Statistics (Data from 1990 to 2010)

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

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

Variable	Type	$\hat{\rho}$	Pr < $\hat{\rho}$	$\hat{\tau}$	Pr < $\hat{\tau}$
ln_twh_p_hydro	Zero Mean	0.01	0.6733	0.51	0.8174
	Single Mean	-6.26	0.2785	-1.73	0.4024
	Trend	-17.81	0.0345	-2.55	0.3024
ln_vmt	Zero Mean	0.01	0.6733	1.93	0.9835
	Single Mean	-2.10	0.7499	-2.16	0.2264
	Trend	-2.89	0.9292	-0.90	0.9375
ln_ngother_industrial	Zero Mean	-0.01	0.6672	-0.38	0.5341
	Single Mean	-12.84	0.0337	-2.39	0.1573
	Trend	-14.73	0.0970	-2.47	0.3371
ln_real_gas_price	Zero Mean	0.81	0.8620	1.33	0.9482
	Single Mean	-0.07	0.9437	-0.03	0.9453
	Trend	-13.11	0.1557	-2.54	0.3084
ln_real_gsp	Zero Mean	0.03	0.6787	1.66	0.9721
	Single Mean	-2.11	0.7486	-1.56	0.4836
	Trend	-9.28	0.3928	-1.71	0.7092
ln_thermal_intensity	Zero Mean	0.39	0.7669	1.38	0.9525
	Single Mean	-0.22	0.9345	-0.13	0.9342
	Trend	-18.57	0.0261	-3.65	0.0498
ln_transport_intensity	Zero Mean	0.01	0.6731	1.95	0.9842
	Single Mean	2.26	0.9970	1.37	0.9981
	Trend	-2.16	0.9570	-0.65	0.9639

Table A2—Unit Root Test Statistics (Data from 1990 to 2012)

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	0.9890	182.9117	123.04
1	1	0.8064	92.6520	93.92
2	2	0.7493	59.8157	68.68
3	3	0.5573	32.1462	47.21
4	4	0.4359	15.8494	29.38
5	5	0.1576	4.3994	15.34
6	6	0.0473	0.9692	3.84

Table A3—Cointegration Rank Test Using Trace (Data from 1990 to 2010)

H0: Rank=r	H1: Rank > r	Eigenvalue	LR(r)	5% Critical Value
0	0	0.9349	148.2205	123.04
1	1	0.7707	88.1306	93.92
2	2	0.6666	55.7307	68.68
3	3	0.5181	31.5668	47.21
4	4	0.4124	15.5074	29.38
5	5	0.1402	3.8117	15.34
6	6	0.0220	0.4897	3.84

Table A4—Cointegration Rank Test Using Trace (Data from 1990 to 2012)

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.

