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EXPECTING THE UNEXPECTED:
EMISSIONS UNCERTAINTY AND ENVIRONMENTAL MARKET DESIGN

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ABSTRACT

We study potential equilibria in California's cap-and-trade market for greenhouse gases (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, much larger than the reduction that could plausibly occur in response to an allowance price within a politically acceptable range. This implies that the market price is very likely to be determined by an administrative price floor or ceiling. Similar factors seem likely to be present in other cap-and-trade markets for GHGs.

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There is broad consensus among economists that pricing greenhouse gases (GHGs), through either a tax or a cap-and-trade market, should be a central component of a cost effective climate policy. A substantial and predictable price on GHGs into the distant future[1] provides incentives for firms and consumers to limit activities that produce GHGs, make long-lived investments in lower-carbon technologies, and stimulates innovation in the development of new low-carbon technologies.

Prices in existing cap-and-trade policies for GHGs, however, have at times been very volatile and, most recently, have been so low as to create little incentive to invest in GHG emissions reductions. The European Union Emissions Trading System (EU-ETS), the world's largest GHG market, experienced a sharp drop in prices – from above 20 euros per tonne[2] in early 2011 to below 4 euros in 2013. The European Commission responded in 2014 by reducing the emissions cap. The Regional Greenhouse Gas Initiative (RGGI), which covers electricity generators in the Northeastern U.S., made a similar administrative reduction to the emissions cap in response to persistently low allowance prices.[3]

In this paper, we study California's cap-and-trade market for GHGs. The market, which opened in 2013, has the broadest scope of any GHG market in the world, covering nearly all anthropogenic emissions except for agriculture. The market includes GHG emissions from electricity generation, industrial production, and transportation fuels. Throughout the first five years, the program has seen prices at or very close to the administrative price floor. Our analysis suggests that in the absence of such administrative intervention, extremely low or high prices are the most likely outcomes.

Two factors drive this conclusion. First, there is a high level of *ex-ante* uncertainty in future emissions. "Business-as-usual" (BAU) GHG emissions are closely tied to economic activity and weather conditions (temperature and rainfall), which are very difficult to forecast. GHG emissions are also subject to the uncertain effects of non-market environmental policies – often referred to in policy debates as "complementary policies" – such as fuel-economy standards, mandated renewable generation shares of electricity production, and energy-efficiency standards.[4] These uncertainties have long been recognized as an issue when fore-

[1] The largest share of GHGs is CO_2, which we discuss broadly as "carbon emissions" and "carbon pricing" following the popular vernacular.

[2] The standard measure of GHG's is metric tonnes of CO_2 equivalent, CO_2e, in order to convert other greenhouse gases into a standardized climate change metric. One tonne of CO_2e is the quantity released from burning approximately 114 gallons of pure gasoline.

[3] The EU-ETS emissions cap reduction seemed to have relatively little effect until May 2017 when the price began to climb from about 4 euros. By May 2018 it was above 13 euros. The RGGI cap reduction has had less effect. In May 2018, the price was about $4 per tonne.

[4] The term "complementary policies" presents some irony, because in economic terms most of these programs are probably more aptly described as substitutes for a cap-and-trade program. However, these policies may increase the political acceptance of cap-and-trade markets by assuring cap-and-trade skeptics that certain pathways to GHG reduction will be required regardless of the allowance price. Some of these policies are also designed to address other market failures, such as imperfect information or principal/agent conflicts in energy consumption.

casting both damages and mitigation cost,[5] but they also create uncertainty in the amount of emissions abatement that will be necessary in order to attain a given cap level.

Second, over the range of GHG prices generally deemed politically acceptable, the price responsiveness of GHG abatement is likely to be small compared to the uncertainty in emissions levels. In California, the price-inelasticity of GHG emissions abatement is exacerbated by the non-market "complementary" environmental policies, an effect that is likely to be present in other regions with GHG cap-and-trade markets. These policies steepen the abatement supply curve by mandating mitigation that would otherwise occur in response to a rising GHG price. The combination of a broad probability distribution of emissions outcomes before pricing effects, and relatively modest price-responsiveness of emissions, results in outcomes skewed towards very high or very low prices.

In recognition of the problems created by uncertain allowance prices, economists have proposed hybrid mechanisms that combine emissions caps with administrative price collars that can provide both upper and lower bounds on allowance prices.[6] Such hybrid mechanisms can greatly reduce allowance price risk while ensuring a better match between *ex-post* costs and benefits (Pizer, 2002). While the EU-ETS has no such bounds, the trading system proposed under the never-enacted Waxman-Markey bill of 2010 included limited price collars, as does California's program. The fact that California's allowance prices have been higher than the other major GHG cap-and-trade programs from its inception through 2017 is almost certainly due to its relatively high floor price.

California's first cap-and-trade allowance auction took place on November 14, 2012 and compliance obligations began on January 1, 2013. At the time, the quantity of available allowances was set for 2013-2020, after which the future of the program was uncertain.[7] There is an auction reserve price (ARP) that sets a soft floor price for the market. There is also an allowance price containment reserve (APCR) designed to have some restraining effect at the high end of possible prices by adding a limited number of allowances to the pool if the auction price hits certain price trigger levels.

Using only information available prior to the commencement of California's market, we develop estimates of the distribution of potential allowance prices that account for uncertainty in BAU emissions, as well as uncertainty in the price-responsiveness of abatement. Our analysis of the distribution of potential market equilibria proceeds in three stages. First, we estimate an econometric model of the drivers of BAU GHG emissions using time-series methods and use it to estimate the probability density of future GHG emissions given the pre-existing trends in the drivers of GHG emissions. Second, we account for GHG reductions

[5] When discussing controversies about mitigation costs, Aldy et. al. (2010) 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."

[6] See, for instance, Jacoby and Ellerman, 2004, and Burtraw et al., 2009.

[7] Legislation extending the program was passed in July 2017, as discussed in more detail below.

from command-and-control regulations and other "non-market" factors outside the cap-and-trade program. These include the effects of complementary policies, exogenous energy price changes, and reduced compliance obligation due to credit for emissions "offsets" (*i.e.,* administratively verified reductions from emitters in locations or sectors not covered by the program). These also include activities that do not reduce actual emissions, but just change contractual counterparties in a way that reassigns responsibility for emissions to entities not covered by the program, known broadly as "reshuffling." While incentives for reshuffling and offsets are affected by the price of allowances, previous analyses suggest that the bulk of this eligible activity would be realized at prices below or very close to the auction reserve price. Third, we use a range of energy price elasticity estimates to account for the emissions abatement that could occur in response to the GHG emissions price.

Combining these analyses, we estimate probabilities that the equilibrium allowance price will lie in four mutually-exclusive regions: (1) at (or very near) the price floor (auction reserve price), (2) above the price floor and below the lowest trigger price of the multi-step APCR (described in more detail below), (3) at or above the lowest trigger price of the APCR and at or below the highest trigger price of the APCR, and (4) above the highest trigger price of the APCR. At the time that the market opened, prices above the APCR were viewed as very unlikely, but if they did occur, most market participants believed they would very likely lead to further administrative intervention.

We find that uncertainties in BAU emissions and in the quantity of abatement available from non-market factors create much greater uncertainty in the amount of abatement needed to meet a cap than price-responsive abatement could plausibly provide within the politically acceptable price range. Therefore, regardless of the level at which the emissions cap is set, there will be a low probability of an "interior equilibrium" in which price-responsive abatement equilibrates emissions with that cap. Rather, the outcome is very likely to be driven primarily by administrative interventions that set a floor or ceiling price.[8]

Based on the information available before the market opened, we find that the California's emissions cap for 2013-2020 was set at a level that implied a 94.8% probability the allowance market would clear at the price floor, with total emissions below the cap.[9] We find a 1.2% probability that the price would be in the interior equilibrium range, above the auction reserve price floor and below the lowest APCR trigger price. The remaining 4% probability weight is on outcomes in which the price is within the trigger prices of the APCR or above the highest

[8]Or *ex-post* emissions cap adjustments, an alternative administrative intervention that has been observed recently in the EU-ETS and RGGI, as noted earlier.

[9]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 of California. We assume that prices between these markets are arbitraged so that all trading platforms reflect prices based upon the overall aggregate supply and demand of allowances and abatement.

trigger price.

In July 2017, California adopted legislation extending the program to 2030 and setting much lower emissions targets for the additional decade. The legislation prescribed a hard price ceiling, but it left many critical aspects of the extended program unsettled, including the level and mechanism of the price ceiling, the price floor at which different shares of the allowance pool would be made available, and the allocation of free allowances to some emitters. Nonetheless, we also report results for a reasonable prototype of a program running through 2030. We find that the emissions cap proposed through 2030 is likely to yield a substantially more balanced probability of an outcome at the price floor or price ceiling. Even in that analysis, however, we still find only a 20% probability of an interior equilibrium.

Unlike Weitzman's (1974) seminal work on prices versus quantities, and much of the analysis that has applied that framework to cap-and-trade markets for pollutants, ours is not a normative analysis.[10] Rather, our positive empirical analysis demonstrates the high likelihood of very high or very low prices in California's market for greenhouse gas emissions. While very high or low prices are not an economic impediment to the operation of cap-and-trade markets, they may be a political impediment, as they seem in practice likely to trigger *ex-post* administrative interventions.

The large uncertainty in the level of BAU emissions from which reductions must occur has not been explicitly recognized in previous studies of cap-and-trade market equilibria, which have tended to employ deterministic models.[11] To account for uncertainty in key parameters, such as energy prices and macroeconomic growth, modelers sometimes performed sensitivity analyses, but the choice of which parameter values to include and the probability to assign to each parameter value has not been based on statistical distributions estimated from historical data, which limits analysts' ability to draw inferences about the relative likelihood of alternative scenarios. The most sophisticated of these studies is Neuhoff et al. (2006), which compares the EU ETS Phase-II cap level with 24 deterministic model-based projections. Assigning equal probabilities to each projection, the authors find that there is a significant chance that BAU emissions will fall below the cap. To limit the likelihood of a price collapse, they conclude that regulators should set more ambitious targets. While we similarly find that BAU emissions are likely to fall below the emissions cap in California, we explicitly model uncertain abatement demand and supply, concluding that these uncertainties are quite large compared to likely levels of price-responsive abatement, yielding a low

[10]See Newell and Pizer (2003) for an application of Weitzman's analysis to a stock pollutant such as GHGs. See Newell, Pizer and Raimi (2014) and Schmalensee and Stavins (2017) for overviews of cap-and-trade programs in practice to date.

[11]To model equilibria in their respective markets RGGI used the Regional Economic Modeling, Inc. model (RGGI, 2005), the U.K. Department of Trade and Industry used ICF's Integrated Planning Model (U.K. DTI, 2006), and the California Air Resources Board (ARB) used ICF's Energy 2020 model (ARB, 2010a).

probability of an interior equilibrium regardless of the stringency of the cap.

The remainder of the analysis proceeds as follows. Section I introduces California's cap-and-trade market, and characterizes the set of possible market outcomes given the attributes of the supply and demand for GHG emissions abatement. Section II describes how we estimate the distribution of BAU GHG emissions over the 2013-2020 period using a cointegrated Vector Autoregression (VAR) model estimated using data from 1990 to 2010. In Section III, we explain how we incorporate the non-market factors that affect future GHG emissions. In Section IV, we analyze the likely impact that a GHG price would have on abatement. We present results in Section V under the baseline scenario for complementary policies and other non-market factors, and we also show how the cap-and-trade program might operate in the absence of complementary policies. Section VI briefly compares our estimated results to actual outcomes through 2015 and discusses analysis of an extended market out to 2030. We conclude in section VII.

I. The California Cap-and-Trade Market

We focus on estimating the potential range and uncertainty in allowance demand, abatement supply, and prices over the original 8-year span of the market. We carry out the analysis based on estimates of the distribution of future emissions using data through 2010. These were the most up-to-date data available by late-2012, months before the market commenced. Presumably, the GHG emissions cap would have to be set at least that long before the beginning of any cap-and-trade market. Consequently, our analysis addresses the question of what distribution of market outcomes a regulator could reasonably expect at the time the emissions cap is set.[12]

The 8-year market was divided into three compliance periods: 2013-2014, 2015-2017, and 2018-2020. In the first compliance period, the market excluded tailpipe emissions from transportation and on-site emissions from small stationary sources (mostly residential and small commercial combustion of natural gas), known as "narrow scope" coverage. In the second compliance period, transportation and small stationary sources were also included, with the total known as "broad scope" coverage. In November of the year following the end of each compliance period, covered entities are required to submit allowances equal to their covered emissions for that compliance period. Banking allowances for later use is permitted with very few restrictions.

Allowances are sold quarterly through an auction held by the ARB. The auction has a reserve price, which was set at \$10.50 in 2013 and has thereafter increased each year by 5% plus the rate of inflation in the prior year. A portion of the

[12]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, because the analysis is based on information available in 2012. Quebec, with total emissions of roughly 1/7 California's, was seen as a likely net purchaser of allowances, which would increase somewhat the probability of higher price outcomes.

capped allowance quantity in the program are allocated to the Allowance Price Containment Reserve (APCR). Of the 2,508.6 million metric tonnes (MMT) of allowances in the program over the 8-year period, 121.8 MMT were assigned to the APCR to be made available in equal proportions at allowance prices of $40, $45, and $50 in 2012 and 2013. These price levels increase annually by 5% plus the rate of inflation in the prior year.