Equation	Parameter	Estimate	Standard Error	Variable
$\Delta ln\_twh_p\_hydro$	μ_1	-3.16497	7.41185	1
	Λ_{11}	-0.90797	0.16030	$ln\_twh\_p_hydro_{(t-1)}$
	Λ_{12}	-0.04557	0.31175	$ln\_vmt_{(t-1)}$
	Λ_{13}	0.43626	0.39916	$ln\_ngother\_industrial_{(t-1)}$
	Λ_{14}	0.51279	0.13009	$ln\_real\_gas\_price_{(t-1)}$
	Λ_{15}	0.25462	0.24442	$ln\_real\_gsp_{(t-1)}$
	Λ_{16}	0.78766	0.15811	$ln\_thermal\_intensity_{(t-1)}$
	Λ_{17}	-0.64422	0.15543	$ln\_transport\_intensity_{(t-1)}$
Δln_vmt	μ_2	3.23031	1.94785	1
	Λ_{21}	-0.03538	0.04213	$ln\_twh\_p_hydro_{(t-1)}$
	Λ_{22}	-0.13503	0.08193	$ln\_vmt_{(t-1)}$
	Λ_{23}	-0.17238	0.10490	$ln\_ngother\_industrial_{(t-1)}$
	Λ_{24}	-0.04776	0.03419	$ln\_real\_gas\_price_{(t-1)}$
	Λ_{25}	0.10388	0.06423	$ln\_real\_gsp_{(t-1)}$
	Λ_{26}	-0.04942	0.04155	$ln\_thermal\_intensity_{(t-1)}$
	Λ_{27}	0.05568	0.04085	$ln\_transport\_intensity_{(t-1)}$
$\Delta ln\_ngother\_industrial$	μ_3	13.56635	3.05399	1
	Λ_{31}	-0.22393	0.06605	$ln\_twh\_p_hydro_{(t-1)}$
	Λ_{32}	-0.58336	0.12845	$ln\_vmt_{(t-1)}$
	Λ_{33}	-0.70553	0.16447	$ln\_ngother\_industrial_{(t-1)}$
	Λ_{34}	-0.16438	0.05360	$ln\_real\_gas\_price_{(t-1)}$
	Λ_{35}	0.46622	0.10071	$ln\_real\_gsp_{(t-1)}$
	Λ_{36}	-0.14971	0.06515	$ln\_thermal\_intensity_{(t-1)}$
	Λ_{37}	0.18797	0.06404	$ln\_transport\_intensity_{(t-1)}$
$\Delta ln\_real\_gas\_price$	μ_4	24.15989	15.84184	1
	Λ_{41}	-0.03031	0.34263	$ln\_twh\_p_hydro_{(t-1)}$
	Λ_{42}	-0.96771	0.66633	$ln\_vmt_{(t-1)}$
	Λ_{43}	-1.35863	0.85315	$ln\_ngother\_industrial_{(t-1)}$
	Λ_{44}	-0.47406	0.27806	$ln\_real\_gas\_price_{(t-1)}$
	Λ_{45}	0.68979	0.52241	$ln\_real\_gsp_{(t-1)}$
	Λ_{46}	-0.55460	0.33795	$ln\_thermal\_intensity_{(t-1)}$
	Λ_{47}	0.56426	0.33222	$ln\_transport\_intensity_{(t-1)}$
Δln_real_gsp	μ_5	10.86102	3.82811	1
	Λ_{51}	-0.27389	0.08279	$ln\_twh\_p_hydro_{(t-1)}$
	Λ_{52}	-0.48400	0.16101	$ln\_vmt_{(t-1)}$
	Λ_{53}	-0.53674	0.20616	$ln\_ngother\_industrial_{(t-1)}$
	Λ_{54}	-0.08437	0.06719	$ln\_real\_gas\_price_{(t-1)}$
	Λ_{55}	0.40840	0.12624	$ln\_real\_gsp_{(t-1)}$
	Λ_{56}	-0.04513	0.08166	$ln\_thermal\_intensity_{(t-1)}$
	Λ_{57}	0.09077	0.08028	$ln\_transport\_intensity_{(t-1)}$
$\Delta ln\_thermal\_intensity$	μ_6	3.88238	7.29254	1
	Λ_{61}	0.22018	0.15772	$ln\_twh\_p_hydro_{(t-1)}$
	Λ_{62}	-0.11361	0.30673	$ln\_vmt_{(t-1)}$
	Λ_{63}	-0.28296	0.39273	$ln\_ngother\_industrial_{(t-1)}$
	Λ_{64}	-0.18772	0.12800	$ln\_real\_gas\_price_{(t-1)}$
	Λ_{65}	0.02615	0.24048	$ln\_real\_gsp_{(t-1)}$
	Λ_{66}	-0.26595	0.15557	$ln\_thermal\_intensity_{(t-1)}$
	Λ_{67}	0.23180	0.15293	$ln\_transport\_intensity_{(t-1)}$
$\Delta ln\_transport\_intensity$	μ_7	-1.29460	2.93945	1
	Λ_{71}	-0.04659	0.06357	$ln\_twh\_p_hydro_{(t-1)}$
	Λ_{72}	0.04246	0.12364	$ln\_vmt_{(t-1)}$
	Λ_{73}	0.08605	0.15830	$ln\_ngother\_industrial_{(t-1)}$
	Λ_{74}	0.04908	0.05159	$ln\_real\_gas\_price_{(t-1)}$
	Λ_{75}	-0.01852	0.09693	$ln\_real\_gsp_{(t-1)}$
	Λ_{76}	0.06735	0.06271	$ln\_thermal\_intensity_{(t-1)}$
	Λ_{77}	-0.06021	0.06164	$ln\_transport\_intensity_{(t-1)}$

Table A5—Error Correction Vector Autoregression Parameter Estimates (Data from 1990 to 2010)