Because of the relatively generous allowance quantities made available in the early year auctions, and the ability of the ARB to shift some additional allowances from later years, emissions during the first two compliance periods were very unlikely to exceed the allowances available. This implies that the eight years of the market were likely to be economically integrated. As a result, we examine the total supply/demand balance over the entire eight years of the program.[13]

As is standard in analyses of market mechanisms for pollution control, we present the market equilibrium as the outcome of a demand for and supply of emissions abatement. We define the demand for emissions abatement as the difference between BAU emissions and the quantity of allowances made available at the auction reserve price. What we loosely term "abatement supply" in this characterization includes both non-market and price-responsive emissions reductions among the covered entities. It also includes activities that arguably do not lower California GHG emissions – offsets and reshuffling – but which an emitter can use to help meet its compliance obligation. For presentational clarity, we also include additional allowance supply that can be released from the APCR at higher prices as part of abatement supply.[14]

The analytical approach is illustrated in Figure 1, which presents a hypothetical probability density function (PDF) of (price inelastic) abatement demand quantities – BAU emissions minus allowances – along with one possible abatement supply curve. The supply curve includes non-market abatement along the horizontal axis, some very inexpensive abatement supply (mostly from offsets and reshuffling) likely cheaper than the auction reserve price, increasing abatement as price rises to the APCR, and then extra allowance supply from the APCR, followed by additional price-responsive abatement at prices above the APCR. In reality, the quantities in each component of the supply curve are uncertain so there is a probability distribution of abatement supply curves as well as abatement demand quantities. Nonetheless, this illustration demonstrates that the probability of an interior equilibrium depends upon the share of the area under the abatement demand PDF that falls in the quantity of price responsive abatement between the floor and ceiling prices. The next section describes our methodology for estimating the PDF of the abatement demand, while section III describes our methodology for estimating the PDF of the quantity of non-market abatement and section IV describes our methodology for estimating the PDF of

[13]Borenstein, Bushnell, Wolak and Zaragoza-Watkins (2014) discusses the details of the compliance rules in more detail and the possibility of short-run allowance shortages.

[14]Equilibrium is determined by the *net* supply of allowances, so including a particular factor as an increase in abatement supply or decrease in abatement demand will not alter the analysis.

price-responsive abatement.

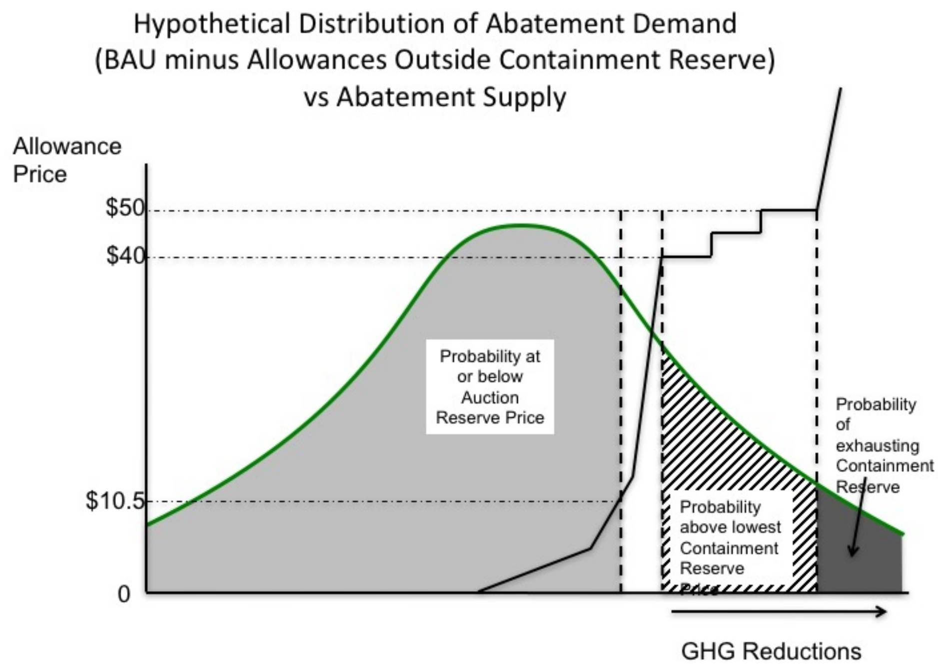

FIGURE 1. HYPOTHETICAL DISTRIBUTION OF ABATEMENT DEMAND AND SUPPLY

In its revised Scoping Plan of 2010, ARB's preferred model projected that 63% of emissions abatement would arise from complementary policies rather than from responses to the cap-and-trade program.[15] It is important to emphasize that these reductions are not costless; indeed many are likely to impose abatement costs greater than 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 could help mitigate volatility in allowance prices.

The supply of price-responsive abatement is further limited by an allowance allocation policy designed to protect in-state manufacturers that are subject to competition from out-of-state producers. These "trade exposed" companies receive free allowances based on the quantity of output (not emissions) that the firm produces. Such output-based allocation reduces the firm's effective marginal

[15] ARB (2010b) at page 38 (Table 10). This projection does not include the effects of exogenous energy price increases, reshuffling, or offsets.

cost of production and, thus, reduces the pass-through of the allowance price to consumers, and the associated reduction in consumption of these goods. But it does so while retaining the full allowance price incentive for the firm to adopt GHG-reducing methods for producing the same level of output.[16]

The combination of large amounts of "zero-price" abatement, and relatively modest price-responsive abatement suggests a "hockey stick" shaped abatement "supply" curve, as illustrated in Figure 1.

A. Price Evolution and Estimated Equilibrium Price in the Market

The analysis we present here models abatement supply and demand aggregated over the 8-year span of the market. We calculate the equilibrium as the price at which the aggregate demand for abatement over the 8 years is equal to the aggregate supply of abatement. Our primary analysis focuses on this program alone, assuming that the market is not integrated into a successor market or some geographically broader program. When the market commenced, there was no clarity on how the program would evolve after 2020 or other regional programs with which it might be merged.

Throughout this analysis, we assume that the emissions market is perfectly 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 unilateral exercise of market power given the characteristics of supply and demand in the market. While we find a potential for short-term exercise of market power, we do not find a plausible incentive to exercise market power in a way that would change the equilibrium price over the full 8-year course of the market.

At any point in time, two conditions will drive the market price, an intertemporal arbitrage condition and a long-run market equilibrium condition. If the markets for allowances at different points in time are competitive and well integrated, then intertemporal arbitrage will cause the *expected* price change over time to be equal to the nominal interest rate (or cost of capital).[17] 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.[18]

[16]For a detailed discussion of the economic incentives created by output-based allocation, 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.

[17]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) show that with inter-temporal trading and policy updating, regulators can exploit the arbitrage condition to implement the first-best policy.

[18]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).

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 present discounted value of all the possible future prices that equilibrate the realized supply (plus allowances and offsets) and realized demand for abatement. As discussed below, we approximate this price evolution process by incorporating price-responsive abatement into the supply-demand analysis.

II. Estimating Business-as-Usual Emissions

The greatest source of uncertainty in the market's supply-demand balance is likely to be the level of emissions that would take place under BAU. Figure 2 presents annual covered GHG emissions in California in the four major sectors covered by the cap-and-trade program. The increased emissions during the 1995-2000 "dot com boom," as well as the drop that began with the 2008 financial crisis, illustrate both that emissions are correlated with the macro economy and that meeting an emissions goal over and 8-year period could require much more or less abatement than would be implied from considering only the expected BAU level.[19]

We construct an econometric model using historical emissions and other economic data to estimate the distribution of BAU emissions over the eight-year market period that accounts for both uncertainty in the parameters of our econometric model and uncertainty in the future values of the shocks to our econometric model using the two-step smoothed bootstrap procedure described in the online appendix.

To derive an estimate of the distribution of future GHG emissions covered by the program, we estimate a vector autoregression (VAR) model with determinants of the major components of state-level GHG emissions that are covered under the program and the key statewide economic factors that impact the level and

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 of a hard price cap, if one existed. Thus, the price would either be approximately zero (if there were excess supply) or at one of the steps of the APCR or the compliance penalty (if there were 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.

[19] In both 1997-2001 and 2007-2011 covered emissions changed by as much in absolute value as the entire emissions cap decline over 2013-2020.

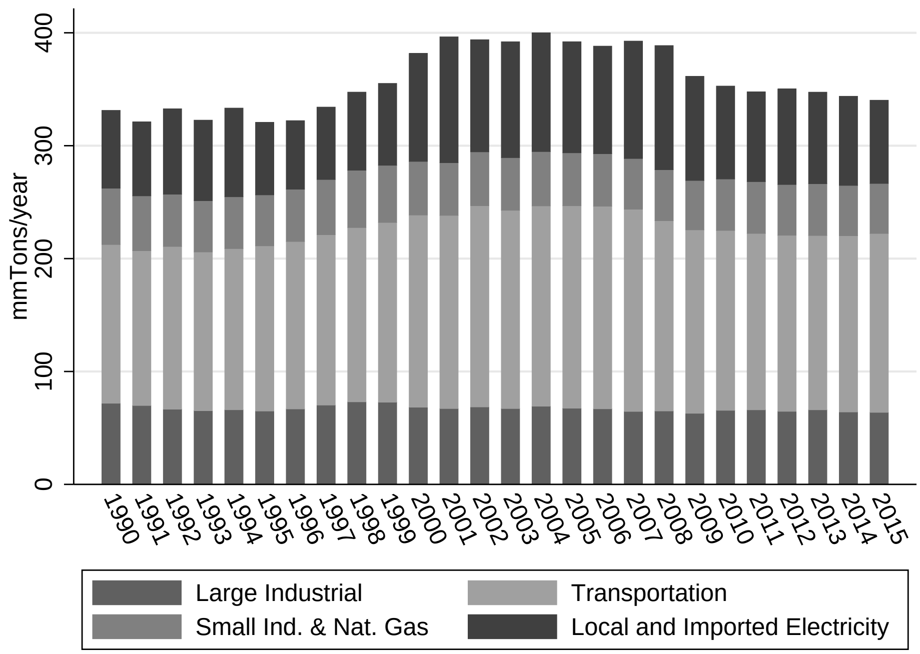

Figure 2. California Emissions from Capped Sectors

growth of GHG emissions.[20] 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 2010, which was the information that was available to policy makers in 2012, just before the market opened.

The short time series puts a premium on parsimony in the model. As a result, we use a 7-variable VAR model. We also impose the restrictions implied by cointegrating relationships between the elements of the 7-dimensionsal vector, which significantly reduces the number of parameters we must estimate to compute a distribution of future BAU values of these seven variables. The model includes three drivers of GHG emissions: in-state electricity production net of hydroelectricity production, vehicle-miles traveled (VMT), and non-electricity-generation natural gas combustion and industrial process GHG emissions.[21] The model also includes the two most important economic factors that drive emissions: real GSP

[20]VARs are the econometric methodology of choice among analysts to construct estimates of the distribution of future values (from 1 to 10 time periods) 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.

[21]The electricity variable accounts for demand changes (after adjusting for imports as discussed below) as well as uncertainty and trends in hydroelectricity production. We account for other zero-GHG generation sources – wind, solar, and nuclear – explicitly, as discussed below.

and the real price of gasoline in California. Finally, to facilitate the estimation of the distribution of future 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 sector and of fossil-fuel electricity generation in California. We simulate realizations from the distribution of BAU emissions from these two sectors as the product of a simulated value of sectoral emissions intensity and a simulated value of the economic driver of transportation (VMT) or electricity emissions (fossil-fuel electricity generation in California).

Summary statistics on the seven variables are presented in Table 1.

Table 1—Summary Statistics of Data for Vector Autoregression

	mean	S.D.	min	max	year min.	year max.
California Generation Net of Hydro (TWh)	159.3	16.5	133.5	185.6	1992	1998
Vehicle Miles Traveled (Billions)	299.7	27.0	258.0	329.0	1991	2005
Industry, Nat Gas & Other Emissions (MMT CO_2e)	114.6	4.6	106.6	123.9	1995	1998
Gross State Product (Real Trillion $2015)	1.83	0.32	1.38	2.25	1990	2008
Wholesale SF Gasoline Price (Real ¢2015/gallon)	198.83	42.05	146.88	300.09	1990	2008
In-state Elec Thermal Intensity (CO_2e tons/MWh)	0.462	0.056	0.372	0.581	2010	1993
Vehicle Emissions Intensity (CO_2e tons/1000 VMT)	0.535	0.016	0.493	0.554	2010	1992

Note: Data are for 1990-2010

Table 2—Summary Statistics of Simulated VAR Variables and Emission

Year	California Electricity net of Hydro Twh	Vehicle Miles Traveled Million Miles	Nat. Gas Ind & other Emissions MMT	Gasoline Price $2015	Gross St. Product $2015 Trillion	Thermal Intensity tons/ MWh	Transport Intensity tons/1000 Miles	Broad Scope Emis. MMT	Cum. Emis. MMT
2013	179.2	331.2	108.7	2.71	2.28	0.360	0.485	355.7	150
	(21.5)	(12.9)	(10.2)	(0.75)	(0.24)	(0.043)	(0.027)	(20.4)	(11)
2014	181.3	334.9	108.4	2.78	2.33	0.355	0.482	356.5	301
	(24.8)	(14.7)	(11.1)	(0.83)	(0.28)	(0.045)	(0.030)	(23.0)	(22)
2015	183.4	338.5	108.0	2.84	2.39	0.350	0.480	357.1	658
	(25.9)	(16.6)	(11.9)	(0.90)	(0.31)	(0.049)	(0.034)	(24.5)	(42)
2016	186.0	342.5	107.5	2.90	2.44	0.346	0.479	358.6	1016
	(26.3)	(18.5)	(12.7)	(0.98)	(0.34)	(0.052)	(0.036)	(26.5)	(66)
2017	186.8	346.5	107.3	2.96	2.50	0.342	0.476	359.3	1376
	(28.6)	(20.0)	(13.6)	(1.05)	(0.38)	(0.055)	(0.039)	(28.3)	(92)
2018	189.6	350.5	107.0	3.01	2.56	0.338	0.475	361.2	1737
	(30.3)	(21.7)	(14.5)	(1.08)	(0.42)	(0.058)	(0.042)	(30.3)	(120)
2019	191.5	354.7	107.0	3.07	2.62	0.334	0.473	362.6	2099
	(31.1)	(23.8)	(15.2)	(1.19)	(0.45)	(0.062)	(0.044)	(32.5)	(150)
2020	193.4	359.0	106.9	3.13	2.68	0.330	0.471	364.0	2463
	(32.8)	(25.4)	(16.2)	(1.27)	(0.49)	(0.065)	(0.047)	(34.5)	(183)

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

The data sources and the details of the procedure we used to specify and estimate the cointegrated VAR and construct the estimate of the distribution of BAU emissions for the 2013 to 2020 time period are presented in the online appendix. In the online appendix, we also assess the impact of model uncertainty by comparing the results of using different econometric models for historical GHG emissions to construct our estimate of the distribution of future GHG emissions. We obtain very similar mean forecasts and similar size confidence intervals for BAU emissions from 2013 to 2020 across all of the models.

A. Results

The parameter estimates for the 7-variable VAR are shown in the online appendix. Table 2 presents the means and standard deviations of the estimated distribution of the seven elements of the VAR for each year from 2013 to 2020.

For each draw from this distribution of the seven variables through 2020, we calculate annual GHG emissions from each sector category: transportation, electricity, and natural gas/industrial. Transportation emissions are the product of estimated VMT and estimated GHG intensity of VMT. Electricity emissions require adjusting estimated in-state generation net of hydro for generation from other zero-GHG sources – renewables (solar, wind, and geothermal) and nuclear power – as described in the online appendix, then multiplying the remainder, which is in-state fossil-fuel generation, by the thermal intensity of fossil-fuel generation. Natural gas/industrial emissions are taken directly from the estimate in the VAR.

The resulting measure of emissions from all sources in the program is shown in the "Broad Scope Emissions" column of Table 2. The final column presents the cumulative emissions covered under the cap-and-trade program, accounting for the fact that transportation emissions and some natural gas/industrial emissions were not included under the narrow scope emissions covered in 2013 and 2014.[22]

Figure 3 illustrates the actual values for broad scope emissions through 2015 and the estimated mean, 2.5th, and 97.5th percentile from the distribution of emissions from 2011 through 2020, based on data through 2010. The vertical dots show the distribution of simulation outcomes. The stair-step line in Figure 3 shows the emissions cap for each year of broad scope coverage, 2015-2020. For the two years of narrow-scope coverage, 2013 and 2014, the emissions cap was within 10 MMT of our mean BAU estimate of those emissions. As can be seen from Figure 3, many realizations fall below the level of capped emissions out to 2020. This is a large contributing factor to the expectation of low allowance prices.

In the next two sections, we describe how we combine these estimates of BAU emissions with abatement opportunities to estimate the distribution of the supply-demand balance in the cap-and-trade market.

[22] In the online appendix, we explain how we decompose the natural gas/industrial emissions category to approximate the share of emissions from this category that is covered in 2013-2014.

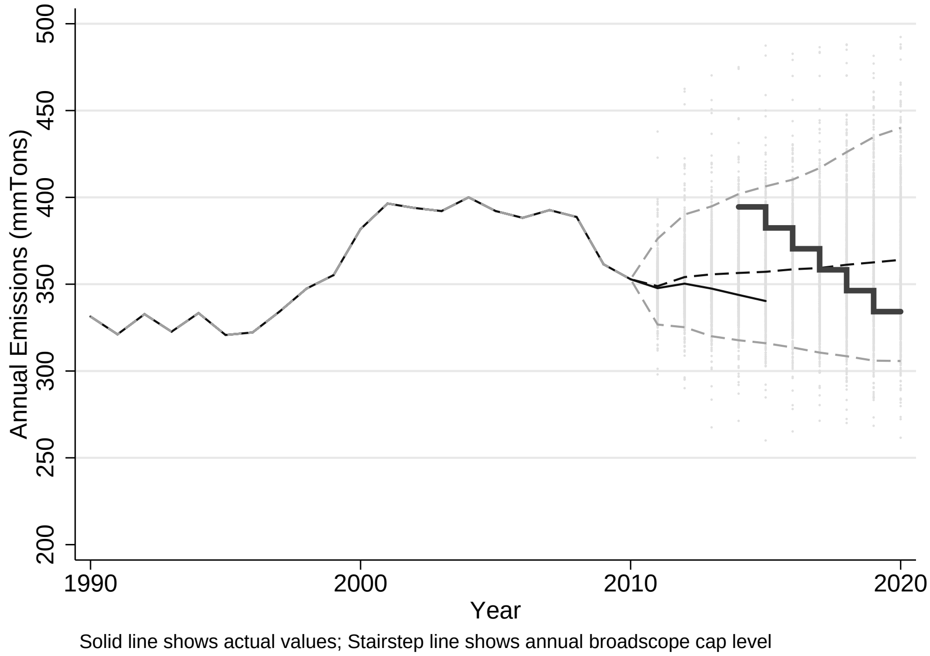

Figure 3. California Broad Scope Mean Emissions Forecast and Confidence Intervals, 2011-2020 (Actual Data, 1990-2015)

III. Impact of Price-Inelastic Abatement

This section describes how we model a number of possible effects of other state energy policies and other activities that were expected to change covered emissions independent of the price in the cap-and-trade market. For each policy, we assume that abatement will fall within a specific range between a more effective abatement case and a less effective abatement case. We then sample from a symmetric $\beta(2,2)$ distribution to create a random draw of abatement for each policy from within our assumed range.[23] Throughout this discussion we characterize "low" and "high" scenarios, with "low" referring to cases in which the result is more likely to be a low allowance price (*i.e.,* more effective abatement), and "high" referring to cases more likely to lead to a high allowance price (*i.e.,* less effective abatement). We combine each of the 1000 realizations from the BAU emissions distribution from the VAR with a simulated outcome of the price-inelastic abatement to derive a

[23] 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. We have also experimented with the assumption that the abatement follows a triangular distribution with the low and high ends of the support at the low and high abatement scenarios and the mode at the average of the low and high scenario. The results differed very little from using the $\beta(2,2)$ distribution.

distribution of 1000 emissions outcomes before price-responsive abatement.

A. *Zero-Carbon Electricity Generation and Energy Efficiency*

In the case of electricity, the main complementary policies are the Renewables Portfolio Standard (RPS) – which in 2011 was increased to mandate that 33% of California electricity supply must come from renewable sources by 2020 – and energy efficiency (EE) investments. We treat the RPS as reducing the *quantity* of carbon-emitting electricity generation, rather than the carbon *intensity* of generation. In the same way as described in the previous section, we adjust the realization of in-state electricity generation net of hydro to account for future deviations from trend in renewable electricity. These potential deviations from trend are based on external data sources discussed in the online appendix. We multiply the value of in-state, fossil-fueled electricity generation net of this realization of renewable generation by the realization from our estimated distribution of the emissions intensity to obtain a realization of the GHG emissions from fossil-fueled generation units located in California.

There is a strong pre-existing trend of energy efficiency improvements already present in the time-series data we used to simulate the distribution of future BAU emissions. As discussed in the online appendix, we therefore make no further adjustments to account for increased energy efficiency beyond those effects already (implicitly) integrated into our forecast of the emissions distribution.

B. *Transportation*

We incorporate the impact of stricter GHG policies in the transportation sector – improved vehicle fuel economy and increases in the use of biofuels – through adjustments to the emissions intensity of VMT realization from the estimated distribution. As described in the online appendix, the low end of this range of emissions intensity is based on a model that ARB used to forecast the impact of GHG policies on fleet composition and fuel economy in the transportation sector. The high end of this range incorporates both ARB's 2011 forecast and the BAU emissions intensity estimation from the VAR. A random draw of emissions intensity from this range, using a $\beta(2,2)$ distribution, is then multiplied by the realization of VMT from our estimated distribution to arrive at a BAU realization of emissions from the transportation sector.

C. *Energy Price Changes Exogenous to Cap-and-Trade*

We also account for the effects on emissions of two potential energy price changes not attributable to the cap-and-trade program. Real prices of electricity in California were expected to rise over the 2013-2020 period due to capital expenditures on transmission and distribution, increased use and integration of renewable energy, and other factors. We take a 2012 forecast of those increases and apply a range of own-price elasticity assumptions, as discussed in the online appendix. The real price of transportation fuels was also likely to rise due to the cost of using more renewable fuels, as mandated under the LCFS. We consider 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, but our estimate of the distribution of BAU gasoline prices implies a wide range of possible prices, as shown in Table 2.

D. Emissions Offsets

As in nearly all GHG cap-and-trade programs in the world, California covered entities are allowed to meet some of their compliance obligations with offset credits. Each entity can use offsets to meet up to eight percent of its obligation in each compliance period. In theory, this means that over the 8-year program, up to 218 MMT of allowance obligations could be met with offsets.[24] In the online appendix, however, we discuss the difficulty of getting approval for offset projects and the fact that the 8% share is not fungible across firms or time, both of which are likely to lead to substantially lower use of offsets. We account for the uncertainty in the amount of offsets likely to be available over the course of the program by taking draws from our best estimate of the range of possible values of offsets.

E. Imported Electricity and Reshuffling

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. However, due to the physics of electricity and the nature of the Western electricity market – which includes states from the Pacific Ocean to the Rocky Mountains – it is not possible to identify the specific generation resource supplying imported electricity. Depending on how the GHG content of imports is administratively determined, electricity importers have an incentive to engage in a variety of trades that lower the reported GHG content of their imports, a class of behaviors broadly labeled reshuffling, as discussed earlier.[25] As explained in the online appendix, we use information on long-term contracts with coal plants to determine the range of possible reshuffling and its impact on allowance demand to cover imported electricity.

[24] Because the offset rule allows 8% of total obligation to be met with offsets, it effectively expands the cap to solve the equation $C - 0.08C = 2508.6MMT$. This implies that $C = 2726.7$ and the total offsets allowed would be $2726.7 - 2508.6 = 218.1$.

[25] Also known as "contract reshuffling" or "resource shuffling." Reshuffling, an extreme form of emission leakage, refers to cases in which actual economic activity doesn't change, but generation from a cleaner source is reassigned by contract to a buyer that faces environmental regulation, while generation from a dirtier source is reassigned to a buyer that does not.

IV. Price-Responsive Abatement

In the online appendix, we discuss in detail the potential abatement from higher allowance prices. 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 for goods and services that produce GHG emissions. Here, we summarize the range of potential impacts we consider and discuss them briefly. The underlying assumptions are shown in more detail in Table A.15 of the online appendix. It is clear from this discussion that the uncertainty in BAU emissions, as well as in the price-inelastic abatement possibilities, are much larger than the potential impact from demand response to cap-and-trade allowance prices.

To evaluate the impact of allowance prices on the demand for GHG emissions, 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 8-year life of the program, as mentioned in section I. Even if very high or low 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. The price in each year will reflect a weighted average of the probabilities of different equilibrium outcomes, eventually ending at the aggregated equilibrium price. In the online appendix, we present the method we use to account for this price evolution. In brief, the price at the beginning of the program is assumed to represent the probability-weighted average of possible final prices, and then is assumed to evolve linearly over the course of the program to the aggregated equilibrium outcome that is ultimately realized.

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 Muehlegger (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 estimates. Fuel economy standards, however, already induce higher fuel economy than consumers would otherwise choose. For natural gas, elasticities estimates are taken from the recent literature. The pass-through of allowance prices to retail natural gas was still unclear in 2012, but seemed likely to be well below 100%. Still, we present results assuming 100% pass-through, because less-than-complete pass-through may be politically untenable in the longer run, and because even with this upper bound case, price-elastic abatement is relatively small. For electricity, elasticities are also taken from the literature, but pass-through seemed likely in 2012 to be quite complicated, with residential customers protected from these costs and commercial and industrial customers absorbing greater than 100% pass-through to cover the shortfall, as discussed in the online appendix. The effect on abatement, however, is nearly the same as imposing

100% pass-through on all customers, so for simplicity we do so.[26]

In the online appendix, we also discuss possible changes in industrial emissions and explain why – due to a combination of low own-price demand elasticities and policies designed to lower pass-through of the allowance price by industrial emitters – these changes are likely to be very small.

The potential range of abatement from each category of price-responsive and non-price-responsive sources are shown in Table 3. To put these figures in context, it is useful to recall from Table 2 that the standard deviation of simulated covered BAU emissions over the 8-year program is 183 MMT. By comparison, the mean of our simulated total price-responsive abatement due to an allowance price increase from the floor (APR) to the ceiling (highest tier of the APCR) is 35.1 MMT, about one-fifth of one standard deviation of the BAU distribution.