Equation	Parameter	Estimate	Standard Error	Variable
$\Delta ln\_twh_p\_hydro$	μ_1	-5.61018	8.83126	1
	Λ_{11}	-0.74263	0.15577	$ln\_twh\_p_hydro_{(t-1)}$
	Λ_{12}	0.34744	0.39158	$ln\_vmt_{(t-1)}$
	Λ_{13}	0.46426	0.42465	$ln\_ngother\_industrial_{(t-1)}$
	Λ_{14}	0.30195	0.08583	$ln\_real\_gas\_price_{(t-1)}$
	Λ_{15}	0.29752	0.25703	$ln\_real\_gsp_{(t-1)}$
	Λ_{16}	0.95089	0.18625	$ln\_thermal\_intensity_{(t-1)}$
	Λ_{17}	-0.11378	0.10290	$ln\_transport\_intensity_{(t-1)}$
Δln_vmt	μ_2	-1.13172	2.19675	1
	Λ_{21}	-0.05129	0.03875	$ln\_twh\_p_hydro_{(t-1)}$
	Λ_{22}	0.05850	0.09741	$ln\_vmt_{(t-1)}$
	Λ_{23}	0.07039	0.10563	$ln\_ngother\_industrial_{(t-1)}$
	Λ_{24}	0.03026	0.02135	$ln\_real\_gas\_price_{(t-1)}$
	Λ_{25}	0.00431	0.06394	$ln\_real\_gsp_{(t-1)}$
	Λ_{26}	0.08697	0.04633	$ln\_thermal\_intensity_{(t-1)}$
	Λ_{27}	-0.01716	0.02560	$ln\_transport\_intensity_{(t-1)}$
$\Delta ln\_ngother\_industrial$	μ_3	16.90635	3.38313	1
	Λ_{31}	-0.24950	0.05967	$ln\_twh\_p_hydro_{(t-1)}$
	Λ_{32}	-0.74309	0.15001	$ln\_vmt_{(t-1)}$
	Λ_{33}	-0.79904	0.16268	$ln\_ngother\_industrial_{(t-1)}$
	Λ_{34}	-0.13292	0.03288	$ln\_real\_gas\_price_{(t-1)}$
	Λ_{35}	0.50473	0.09846	$ln\_real\_gsp_{(t-1)}$
	Λ_{36}	-0.21129	0.07135	$ln\_thermal\_intensity_{(t-1)}$
	Λ_{37}	0.19352	0.03942	$ln\_transport\_intensity_{(t-1)}$
$\Delta ln\_real\_gas\_price$	μ_4	14.77866	19.88947	1
	Λ_{41}	-0.10720	0.35081	$ln\_twh\_p_hydro_{(t-1)}$
	Λ_{42}	-0.66138	0.88191	$ln\_vmt_{(t-1)}$
	Λ_{43}	-0.72329	0.95638	$ln\_ngother\_industrial_{(t-1)}$
	Λ_{44}	-0.15036	0.19331	$ln\_real\_gas\_price_{(t-1)}$
	Λ_{45}	0.37791	0.57887	$ln\_real\_gsp_{(t-1)}$
	Λ_{46}	-0.30195	0.41947	$ln\_thermal\_intensity_{(t-1)}$
	Λ_{47}	0.17535	0.23175	$ln\_transport\_intensity_{(t-1)}$
Δln_real_gsp	μ_5	6.03318	4.32473	1
	Λ_{51}	-0.26997	0.07628	$ln\_twh\_p_hydro_{(t-1)}$
	Λ_{52}	-0.24214	0.19176	$ln\_vmt_{(t-1)}$
	Λ_{53}	-0.24046	0.20795	$ln\_ngother\_industrial_{(t-1)}$
	Λ_{54}	0.00934	0.04203	$ln\_real\_gas\_price_{(t-1)}$
	Λ_{55}	0.28161	0.12587	$ln\_real\_gsp_{(t-1)}$
	Λ_{56}	0.11825	0.09121	$ln\_thermal\_intensity_{(t-1)}$
	Λ_{57}	0.05794	0.05039	$ln\_transport\_intensity_{(t-1)}$
$\Delta ln\_thermal\_intensity$	μ_6	10.43990	8.05869	1
	Λ_{61}	0.17007	0.14214	$ln\_twh\_p_hydro_{(t-1)}$
	Λ_{62}	-0.49889	0.35733	$ln\_vmt_{(t-1)}$
	Λ_{63}	-0.57207	0.38750	$ln\_ngother\_industrial_{(t-1)}$
	Λ_{64}	-0.18345	0.07832	$ln\_real\_gas\_price_{(t-1)}$
	Λ_{65}	0.12927	0.23454	$ln\_real\_gsp_{(t-1)}$
	Λ_{66}	-0.47660	0.16996	$ln\_thermal\_intensity_{(t-1)}$
	Λ_{67}	0.13908	0.09390	$ln\_transport\_intensity_{(t-1)}$
$\Delta ln\_transport\_intensity$	μ_7	-3.31294	3.25415	1
	Λ_{71}	-0.01845	0.05740	$ln\_twh\_p_hydro_{(t-1)}$
	Λ_{72}	0.15339	0.14429	$ln\_vmt_{(t-1)}$
	Λ_{73}	0.17232	0.15648	$ln\_ngother\_industrial_{(t-1)}$
	Λ_{74}	0.04696	0.03163	$ln\_real\_gas\_price_{(t-1)}$
	Λ_{75}	-0.06075	0.09471	$ln\_real\_gsp_{(t-1)}$
	Λ_{76}	0.11298	0.06863	$ln\_thermal\_intensity_{(t-1)}$
	Λ_{77}	-0.04184	0.03792	$ln\_transport\_intensity_{(t-1)}$