Table 3—Summary of Abatement Supply

	Abatement over 8 Years			
	Mean	S.D.	2.5%	97.5%
Allowance Price Responsive Abatement				
Electricity				
Price Response (floor)	3.4	0.5	2.5	4.3
Price Response (ceiling)	9.7	1.4	7.1	12.3
Transport				
Price Response (floor)	3.6	0.5	2.6	4.5
Price Response (ceiling)	12.2	1.8	8.9	15.4
Natural Gas				
Price Response (floor)	11.0	2.5	6.5	15.6
Price Response (ceiling)	31.2	6.9	18.6	44.0
Non-Price Responsive Abatement				
Exogenous Electricity Rate Effects	9.6	1.4	7.1	12.2
Fuel Economy & LCFS	78.3	45.7	5.5	179.4
Renewable Portfolio Std.	63.1	10.1	43.3	84.2
Electricty Imports	64.0	20.1	27.6	100.1
Offsets	97.7	14.2	71.3	123.2
Total at Price Ceiling	365.9			
Total at Price Floor	330.8			

Notes: Price responsive abatement based upon a Beta(2,2) distribution where the endpoints are determined by elasticities of -0.1 to -0.2 for electricity and gasoline, and -0.1 to -0.3 for natural gas.

[26]This would not be the case if residential customer demand were much more or less elastic than demand from commercial and industrial customers. There is not, however, consistent evidence in either direction.

V. Estimated Market Clearing in the Cap-and-Trade Market

To estimate the distribution of possible price outcomes in the allowance market, we combine the 1000 realizations from the distribution of BAU emissions with 1000 realizations from the distribution of additional abatement sources discussed in sections III and IV. Each of the abatement effects is drawn independently. However, the two largest sources of policy-driven abatement – GHG abatement from vehicles and electricity generation – are positively correlated with BAU emissions by construction. In the case of vehicles, this is because GHG intensity of VMT is multiplied by the realization of BAU VMT to obtain the realization of transportation GHGs. Similarly, GHG emissions from electricity generation in each draw are the interaction of the realization of thermal intensity and the realization of kilowatt-hours of thermal generation, after deducting the realization of renewable generation.

Given the very limited amount of data available on abatement activities and our use of sources from the literature for many of the abatement assumptions, basing correlations of BAU emissions and GHG abatement on empirical analysis isn't likely to be credible. Nor, unfortunately, are even the signs of these correlations clear.[27] Thus, we append an independently distributed draw of each additional abatement source to each realization of BAU emissions.

We consider four mutually exclusive and exhaustive potential market clearing price ranges, as was illustrated in Figure 1: (1) at or near the auction reserve price, with all abatement supply coming from price-inelastic and very low-cost abatement, plus 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) at or above the lowest trigger price of the APCR, but at or below the highest APCR trigger price, and (4) above the highest price of the APCR.[28]

Based on the 1000 realizations from the distribution of BAU emissions, complementary policies, offsets, reshuffling, and price responsive abatement, Figure 4 presents our estimate of the PDF of the abatement demand quantity and an estimated abatement supply curve, along with 2.5% and 97.5% bounds on the curve. This is effectively the empirical implementation of Figure 1. Our results suggest a 94.8% probability of the price equilibrating at or very near the auction

[27]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 on regulators to approve controversial offset applications. Similarly, it is unclear whether higher BAU emissions associated with a strong economy would be positively or negatively correlated with the willingness of utilities (and their regulators) to reshuffle contracts or the willingness to accept a higher level of offsets.

[28]California considered program modifications to address the possibility of the price containment reserve being exhausted, but none was adopted prior to the launch of the program. 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 other policy responses. We simply report the estimated probability of reaching this case and note that prices could be much higher than the highest APCR price.

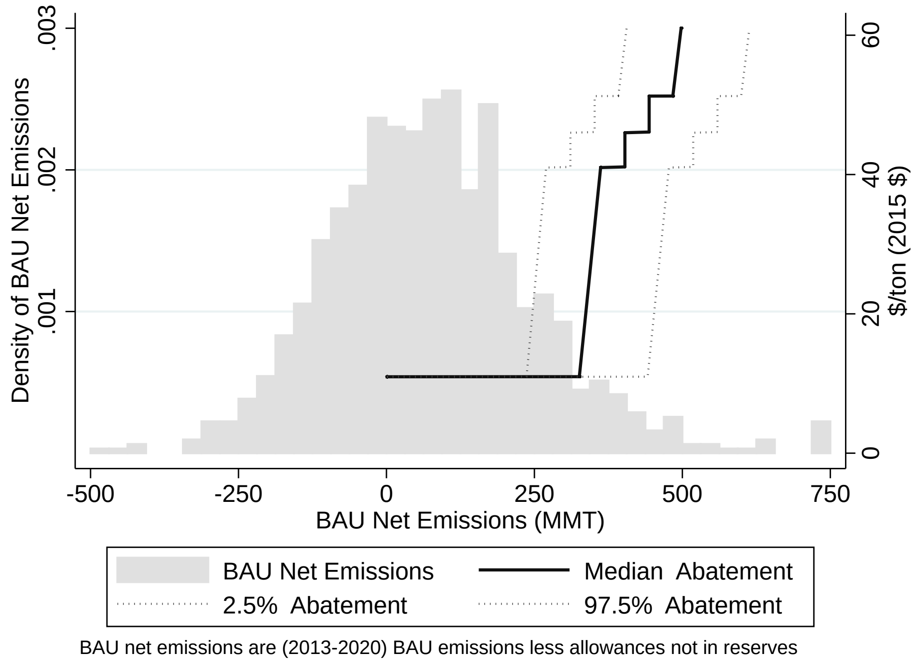

Figure 4. Net Emissions and Abatement Supply (2013-2020)

reserve price, implying that the emissions cap was set high relative to the expected emissions due to business as usual, complementary policies, and the offsets and reshuffling that would take place at very low prices. Of the remaining probability, we estimate a 1.2% chance of a price below the lowest APCR trigger price, what we have referred to as an interior solution. We estimate a 2.8% chance of a price within the APCR price range, and a 1.2% probability of a price above the highest APCR trigger price. Thus, while the likelihood is low, if emissions were high enough to drive the market off the floor, the price would be more than twice as likely to end up in or above the APCR than at an interior equilibrium, where price equilibrates a fixed supply with demand.

Of course, the low probability of an interior solution results to some extent from the emissions cap being set very high relative to the distribution of BAU emissions net of price-inelastic policies. This likely was not intentional. As of late 2010, after the state's emissions reductions targets had been set, ARB still projected emissions from capped sectors during the decade of 2010-2020 to remain level at about 430 MMT per year absent expanded policy intervention (ARB, 2010c).[29]

[29]To construct their forecast of 2020 BAU emissions, ARB combined sector-specific average annual emissions levels for the three most recent years for which the GHG Emissions Inventory data were available (2006-2008) with sector-specific growth projections from the California Energy Commission's 2009

One might ask how high the probability of an interior solution could have been if the cap were set at a lower level. We investigated this question by re-running our analysis at every integer cap level between 2000 and 3000 MMT to find the cap level that would yield the highest probability of an interior solution. We found that occurred at an emissions cap of 2416 MMT (about 290 MMT lower than the actual cap), resulting in an 8.1% probability of an interior solution with the remaining probabilities fairly balanced between lower and higher priced outcomes.[30] In other words, due to the relatively low price responsiveness of abatement, particularly in the presence of complementary policies, and the wide support of the probability density of the BAU emissions, we estimate that no emissions cap level would yield even a 10% probability of an interior solution.

A. How much difference do complementary policies make?

As section III 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. An important question, motivated by the results just discussed, is how much the probability distribution of equilibrium allowance prices would change if complementary policies were not present and the cap-and-trade program were relied upon as the primary mechanism for reducing GHGs.

Removing complementary policies has two significant effects on the analysis. First, it lowers the level of price-inelastic abatement, which in this case causes the price-elastic region of the abatement supply curve to coincide with a higher probability region of the BAU emissions PDF. Second, it increases the price-elasticity of abatement supply by removing the dampening effects that were caused by the complementary policies, as discussed earlier.

In this subsection, we re-estimate the distribution of possible outcomes under a counter-factual without complementary policies. To do this, we make assumptions about alternative paths of regulatory rules – such as the RPS mandate and automotive fuel-economy standards. We also make assumptions about price-responsive consumption changes that would result if complementary policies were not pursued. Thus, we are assessing a more idealized implementation of California's cap-and-trade program, with no other programs to reduce GHG emissions, but all sectors 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;[31]

Integrated Energy Policy Report. Therefore, ARB's methodology explicitly omitted BAU uncertainty and implicitly supposed that the emissions intensity of activity in each sector would, absent further policy intervention, remain constant through 2020.

[30] A 50% probability of an outcome at or near the auction reserve price, a 26.5% probability of an outcome in the APCR, and a 15.4% probability above the APCR.

[31] This is based on forecasts of renewable generation costs as of 2012, which suggested that neither

2) No effect of complementary or other policies on the realization of vehicle emissions intensity from the VAR;

3) No LCFS, so no impact of the LCFS on the price of fuels;

4) Higher price elasticity of response to energy price changes.[32]

The effects of assumptions 1 through 3 are indicated in Table 3, which presents the magnitudes of these shifts of abatement supply that are removed. The effects of assumption 4 are slightly more complicated and amount to roughly doubling the price responsiveness of abatement. The details are described more completely in section A.3.1 of the online appendix.

Under this scenario with no complementary policies, our BAU distribution estimate yields a substantially smaller chance of the market clearing at or very close to the price floor, 79.4% vs. 94.8%, and a much larger probability of an interior solution in which the market clears at a price above the ARP but still below the APCR, 8.3% vs. 1.2% under the baseline scenario. The probability of very high prices more than triples, with an 8.5% probability of settling in the APCR, and a 3.8% probability of exhausting the APCR.

While eliminating complementary policies substantially changes the probabilities, it does not change our fundamental finding that the great majority of the probability distribution lies outside the area of an interior equilibrium. Over 90% of the outcome distribution still occurs at the administratively-determined price floor and ceiling constraints on price, or above the APCR in a range that is likely to be politically unacceptable.

VI. Market Performance To Date and Program Extension

Since the first allowance auction in November 2012, the market performance has been consistent with expectations of excess allowance supply. In the 21 quarterly auctions through 2017, the allowance price averaged $0.67 above the floor, and 5 auctions (February 2016 through February 2017) failed to sell all of the allowances on offer, setting the price at the floor.[33] This softness in the allowance market reflects the gap between the reported actual emissions under the program in its first years of operation and the level of the cap.

In Table 4, we take a closer look at the emissions results for the year 2015. The top panel of Table 4 compares our estimated distribution to 2015 reported values for the seven variables in the VAR of BAU emissions. The bottom panel combines our estimates of abatement with our BAU projections to compare our

wind nor solar would be cost competitive during 2013-2020, even with a GHG price in the range of the APCR.

[32]More specifically, elasticities for transportation fuels, natural gas, and electricity are all drawn from a distribution that ranges from -0.3 to -0.5.

[33]These statistics describe the front-year allowance auctions. Auctions for later-year allowances, which take place at the same time, have generally yielded lower prices.

distribution of forecast emissions after abatement with the actual measured emissions by sector. These values reflect the distribution of projected BAU emissions, less exogenous and price-responsive abatement, as described in the previous section. Note that offsets, which are not directly attributable to any of these specific sectors, are not captured here.

Table 4—Actual vs. Forecast Values of Model Variables for 2015

	2015 Actual	mean forecast	2.5% forecast	97.5% forecast
California Generation Net of Hydro (TWh)	182201	183360	139447	246703
Vehicle Miles Traveled (Billions)	335	338	308	372
Gross State Product (Real Trillion $2015)	2.48	2.39	1.85	3.03
Wholesale SF Gasoline Price (Real ¢2015/gallon)	229.02	284.06	157.27	475.91
In-state Electricity Thermal Intensity (tons/MWh)	0.364	0.350	0.265	0.457
Industry, Nat. Gas, other (MMT before abatement)	NA	107.955	87.359	134.235
Vehicle Emissions Intensity (tons/1000 VMT)	0.473	0.460	0.426	0.488
Transport Emissions (MMT after abatement)	158.5	155.7	131.1	181.9
In-state Electricity Emissions (MMT after abatement)	43.0	39.2	22.0	64.5
Industry, Nat. Gas, other (MMT after abatement)	108.0	106.1	85.4	132.5
Electricity Import Emissions (MMT after abatement)	30.7	32.5	27.7	37.1
Total Broad Scope Emissions (MMT after abatement)	340.3	333.5	297.6	376.8

Table 4 indicates that despite the perception of a soft emissions market, 2015 emissions were slightly above our mean estimate. In fact, the upper panel shows that other than VMT being slightly lower than our mean forecast, all other variables in the VAR were stimulative of GHG emissions compared to our mean forecast. The bottom panel shows that every sector except one, electricity imports (which include both real reductions and reshuffling), produced net emissions (after abatement) above our mean forecast.

A. *Extension of Program through 2030*

In July 2017, California adopted Assembly Bill 398, extending the current cap-and-trade program through 2030. Several details of the new program remain unresolved at the time of this writing, but the annual emissions cap will be reduced from 330 MMT in 2020 to 200 MMT by 2030. In an extension of this paper, Borenstein, Bushnell and Wolak (2017) apply the same approach to estimating the supply-demand relationship under rules that are likely close to those that will govern the extension of the market out to 2030, utilizing the data on market outcomes through 2015. They find that the emissions cap through 2030 lies much closer to the center of the "adjusted" BAU distribution (*i.e.,* after adjusting the distribution for complementary policies, exogenous energy price changes, offsets, and reshuffling). As a result, under our primary analysis with a hard price ceiling of $85 in 2030 (in 2015 dollars), they estimate a 46% probability of the equilibrium price being at the price floor, a 34% of the price ceiling, and a 20% probability of

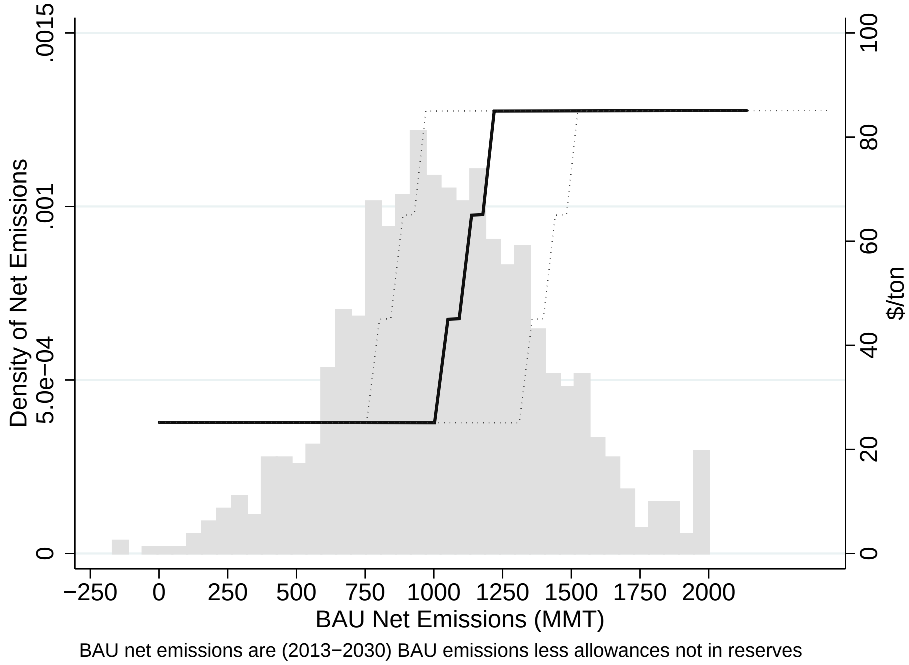

Figure 5. Net Emissions and Abatement Supply (2013-2030)

an outcome between the floor and the ceiling. The higher estimated probability of an interior equilibrium results from a combination of the cap level being close to the center of the "adjusted" BAU distribution and an assumption of higher price elasticities due to estimating over a time period that is nearly twice as long as the originally-legislated 8-year market.

The outcome of that analysis again makes clear that the probability of an interior equilibrium depends very much on the level of the cap compared to the adjusted BAU distribution. Still, the analysis through 2030 demonstrates that even if the cap lies very close to the center of the adjusted BAU distribution and abatement is much more price-elastic, the probability of an interior solution remains low.

VII. Conclusion

If cap-and-trade programs for greenhouse gases are to successfully expand around the world, it is important to understand the possible outcomes of these markets. We have analyzed supply and demand in the California cap-and-trade market over its first authorized period, 2013-2020, in order to estimate the distribution of possible price 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 demands. Combining this with a steep supply curve of abatement creates an inflexible net allowance supply. These two findings suggest 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 substantial uncertainty in the BAU emissions from which any assessment of needed abatement must start. Typically, analyses of targets for GHG reduction programs 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 due in part to the demand for emitting GHGs and the lack of scalable costs-effective abatement technologies, but exacerbated by the complementary policies – such as the renewable portfolio standard and auto fuel-economy standards – that have been adopted by California. These complementary policies, analogues of which exist in all other regions with cap-and-trade markets, effectively mandate many of the changes that consumers and producers might otherwise have made in response to an emissions price.

The "hockey stick" shape of the abatement supply curve – driven by the large quantity of abatement required by complementary policies and then the inelasticity of additional supply beyond that – combined with significant uncertainty in the demand for abatement – driven by uncertainty in BAU emissions – implies that extreme prices (both high and low) are most likely. Using the information available at the time the market began, we find a 94.8% 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 4% chance that the price would rise to the point of triggering regulatory intervention to contain further increases. We estimate only a 1.2% probability of the market clearing in an intermediate region that is not primarily determined by the price containment policies. These results might be interpreted as demonstrating only that California's emissions cap was set "too high," thereby driving prices to the floor. However, our sensitivity analysis demonstrates that even if the cap were set with a goal of maximizing the likelihood of an intermediate price, such an outcome would arise with less than a 9% probability.

Some might also infer 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 face greater uncertainty about whether politicians will be willing to stick with a given capped quantity throughout the market period.[34] Second, though abatement supply elasticity would likely be greater over a longer period, so would the uncertainty of BAU emissions. California's program has now been extended to the year 2030, with much more ambitious reduction targets. Still, even with the tighter cap and longer time horizon for price-responsive abatement to work, we estimate only a 20% chance of an intermediate price outcome by 2030.

While California may be somewhat unusual in factors that make its abatement supply curve inelastic, our analysis in Borenstein et al (2016) suggests that other cap-and-trade markets for GHGs could potentially face similar concerns. Other regions do have access to larger amounts of CO_2 abatement with costs ranging from \$20 to \$60/tonne, primarily through the ability to switch electricity production from coal to natural gas or renewable sources. However these regions also face significant uncertainty in BAU emissions that it seems could exceed the range of price-responsive abatement supply. A detailed empirical analysis of these other markets is beyond the scope of this paper, but is a potentially valuable exercise. The applicability of our findings to cap-and-trade markets for other pollutants, such as SO_2 or NO_x, is simply to point out that it is critical to understand the *ex ante* uncertainty in emissions in comparison to the potential for price-responsive abatement. In the cases of SO_2 and NO_x there was greater availability of cost-effective abatement technologies at a politically acceptable cost than is currently the case for GHGs.

Another reaction to our findings has been to conclude that pricing greenhouse gases is an ineffective policy as compared to technology standards and direct regulation. Our work does not support this inference. Pricing GHGs creates incentives for technological advance, and could create large incentives for switching from high-GHG to low-GHG technologies as their 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 is quite low. Furthermore, while we demonstrate that one should expect large uncertainty in the implied prices from a cap-and-trade scheme, there is also substantial uncertainty about the effectiveness and the costs of non-market-based regulations directed at reducing carbon emissions.

[34] Such uncertainty seems well-founded given recent emissions cap reductions in both RGGI and EU-ETS.

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Expecting the Unexpected: Emissions Uncertainty and Environmental Market Design
Online Appendix

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This appendix presents detailed descriptions of the modeling methods, assumptions, and additional results from the paper "Expecting the Unexpected: Emissions Uncertainty and Environmental Market Design." The Appendix is organized into three major sections: the model of business-as-usual (BAU) emissions, abatement supply, and additional results. Section A.1 provides a description of the primary method and data we use to estimate the distribution of future BAU GHG emissions, as well as three alternative approaches varying in sophistication and parsimony. Section A.2 details how we construct exogenous abatement and abatement that is responsive to the price in the cap-and-trade market and abatement that is responsive to that price. Section A.3 presents additional estimates derived using alternative assumptions and modeling approaches outlined in the main text.

A.1 Modeling Business as Usual GHG Emissions

This section presents the details of our cointegrated vector autoregression (VAR) modeling framework and the methodology we employ to estimate the joint distribution of annual BAU GHG emissions from 2013 to 2020. There are three sources of uncertainty associated with modeling BAU emissions over 2013 to 2020. The first source is uncertainty over the correct parametric form of the true data generation process. The second source is uncertainty over the value of the vector of parameters of the true data generation process. The third source is uncertainty over the future values of unobservable (to the econometrician) factors driving the data generation process. Our modeling framework accounts for the second and third sources of uncertainty, and our sensitivity analysis assesses the impact of the first source of uncertainty.

The remainder of this section presents the details of our cointegrated vector autoregression (VAR) modeling framework and the methodology we employ to estimate the joint distribution of annual business-as-usual (BAU) GHG emissions from 2013 to 2020. To assess the sensitivity of our estimate of the joint distribution of future BAU emissions to our parametric econometric model choice, we also present estimation and simulation results for three alternative statistical models for BAU emissions. There is significant agreement between the mean forecast of annual broad scope GHG emissions and mean forecast of cummulative covered GHG emissions for the period 2013 to 2020 from these models. The models produce somewhat different confidence intervals for GHG emissions over the 2013 to 2020 period, but they all support our conclusion that BAU GHG emissions uncertainty creates a low probability of an interior allowance price equilibrium in the cap-and-trade program.

A.1.1 Overview of Estimation

Several features of our cointegrated VAR are chosen to match the time series relationships between the seven variables implied by economic theory and existing state policies to determine BAU 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 below for each of the individual time series are consistent with this modeling assumption. We also impose restrictions on the parameters of the VAR implied by cointegrating relationships between these seven variables that are supported by the results of cointegration tests reported below. 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. We have confirmed this result by comparing the size of the confidence intervals for BAU emssions from our VAR model with and without the restrictions on the parameters of the VAR implied by these cointegrating relationships imposed. The confidence intervals without the cointegration restrictions imposed are uniformly larger for all years from 2013 to 2020.

The cointegrated VAR relies on seven annual magnitudes for the sample period 1990 to 2010. Let $X_t = (X_{1t}, X_{2t}, ..., X_{7t})'$ denote the vector composed of the following annual variables:

$X_{1t} =$ In-state California electricity production net of hydroelectric generation (TWh)
$X_{2t} =$ Total VMT (Thousands of Miles)
$X_{3t} =$ GHG from Non-Electricity Natural Gas Combustion and Other Industrial Processes (MMT)
$X_{4t} =$ Real Retail Gasoline Price ($2015/Gallon)
$X_{5t} =$ Real Gross State Product ($2015)
$X_{6t} =$ Emissions Intensity of In-State Thermal Generation (Metric Tonnes/MWh)
$X_{7t} =$ Emissions Intensity of VMT (Metric Tonnes/Thousand Miles)

where the definitions of the units abbreviations are: TWh = terawatt-hours, MMT = millions of metric tonnes, VMT = vehicle miles traveled, MWh = megawatt-hours. All dollar magnitudes are expressed in 2015 real dollars, converted using the annual Consumer Price Index (CPU-U). All GHG emissions are in metric tonnes of CO_2-equivalents. We include real Gross State Product (GSP) 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 changes in transport fuel prices change the energy intensity of economic activity and total vehicle miles traveled.

We estimate the VAR in terms of the logarithms of the elements $X_t = (X_{1t}, X_{2t}, ..., X_{7t})$. We then use a bootstrap-based re-sampling scheme to compute an estimate of the distribution of X_t from 2013 to 2020 that account for both estimation error in the parameters of the VAR and uncertainty in the future realizations of the stochastic process driving the VAR. A number of transformations of several elements of X_t are required to simulate the distribution of GHG emissions for 2013 to 2020. In the next subsection, we discuss estimation of the VAR and how it is used to simulate future values of the elements of X_t. In the following subsection, we explain the transformations of the simulated value of X_t to derive estimates of the distribution of BAU GHG emissions from 2013 to 2020.

A.1.2 Data Sources and Construction

To compute the GHG emissions intensities of the in-state electricity production and transportation sector from 1990 to 2010 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 2010 is the final GHG emissions-related time series required to estimate the VAR.[1] To construct these data, we start with data on annual emissions for each covered sector in California for 1990 to 2010.

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).[2] 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 California Air Resources Board (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.[3]

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. Because combustion emissions from small commercial and industrial entities are captured upstream starting in the second compliance period, in the second and third compliance periods, we use the unadjusted Inventory data as our measure of industrial capped source emissions covered. 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. Empirically, this approach does not appear to impact either our expected time path or the degree of uncertainty in the future time path of broad-scope emissions.

The remaining data that enter the VAR come from a variety of California state and federal sources:

California GSP is collected from the Bureau of Economic Analysis (BEA).[4] Gasoline prices are collected from the Energy Information Administration (EIA).[5] In-state electric generation is collected from the California Energy Commission (CEC).[6]

Additionally, we adjust transportation sector emissions to account for differences between how emissions and activity are measured. 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,

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

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

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

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

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

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

Table A.1: VAR Estimation Dataset

Year	California Electricity net of Hydro (Twh)	Vehicle Miles Traveled (Billions)	Nat. Gas, Ind. & Other (MMT)	Gasoline Price (¢2015)	Gross St. Product ($2015 Trillion)	Therm. Intensity (tons/ MWh)	Trans. Intensity (tons/1000 Miles)
1990	146.6	259	121.7	185.22	1.42	0.495	0.543
1991	142.8	258	118.3	173.40	1.40	0.495	0.532
1992	156.7	263	112.9	176.53	1.38	0.518	0.548
1993	137.2	266	110.9	174.50	1.38	0.581	0.528
1994	165.3	272	112.0	168.95	1.42	0.509	0.525
1995	140.4	276	110.1	168.06	1.48	0.488	0.530
1996	133.5	278	113.2	173.60	1.53	0.511	0.534
1997	136.1	279	119.0	166.34	1.69	0.493	0.541
1998	148.3	291	123.9	146.88	1.76	0.487	0.531
1999	152.0	300	123.5	165.96	1.86	0.508	0.530
2000	178.0	307	115.9	195.64	1.96	0.484	0.554
2001	177.5	311	113.8	184.10	1.90	0.474	0.550
2002	155.4	322	116.2	158.35	1.93	0.464	0.554
2003	158.0	324	113.8	188.39	2.00	0.438	0.542
2004	164.3	329	117.3	206.33	2.10	0.406	0.539
2005	161.8	329	114.3	232.51	2.18	0.400	0.545
2006	170.0	327	113.4	251.02	2.23	0.396	0.549
2007	185.6	328	109.5	273.18	2.25	0.393	0.546
2008	184.9	327	110.1	300.09	2.20	0.387	0.516
2009	178.7	324	106.6	227.17	2.14	0.397	0.502
2010	171.4	323	111.1	259.27	2.16	0.372	0.493

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 Figure 1 in the text reflect this partition of on-road and off-road emissions. The details of this partitioning are further described in Section A.2.