Table A6—Error Correction Vector Autoregression Parameter Estimates (Data from 1990 to 2012)

Online 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:

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

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

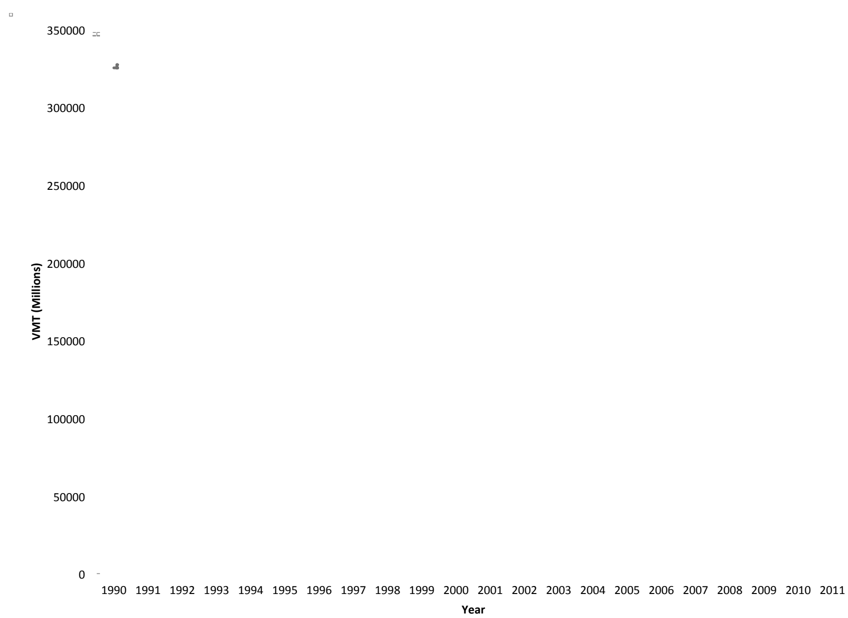

Figure B1. Annual California On-road VMT 1990-2011

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

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

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

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

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

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

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.[47] 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.[48] Long-run elasticities are generally between -0.3 and -0.5.[49] 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.[50]

[47]Each of these price levels escalates over time in real terms, so we calculate the price-sensitive abatement for each year separately.
[48]See Hughes, Knittel and Sperling, 2008.
[49]See Dahl, 2012
[50]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.[51] 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),[52] 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.[53] (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.

[51]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%.

[52]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.

[53]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,[54] 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.[55]

The CPUC estimates that 85% of revenues will go to residential customers, who make up about 34% of demand.[56] 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.

[54] 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.

[55] 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.

[56] 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.[57] 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.[58] 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.[59]

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

[57] 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.

[58] 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.

[59] 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,[60] we assume that this price will increase by 2.15% (real) per year due to exogenous (to Cap and Trade) factors.[61] 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.[62]

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.[63] 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.

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

[61] 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).

[62] 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.

[63] 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[64] 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.[65] 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.

[64]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.

[65]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.[66] 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.

[66]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.