A.1.3 Estimation of Cointegrated Vector Autoregression

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 VAR can be written as

$$\Theta(L) \cdot Y_t = \mu + \epsilon_t \qquad (A.1)$$

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 $(I - \Theta L)$ where Θ is a (7x7) matrix of constants, μ is a (7x1) vector of constants, and ϵ_t is a (7x1) white noise sequence with a (7x1) zero mean vector and a (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 (A.1) allows each element of Y_t to be non-stationary (contain a unit root) and exhibit 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. In the next subsection, we perform several Dickey and Fuller (1979) tests and two of the Dickey-Fuller GLS tests proposed by Elliott, Rothenberg, and Stock (1996) of the null hypothesis that the time series contains a unit root for each element of Y_t. All of these tests find little evidence against the null hypothesis that each element of Y_t contains a unit root. Diebold and Kilian (2000) present Monte Carlo evidence that the forecasting performance of a univariate AR(1) model can be improved by using a unit root test to determine whether to use the levels or first-difference version of the model. Our unit root tests are consistent with the decision to model the vector ΔY_t as 2nd-order stationary process.

Diebold and Kilian (2000, p. 287) also argue that "differencing provides insurance against problems due to small-sample bias and explosive roots problems, at a cost." They argue that the problems associated with forecasting future values from an AR(1) process are most severe for situations with a small number of observations and longer forecast horizons, where the insurance is more than worth the cost. Because our empirical analysis relies on a small number of observations and has a relatively long forecast horizon, this logic provides an additional reason, besides the results of our unit root tests, for specifying our VAR in first-differences.

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 there are linear combinations of the elements of Y_t that are likely to be 2nd-order stationary in levels. Vector-valued time series processes whose elements are 2nd-order stationary in first-differences and have stationary linear combinations of the levels of their elements are said to be cointegrated. Engle and Granger (1987) provide a complete discussion of this concept and its implications for the specification and estimation of multivariate linear time series models. For a k-dimensional random vector, Y_t, with each element stationary in first-differences, the number of distinct 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 $\Lambda \equiv -(I - \Theta)$. The existence of cointegrating relationships among elements of Y_t imposes restrictions on the elements of Λ that will yield more precise estimates of Λ (and Θ) and shorter confidence intervals for future values of GHG emissions.

Suppose that the rank of the matrix Λ is equal to r $(0 < r < 7)$. This implies that the following *error correction representation* exists for Y_t:

$$\Delta Y_t = \mu + \Lambda Y_{t-1} + \epsilon_t \tag{A.2}$$

where $\Lambda = -\gamma\alpha'$ for γ a (7 x r) rank r matrix of parameters and α a (7 x r) rank r matrix of parameters. Define the (r x 1) vector $Z_t = \alpha' Y_t$ which is composed of the stationary linear combinations of Y_t. This notation implies that ΛY_{t-1} is equal to $-\gamma Z_{t-1}$.

Johansen (1988) devised a test of the cointegrating rank of a VAR whose elements are 2nd-order stationary in first-differences. We utilize Johansen's (1988) maximum likelihood estimation procedure to recover consistent, asymptotically normal estimates of μ, Ω, and Λ with these co-integrating restrictions imposed. Using these parameter estimates, we then compute an estimate of the joint distribution of $(Y'_{2013}, Y'_{2014}, ..., Y'_{2020})'$ conditional on the value of Y_{2010} that takes into account both our uncertainty in the values of μ, Ω, and Λ because of estimation error and uncertainty due to the fact that $(Y'_{2013}, Y'_{2014}, ..., Y'_{2020})'$ depends on future realizations of ϵ_t for $t = 2011, ..., 2020$. We then apply the transformation $X_{it} = exp(Y_{it})$ to element of Y_t to obtain an estimate of the joint distribution of $(X_{2013}, X_{2014}, ..., X_{2020})$ conditional on the value of X_{2010}.[7]

We employ a two-stage smoothed bootstrap approach to compute an estimate of the distribution of $(X'_{2013}, X'_{2014}, ..., X'_{2020})'$.[8] The first step computes an estimate of the joint distribution of the estimates of

[7]We carried out similar estimation using data through 2012. The procedure was identical, except it was no longer necessary to simulate values for for 2011 and 2012 to create simulated values for 2013 through 2020. For this reason, the confidence intervals for future values of the elements of X_t from 2013 to 2020 based on data through 2012 were typically somewhat smaller than those based on data up to 2010. We focus on the results using data through 2010, because those were the data available at the time that final decisions on the market design were made in 2012.

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

μ, Ω, and Λ by resampling from the smoothed empirical distribution of the (7x1) vector of residuals from the estimated VAR with the restrictions implied by cointegration imposed. Specifically, let $\hat{\mu}$, $\hat{\Omega}$, and $\hat{\Lambda}$ equal the estimates of the elements of the VAR imposing the cointegration of rank r restriction that $\hat{\Lambda} = -\hat{\gamma}\hat{\alpha}'$. We compute

$$\hat{\epsilon}_t = Y_t - \hat{\mu} - \hat{\Lambda}_1 Y_{t-1} \tag{A.3}$$

for t =1991 to 2010. Note that we can only compute values of $\hat{\epsilon}_t$ for t =1991 to 2010, because our sample begins in 1990 and the $(t-1)$th observation is required to compute the value of $\hat{\epsilon}_t$ for period $t = 1991$. We construct the kernel density estimate of the $\hat{\epsilon}_t$ as

$$\hat{f}(t) = \frac{1}{Th^7} \sum_{t=1}^{T} K\{\frac{1}{h}(t - \hat{\epsilon}_t)\} \tag{A.4}$$

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 $h = 0.5$. Our estimate of the distribution of GHG emissions from 2013 to 2020 is insensitive to the value chosen for h, as long as it is less than 1.

We then draw $T = 20$ values from (A.4) and use the parameter estimates and these draws to compute re-sampled values of Y_t for $t = 1, 2, ..., T = 20$. Let $(\hat{\epsilon}_1^m, \hat{\epsilon}_2^m, ..., \hat{\epsilon}_{20}^m)'$ denote the mth draw of the 20 values of $\hat{\epsilon}_t$ from $\hat{f}(t)$. We compute the Y_t^m, the 20 resampled values of Y_t for t =1991 to 2010, by applying the following equation starting with the value of Y_t in 1990 ($Y_{1990}^m = Y_{1990}$ for all m)

$$Y_t^m = \hat{\mu} + I + \hat{\Lambda}_1 Y_{t-1}^m + \hat{\epsilon}_t^m. \tag{A.5}$$

We then estimate the values of μ, Ω, and Λ by applying Johansen's (1988) ML procedure using the Y_t^m and imposing the cointegration rank restriction that $\Lambda = -\gamma\alpha'$. Call the resulting estimates $\hat{\mu}^m$, $\hat{\Omega}^m$, and $\hat{\Lambda}^m$. Repeating this process $M = 1000$ times yields the bootstrap distribution of $\hat{\mu}$, $\hat{\Omega}$, and $\hat{\Lambda}$. 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 Λ 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 $\hat{\Lambda}^m$, we draw $H = 10$ values from $\hat{f}(t)$ in equation (A.4), calling these values $(\hat{\epsilon}_{T+1}^m, \hat{\epsilon}_{T+2}^m, ...\hat{\epsilon}_{T+H}^m)'$. Using these draws and $\hat{\mu}^m$, $\hat{\Omega}^m$, and $\hat{\Lambda}_1^m$ we compute future values Y_{T+k} for $k = 1, 2, ..., H$ given the actual value of Y_T using the following equation:

$$Y_{T+k|T}^m = \hat{\mu}^m + (I + \hat{\Lambda}^m)Y_{T+k-1|T}^m + \hat{\epsilon}_{T+k}^m \quad \text{for} \quad k = 1, 2, ..., 10 \tag{A.6}$$

This yields one realization of the future sample path of Y_t for t =2011, 2012,..., 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 from 2011 to 2020, as described in section A.1.5. This two-step process of computing $\hat{\mu}^m$, $\hat{\Omega}^m$, and $\hat{\Lambda}^m$ and then simulating $Y_{T+k|T}^m$ for $k = 1, 2, ..., 10$ replicated $m = 1$ to $M = 1000$ times produces 1,000 realizations from the simulated distribution of $(X_{2011}', ..., X_{2020}')'$. Discarding the first two elements of this vector yields a realization from the distribution of $(X_{2013}', X_{2014}', ..., X_{2020}')'$ conditional on data through 2010.

We explored a number of alternative approaches to computing the joint distribution $(X_{2013}, X_{2014}, ..., X_{2020})$. For example, rather than re-sampling from the smoothed distribution of the $\hat{\epsilon}_t$, we applied the wild bootstrap to generate the values of $\hat{\epsilon_t^m}$ used in (A.5) to compute the Y_t^m for each value of t and m using the procedure recommended by Davidson and Flachaire (2008). In the second step of this approach, we draw the values of ϵ_{T+k} for $k = 1, 2, ..., 10$ from $\hat{f}(t)$ (equation (A.4)), as described above. The estimated joint distribution of $(X'_{2011}, ..., X'_{2020})'$ from this procedure was virtually identical to that obtained from the two-step smoothed bootstrap approach.

A.1.4 Unit Root/Cointegration Tests and Estimation of VAR

This subsection 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 VAR model used to estimate the distribution of $(X'_{2013}, X'_{2014}, ..., X'_{2020})'$.

We present three versions of the Dickey-Fuller (DF) unit root tests for each element of Y_t and report two test statistics for each hypothesis test and two versions of the Dickey-Fuller GLS (DF-GLS) test proposed by Elliott, Rothenberg and Stock (1996). Let Y_{it} equal the ith element of Y_t. The zero mean version of the DF 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: $\alpha < 1$.

In Table A.2 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 "$\hat{\tau}$".

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

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

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

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

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

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

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

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

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

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

Table A.2 presents the results of these unit root tests for the seven elements of Y_t. For all three versions of the unit root test and two test statistics, there is little evidence against the unit root 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.

The final two variables in the first column of this table report the results of these unit root tests applied to the logarithm of annual broad scope emissions and the first-difference of the logarithm of annual broad scope emissions. For the logarithm of broad scope emissions, we find little evidence against the null hypothesis of a unit root, but for the first-difference of the logarithm of broad scope emissions, we find strong evidence against the null hypothesis for all three tests, which is consistent with this variable being stationary in first-differences.

Table A.3 reports the results of the DF-GLS tests with and without a time trend. The columns with the heading $\hat{\tau}$ contain the values of the test statistic with one lag for the first-differenced or de-trended variable in the DF regression. The columns with the heading $5\% Critical Value$ are the critical values for size $\alpha = 0.05$ test of the null hypothesis of a unit root. The results of the DF-GLS are also consistent with each of the elements of Y_t having a unit root.

Tables A.3 presents the results of our cointegration rank tests for the 1990 to 2010 period. This hypothesis test is formulated in terms of the notation of the error correction version of the cointegrated VAR model:

$$\Delta Y_t = \mu + \Lambda Y_{t-1} + \epsilon_t \tag{A.7}$$

where Λ is (7x7) matrix that satisfies the restriction $\Lambda = -\gamma\alpha'$ and γ and α are (7 x r) matrices of rank r. The 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 Table A.4 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 the 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. 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

Table A.2: Unit Root Test Statistics (Data from 1990 to 2010)

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	0.04	0.6777	1.74	0.9755
	Single Mean	-1.95	0.7666	-2.15	0.2288
	Trend	0.17	0.9928	0.05	0.9937
ln_ngother_industrial	Zero Mean	-0.01	0.6654	-0.34	0.5494
	Single Mean	-14.84	0.0137	-2.49	0.1329
	Trend	-16.49	0.0470	-2.52	0.3156
ln_real_gas_price	Zero Mean	0.07	0.6854	0.80	0.8764
	Single Mean	-2.00	0.7609	-0.74	0.8143
	Trend	-9.33	0.3785	-2.13	0.4976
ln_real_gsp	Zero Mean	0.03	0.6761	1.58	0.9670
	Single Mean	-1.93	0.7689	-1.45	0.5360
	Trend	-15.59	0.0642	-1.82	0.6543
ln_thermal_intensity	Zero Mean	0.35	0.7540	1.24	0.9384
	Single Mean	-0.25	0.9317	-0.12	0.9335
	Trend	-16.60	0.0451	-3.50	0.0680
ln_transport_intensity	Zero Mean	0.12	0.6967	0.69	0.8551
	Single Mean	-5.39	0.3507	-0.78	0.8019
	Trend	-3.66	0.8848	-0.63	0.9645
ln_broad_emissions	Zero Mean	0.005	0.7164	0.23	0.7219
	Single Mean	-2.53	0.7098	-1.19	0.6336
	Trend	-1.86	0.9651	-0.54	0.9716

Table A.3: DF-GLS Unit Root Test Statistics (Data from 1990 to 2010), Lag=1

Variable	Time Trend		No Time Trend	
	$\hat{\hat{\tau}}$	5 % critical value	$\hat{\hat{\tau}}$	5 % critical value
ln_twh_p_hydro	-2.803	-3.485	-1.283	-2.559
ln_vmt	-1.036		-0.732	
ln_ngother_industrial	-2.443		-2.015	
ln_real_gas_price	-1.984		-0.834	
ln_real_gsp	-2.168		-1.063	
ln_thermal_intensity	-2.418		-0.385	
ln_transport_intensity	-1.388		-1.249	
ln_broadscope_emissions	-0.948		-1.096	

(A.7) that we estimate to simulate the joint distribution of GHG emissions from 2013 to 2020. 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 Λ from 49 to 28 ($= (7x2)x2$), the total number of elements in γ and

α. Consistent with the logic that imposing valid restrictions on parameters of a linear regression reduces the variance of the resulting parameter estimates and therefore the variance of prediction errors for the dependent variable, imposing these restrictions on our VAR reduces the variance and size of the confidence intervals for time path of GHG emissions from 2013 to 2020.

Table A.4: Cointegration Rank Test Using Trace (Data from 1990 to 2010)

H0: Rank=r	H1: Rank > r	Eigenvalue	LR(r)	5% Critical Value
0	0	0.9819	175.6426	123.04
1	1	0.8253	95.4013	93.92
2	2	0.7285	60.5051	68.68
3	3	0.5885	34.4257	47.21
4	4	0.4416	16.6650	29.38
5	5	0.1659	5.0107	15.34
6	6	0.0668	1.3824	3.84

Table A.5 presents the results of estimating our co-integrated VAR model for Y_t for the 1990-2010 sample period in term of the model notation given (A.7). The variable Λ_{ij} in Table A.5 is the (i,j) element of Λ, which also equals $-\gamma\alpha$, and μ_j is the jth element of μ. The model was estimated under the assumption that Λ has rank $r = 2$.[9] We report the parameter estimates in terms of the elements of Λ rather than in terms of γ and α because these parameters have the usual (dynamic) linear regression interpretation. As Lutkepohl (1994) and Johansen (2005) emphasize this interpretation does not hold for the coefficients of the cointegrating relationships. Johansen (2005) discusses issue and provides an interpretation for the coefficients of cointegrating relationships.

Under the assumption that a rank $r = 2$ cointegrated VAR model is a valid description of the time series properties of Y_t, the null hypothesis that 7-dimensional vectors ϵ_t $t = 1, 2, ..., T$ in (A.7) are independent and identically distributed with $E(\epsilon_t) = 0$ and $E(\epsilon_t \epsilon_t') = \Omega$ should not be rejected. Hosking (1980) derives a multivariate portmanteau statistic that tests the null hypothesis that the disturbances to an M-dimensional vector ARMA(p,q) process are independently and identically distributed M-dimensional random vectors with mean zero and an arbitrary positive definite contemporaneous covariance matrix. Under this null hypothesis, the portmanteau test statistic is asymptotically distributed as a chi-squared random variable with $M^2(S - p - q)$ degrees of freedom, where S is the number of sample autocovariance matrices of the vector of residuals from the estimated vector ARMA(p,q) model included in the statistic. This statistic reduces to the standard univariate Box and Pierce (1970) statistic for the case that M=1. The first panel of Table A.6 presents the values of the multivariate portmanteau statistic for $S = 1, 2, ..., 5$ for the rank $r = 2$ VAR for the 1990 to 2010 sample period. For all values of S, the p-value associated with the value of the test statistic is significantly larger than 0.05, indicating that a size 0.05 test of the null hypothesis of white noise disturbances is not rejected.

[9] We were concerned about the ability of the Johansens cointegration testing procedure to detect the rank of Λ. Therefore we performed the following two Monte Carlo studies to investigate this question. First we took the parameters we estimated for our rank 2 cointegrated VAR (given in Table A.5) and generated 1,000 samples of size 20 from this model assuming the errors were multivariate normally distributed and performed the Johansen testing procedure of finding the smallest value of r for which we did not reject the null hypothesis that the rank of Λ matrix was equal to r. We found that for approximately 90 percent of our resamples the procedure found $r = 2$ or $r = 3$ to be the rank of Λ. We then took the parameters we estimated from a rank 1 cointegrated VAR and generated 1,000 samples of size 20 from this model assuming the errors were multivariate normally distributed and performed the Johansen testing procedure. For this model we found that for approximately 90 percent of our resamples the procedure found $r = 1$ or $r = 2$ to be the rank of Λ. Because our estimate of the distribution of BAU GHG emissions for 2013 to 2020 did not appreciably change between a rank 1, 2, or 3 cointegrated VAR, this Monte Carlo evidence increased our confidence in the usefulness of the Johansen testing procedure for determining the rank of Λ.

Table A.5: Error Correction Vector Autoregression Parameter Estimates (Data from 1990 to 2010)

Equation	Parameter	Estimate	Standard Error	Variable
$\Delta ln\_twh_p\_hydro$	μ_1	4.08472	1.47269	1
	Λ_{11}	-1.06458	0.18121	$ln\_twh\_p\_hydro_{(t-1)}$
	Λ_{12}	0.18191	0.32220	$ln\_vmt_{(t-1)}$
	Λ_{13}	0.03403	0.30736	$ln\_ngother\_industrial_{(t-1)}$
	Λ_{14}	0.39486	0.15354	$ln\_real\_gas\_price_{(t-1)}$
	Λ_{15}	0.39087	0.21521	$ln\_real\_gsp_{(t-1)}$
	Λ_{16}	0.56739	0.11426	$ln\_thermal\_intensity_{(t-1)}$
	Λ_{17}	-0.44492	0.09246	$ln\_transport\_intensity_{(t-1)}$
Δln_vmt	μ_2	0.87233	0.32153	1
	Λ_{21}	-0.01900	0.03956	$ln\_twh\_p\_hydro_{(t-1)}$
	Λ_{22}	-0.20589	0.07034	$ln\_vmt_{(t-1)}$
	Λ_{23}	-0.19803	0.06710	$ln\_ngother\_industrial_{(t-1)}$
	Λ_{24}	-0.08705	0.03352	$ln\_real\_gas\_price_{(t-1)}$
	Λ_{25}	0.13421	0.04699	$ln\_real\_gsp_{(t-1)}$
	Λ_{26}	-0.03695	0.02495	$ln\_thermal\_intensity_{(t-1)}$
	Λ_{27}	0.03226	0.02019	$ln\_transport\_intensity_{(t-1)}$
$\Delta ln\_ngother\_industrial$	μ_3	2.24336	0.69328	1
	Λ_{31}	-0.13072	0.08531	$ln\_twh\_p\_hydro_{(t-1)}$
	Λ_{32}	-0.44110	0.15168	$ln\_vmt_{(t-1)}$
	Λ_{33}	-0.43600	0.14469	$ln\_ngother\_industrial_{(t-1)}$
	Λ_{34}	-0.16003	0.07228	$ln\_real\_gas\_price_{(t-1)}$
	Λ_{35}	0.32993	0.10131	$ln\_real\_gsp_{(t-1)}$
	Λ_{36}	-0.03466	0.05379	$ln\_thermal\_intensity_{(t-1)}$
	Λ_{37}	0.03445	0.04353	$ln\_transport\_intensity_{(t-1)}$
$\Delta ln\_real\_gas\_price$	μ_4	4.78092	2.88632	1
	Λ_{41}	-0.06159	0.35516	$ln\_twh\_p\_hydro_{(t-1)}$
	Λ_{42}	-1.19050	0.63147	$ln\_vmt_{(t-1)}$
	Λ_{43}	-1.13876	0.60239	$ln\_ngother\_industrial_{(t-1)}$
	Λ_{44}	-0.51752	0.30092	$ln\_real\_gas\_price_{(t-1)}$
	Λ_{45}	0.75326	0.42178	$ln\_real\_gsp_{(t-1)}$
	Λ_{46}	-0.23754	0.22394	$ln\_thermal\_intensity_{(t-1)}$
	Λ_{47}	0.20511	0.18121	$ln\_transport\_intensity_{(t-1)}$
Δln_real_gsp	μ_5	2.86832	0.60402	1
	Λ_{51}	-0.23650	0.07432	$ln\_twh\_p\_hydro_{(t-1)}$
	Λ_{52}	-0.47457	0.13215	$ln\_vmt_{(t-1)}$
	Λ_{53}	-0.48157	0.12606	$ln\_ngother\_industrial_{(t-1)}$
	Λ_{54}	-0.14398	0.06297	$ln\_real\_gas\_price_{(t-1)}$
	Λ_{55}	0.40012	0.08827	$ln\_real\_gsp_{(t-1)}$
	Λ_{56}	0.01012	0.04686	$ln\_thermal\_intensity_{(t-1)}$
	Λ_{57}	0.00015	0.03792	$ln\_transport\_intensity_{(t-1)}$
$\Delta ln\_thermal\_intensity$	μ_6	-1.49663	1.35355	1
	Λ_{61}	0.26104	0.16655	$ln\_twh\_p\_hydro_{(t-1)}$
	Λ_{62}	0.08341	0.29613	$ln\_vmt_{(t-1)}$
	Λ_{63}	0.11325	0.28249	$ln\_ngother\_industrial_{(t-1)}$
	Λ_{64}	-0.03922	0.14112	$ln\_real\_gas\_price_{(t-1)}$
	Λ_{65}	-0.17372	0.19780	$ln\_real\_gsp_{(t-1)}$
	Λ_{66}	-0.11031	0.10502	$ln\_thermal\_intensity_{(t-1)}$
	Λ_{67}	0.08449	0.08498	$ln\_transport\_intensity_{(t-1)}$
$\Delta ln\_transport\_intensity$	μ_7	0.65427	0.60212	1
	Λ_{71}	-0.07058	0.07409	$ln\_twh\_p\_hydro_{(t-1)}$
	Λ_{72}	-0.09105	0.13173	$ln\_vmt_{(t-1)}$
	Λ_{73}	-0.09568	0.12567	$ln\_ngother\_industrial_{(t-1)}$
	Λ_{74}	-0.02021	0.06277	$ln\_real\_gas\_price_{(t-1)}$
	Λ_{75}	0.08864	0.08799	$ln\_real\_gsp_{(t-1)}$
	Λ_{76}	0.01441	0.04672	$ln\_thermal\_intensity_{(t-1)}$
	Λ_{77}	-0.00968	0.03780	$ln\_transport\_intensity_{(t-1)}$

Table A.6: Portmanteau Test Statistics of Model Residuals

Model	Lag	Statistic	p-value
Rank = 2 Cointegrated VAR	1	42.3699	0.9111
	2	102.8449	0.4735
	3	147.1996	0.6943
	4	198.9458	0.6084
	5	264.7963	0.2707
Two Sample Error − Correction Model	1	8.2422	0.5674
	2	20.5808	0.3017
	3	26.5530	0.5275
	4	40.3913	0.2787
	5	50.3961	0.2438
Bivariate Model	1	0.5815	0.9810
	2	2.1195	0.9860
	3	5.4634	0.9670
	4	7.9841	0.9740
	5	14.5774	0.8332

A.1.5 Simulating BAU GHG emissions for 2013-2020

As discussed in the text, California's cap-and-trade program phases in the covered entities in two tranches. Our approach simulates the distribution of BAU 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. In order to simulate covered emissions for 2013-2020, we do three transformations of the simulated values from the VAR: (a) parsing GHG from non-electricity natural gas combustion and other industrial emissions between narrow scope and broad scope categories, (b) deriving GHG emissions from in-state electricity generation, and (c) deriving GHG emissions from transportation.

GHG from Non-Electricity Natural Gas Combustion and Other Industrial Processes: We parse X_{3t} into the portion of these emissions that are and are not covered by the program under the narrow scope during 2013 and 2014. Based on historical data, we assume that 59 percent of these emissions are from industrial processes and natural gas combustion by large industrial sources and are therefore included in narrow scope emissions that are covered by the emissions cap during the first two years of the program. The remaining 41 percent of industrial GHG and other natural gas emissions are included in broad scope emissions that are covered by the program from 2015 through 2020.

Electricity Sector Emissions: While GHG from Non-Electricity Natural Gas Combustion and Other Industrial Processes (X_{3t}) is already in terms of metric tonnes of GHG, in order to obtain the other two components of total GHG emissions covered under the program – electricity generation and transportation – we need to transform components of the simulated values. For electricity, 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, forecasts for which are discussed below. The remaining residual production is assumed to be provided by thermal generation. This residual amount is multiplied by the thermal intensity, X_{6t} to derive emissions from in-state electricity generation, which are included in the cap-and-trade program in all years from 2013 to 2020.

Imported electricity is a substantial category of emissions covered under the state's cap-and-trade program, likely to constitute more than 10% of total emissions. However, due to the physics of an integrated electricity grid, it is impossible to partition 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. Hobbs, Bushnell, and Wolak (2010) and Bushnell, Chen and Zaragoza-Watkins (2014) discuss this issue and its implications for the design of the California market for GHG emissions. Consequently, GHG emissions from electricity imports deemed to be covered by the cap-and-trade program are determined largely by an administrative process set by the ARB.

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 electrical energy 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. The incentive of California load-serving entities to claim electricity from GHG emissions-intensive sources is "delivered" to California changes dramatically with the introduction of a cap-and-trade program that puts a price on GHG emissions from electricity imports. Consequently, claimed GHG annual emissions from electricity imports from 1990 to 2010 are unlikely to be informative about claimed emissions from electricity imports during the cap-and-trade program. For these reason, we do not include GHG emissions from electricity imports in any of our models for BAU emissions. We instead use the administratively determined value for GHG emissions from electricity imports from the ARB's MRR for 2012 of 40.17 MMT and adjust this value for our estimated amount of reshuffling and other changes in imports during that year.

Transportation Emissions: We calculate transportation emissions much the same way as electricity sector emissions. Both total VMT (X_{2t}) and the emissions intensity of VMT (X_{7t}) are simulated for the years 2015-2020, the years in which transportation emissions are covered by the cap-and-trade program. For each of the 1000 simulated paths of the VAR variables, these two simulated values are multiplied together to yield an annual value for transportation emissions.

Adding together the emissions for each of the three sectors gives the simulated annual total covered GHG emissions. Summing these annual simulated emissions for the years 2013-2020 produces the simulated aggregate GHG emissions over the life of the program. By carrying out 1000 simulations, as described above, we derive an estimate of the distribution of BAU GHG emissions from 2013 to 2020.

A.1.6 Alternative Approaches to Modelling BAU Emissions

In order to assess the sensitivity of our estimate of the joint distribution of annual GHG emissions for 2013 to 2020 to our modeling assumptions, this section considers three alternative methodologies for recovering an estimate of this distribution.

A.1.6.1 Two-Sample Error Correction Model

The first alternative methodology utilizies a two-equation model that takes advantage of the availability of a longer time series for the four non-GHG emissions-related variables in the VAR. This approach first estimates a cointegrated vector autoregression for the four non-GHG emissions variables on a sample that starts in 1975 and ends in 2010. Let $Z_t = (Y_{1t}, Y_{2t}, Y_{4t}, Y_{5t})'$ equal this 4-dimensional vector. Then a three-variable model using $E_t = (Y_{2t}, Y_{5t}, Y_{6t})'$ with the contemporanous first-difference of Z_t as covariate and an error correction term is estimated.

Variables that start in 1990 are:

$$
\begin{aligned}
exp(E_{1t}) =&\ \text{GHG from Non-Electricity Natural Gas Combustion and Other Industrial Processes (MMT)}\\
exp(E_{2t}) =&\ \text{Emissions Intensity of In-State Thermal Gen. (Metric Tonnes/MWh)}\\
exp(E_{3t}) =&\ \text{Emissions Intensity of VMT (Metric Tonnes/Thousand Miles)}
\end{aligned}
$$

Variables that start in 1975 are:

$$\begin{aligned} exp(Z_{1t}) &= \text{ CA electricity production net of hydroelectric generation (TWh)} \\ exp(Z_{2t}) &= \text{ Total VMT (Thousands of Miles)} \\ exp(Z_{3t}) &= \text{ Average Real Retail Gasoline Price (\$2015/gallon)} \\ exp(Z_{4t}) &= \text{ Real Gross State Product (\$2015)} \end{aligned}$$

Consistent with the unit-root test results presented in subsection A.1.4, the first difference of Y_t and Z_t are each assumed to be 2nd-order stationary. We model ΔZ_t from 1976 to 2010 as a cointegrated VAR process:

$$\Delta Z_t = \nu + \Pi Z_{t-1} + \eta_t. \tag{A.8}$$

Table A.7 presents the results of Johansen's test for the cointegrating rank for Π for the sample period 1975 to 2010. The results of this testing procedure are consistent with assuming that the 4×4 matrix Π is rank 1. The size 0.05 test of the null hypothesis that $r = 0$ is rejected, but the null hypothesis is not rejected for $r \geq 1$. We then apply Johansen's maximum likelihood procedure to estimate ν, Π and the covariance matrix of η_t in (A.8).

We model ΔE_t from 1991 to 2010 as an error-correction model treating ΔZ_t as an exogenous regressor and including an error correction term in each equation, as shown in (A.9).

$$\Delta E_t = \mu + \phi w_{t-1} + \Gamma \Delta Z_t + \epsilon_t \tag{A.9}$$

where $w_t = \beta' Y_t$ is the stationary linear combination of the seven elements of Y_t implied by our earlier hypothesis-testing result that the elements of Y_t are cointegrated. There are two possible reasons that this two-sample model could lead to a more precise estimate of the joint distribution of GHG emissions from 2013 to 2020. First, as noted above, our estimates of the parameters of (A.8) take advantage of significantly longer time series on Z_t. Second, we include ΔZ_t in (A.9) as opposed to ΔZ_{t-1} in the equations to predict the elements of E_t as is the case for model (A.2) presented in section A.1.3.

We first estimate the elements of β by a least squares regression of one element of Y_t on the remaining six elements of Y_t and estimating w_t as the residual from this regression as recommended by Engle and Granger (1987). Because, as noted in Engle and Granger (1987), $T^{1-\delta}(\hat{\beta} - \beta)$ converges in probability to zero for $\delta > 0$, we condition our estimate of the distribution of future GHG emissions on this value β. We then apply OLS to each of the three equations of (A.9) to compute estimates $\hat{\mu}$, $\hat{\phi}$ and $\hat{\Gamma}$.

We then compute

$$\hat{\eta}_t = \Delta Z_t - \hat{\nu} - \hat{\Pi} Z_{t-1} \tag{A.10}$$

for t =1976 to 2010 and

$$\hat{\epsilon}_t = \Delta E_t - \hat{\mu} - \hat{\phi} w_{t-1} - \hat{\Gamma} \Delta Z_t \tag{A.11}$$

for t =1991 to 2010.

Next we want to construct 1,000 realizations of the future sample path of Y_t and Z_t for t =2011, 2012,..., 2020 given Z_T, Z_{T-1}, and Y_T using the following procedure. Because of the longer time series available to estimate the parameters of (A.8), we do not account for the estimation error in the parameters of (A.8) in estimating the distribution of Z_t for 2011 to 2020. Our estimates of the uncertainty in future values of the elements of Z_t only depend on our uncertainty about future values of η_t.

We then follow the smoothed bootstrap procedure described in section A.1.3 applied to (A.9) to estimate the distribution E_t for 2013 to 2020 conditional on the actual values of Z_t in 2009 and 2010 and simulated values of Z_t for 2011 to 2020. This procedure accounts for estimation error in μ, ϕ, and Γ as well as the uncertainty in future values of ϵ_t in (A.9). Each of the 1,000 realizations of the future sample paths of ΔZ_t

are fed into the simulation of each of the 1,000 future sample paths of ΔE_t, which yields 1,000 realizations of the future sample path of Y_t from 2011 to 2020. We apply the transformations described earlier to the simulated values of Y_t from 2013 to 2020 to produce our estimates of the distribution of future GHG emissions by each covered sector for this time period.

Table A.8 presents the maximum likelihood estimates of the parameters of (A.8). Table A.9 presents the OLS estimates of the parameters of cointegrating regression $\hat{\beta}$. Table A.10 presents the OLS estimates of the parameters of (A.9). The second panel of Table A.6 presents multivariate portmanteau statistics for the residuals from estimating (A.9). For all values of S, a size 0.05 test of the null hypothesis that ϵ_t from (A.9) is white noise cannot be rejected.

Table A.7: Cointegration Rank Test Using Trace (Data from 1975 to 2010)

H0: Rank=r	H1: Rank > r	Eigenvalue	LR(r)	5% Critical Value
0	0	0.7061	63.3803	47.8564
1	1	0.2905	20.5214	29.7976
2	2	0.1845	8.5080	15.4948
3	3	0.0384	1.3688	3.8415

Note: The Johansen cointegration test of (*ln_twh_p_hydro*, *ln_vmt*, *ln_real_gas_price*, *ln_real_gsp*) from 1975 to 2010 shows that it is of rank 1.

Table A.8: Cointegrated Vector Autoregression Parameter Estimates for Z_t from 1975 to 2010)

Equation	Parameter	Estimate	Standard Error	Variable
$\Delta ln\_twh\_p\_hydro$	ν_1	-2.0216	0.4309	1
	Π_{11}	-0.4985	0.1050	$ln\_twh\_p\_hydro_{(t-1)}$
	Π_{12}	-0.4243	0.0894	$ln\_vmt_{(t-1)}$
	Π_{13}	-0.3870	0.0815	$ln\_real\_gas\_price_{(t-1)}$
	Π_{14}	0.6244	0.1316	$ln\_real\_gsp_{(t-1)}$
Δln_vmt	ν_2	-0.3197	0.0944	1
	Π_{21}	-0.0842	0.0230	$ln\_twh\_p\_hydro_{(t-1)}$
	Π_{22}	-0.0716	0.0196	$ln\_vmt_{(t-1)}$
	Π_{23}	-0.0653	0.0179	$ln\_real\_gas\_price_{(t-1)}$
	Π_{24}	0.1054	0.0288	$ln\_real\_gsp_{(t-1)}$
$\Delta ln\_real\_gas\_price$	ν_3	-0.3539	0.4383	1
	Π_{31}	-0.0879	0.1068	$ln\_twh\_p\_hydro_{(t-1)}$
	Π_{32}	-0.0748	0.0909	$ln\_vmt_{(t-1)}$
	Π_{33}	-0.0682	0.0829	$ln\_real\_gas\_price_{(t-1)}$
	Π_{34}	0.1101	0.1338	$ln\_real\_gsp_{(t-1)}$
Δln_real_gsp	ν_4	-0.5120	0.0964	1
	Π_{41}	-0.1317	0.0235	$ln\_twh\_p\_hydro_{(t-1)}$
	Π_{42}	-0.1121	0.0200	$ln\_vmt_{(t-1)}$
	Π_{43}	-0.1022	0.0182	$ln\_real\_gas\_price_{(t-1)}$
	Π_{44}	0.1649	0.0294	$ln\_real\_gsp_{(t-1)}$

Note: Rank 1 error correction vector autoregression estimates of (*ln_twh_p_hydro*, *ln_vmt*, *ln_real_gas_price*, *ln_real_gsp*) from 1975 to 2010.

Table A.9: OLS Estimates of Parameters of Cointegrating Vector (Data from 1990 to 2010)

Equation	Parameter	Estimate	Variable
$ln\_ngother\_industrial$	β_0	3.5404	1
	β_1	-0.0748	$ln\_thermal\_intensity$
	β_2	0.2844	$ln\_transport\_intensity$
	β_3	-0.0424	$ln\_twh\_p\_hydro$
	β_4	-1.0858	ln_vmt
	β_5	-0.1974	$ln\_real\_gas\_price$
	β_6	0.6085	ln_real_gsp

Table A.10: Error Correction Model Parameter Estimates (Data from 1990 to 2010)

Equation	Parameter	Estimate	Standard Error	Variable
$\Delta ln\_ngother\_industrial$	μ_1	-0.0110	0.0045	1
	Γ_{11}	-0.0196	0.0406	$\Delta ln\_twh\_p\_hydro_{(t)}$
	Γ_{12}	-0.3230	0.2707	$\Delta ln\_vmt_{(t)}$
	Γ_{13}	-0.0859	0.0333	$\Delta ln\_real\_gas\_price_{(t)}$
	Γ_{14}	0.5274	0.1209	$\Delta ln\_real\_gsp_{(t)}$
	ϕ_1	-0.9792	0.1507	$w_{(t-1)}$
$\Delta ln\_thermal\_intensity$	μ_2	-0.0081	0.0137	1
	Γ_{21}	-0.2327	0.1244	$\Delta ln\_twh\_p\_hydro_{(t)}$
	Γ_{22}	0.4686	0.8288	$\Delta ln\_vmt_{(t)}$
	Γ_{23}	0.0149	0.1020	$\Delta ln\_real\_gas\_price_{(t)}$
	Γ_{24}	-0.4616	0.3701	$\Delta ln\_real\_gsp_{(t)}$
	ϕ_2	0.1855	0.4613	$w_{(t-1)}$
$\Delta ln\_transport\_intensity$	μ_3	-0.0146	0.0051	1
	Γ_{31}	0.0275	0.0464	$\Delta ln\_twh\_p\_hydro_{(t)}$
	Γ_{32}	0.3359	0.3095	$\Delta ln\_vmt_{(t)}$
	Γ_{33}	0.0127	0.0381	$\Delta ln\_real\_gas\_price_{(t)}$
	Γ_{34}	0.2787	0.1382	$\Delta ln\_real\_gsp_{(t)}$
	ϕ_3	0.3826	0.1723	$w_{(t-1)}$

Note: Vector autoregression estimates of ($ln\_ngother\_industrial$, $ln\_thermal\_intensity$, $ln\_transport\_intensity$) from 1990 to 2010 with $w_{(t-1)}$, the residual from cointegrating regression, and ΔZ_t as regressors.

A.1.6.2 Bivariate Model

Our second alternative approach to simulating the distribution of future GHG emissions employs a cointegrated bivariate vector autoregression for broad scope and narrow scope GHG emissions from 1990 to 2010. This model assumes that each element of the vector

$$D_t = (logarithm\ of\ broad\ scope\ emissions_t,\ logarithm\ of\ narrow\ scope\ emissions_t)'$$

are difference stationary and follow a cointegrated bivariate vector autoregressive process. Table A.11 presents the results of Johansen's test for the cointegrating rank applied to this bivariate time series. These testing results are consistent with a rank 1 process. Table A.12 presents the results of applying Johansen's maximum likelihood procedure to the model:

$$\Delta D_t = \mu + \Lambda D_{t-1} + \Gamma \Delta D_{t-1} + \epsilon_t \qquad (A.10)$$

The third panel of Table A.6 presents the multivariate portmanteau statistics for the residuals from (A.10). For all values of S, a size 0.05 test of the null hypothesis that ϵ_t from (A.10) is white noise cannot be rejected.

We then follow our two-step smoothed bootstrap procedure to construct 1,000 simulations of the future time path of broad scope and narrow scope emissions that accounts for both estimation error in μ, Λ and Γ and uncertainty in the future values of ϵ_t in (A.10).

Table A.11: Cointegration Rank Test Using Trace (Data from 1990 to 2010)

H0: Rank=r	H1: Rank > r	Eigenvalue	LR(r)	5% Critical Value
0	0	0.5170	17.8414	15.4948
1	1	0.1515	3.2868	3.8415

Note: The Johansen cointegration test of ($ln\_narrowscope\_emissions$, $ln\_broadscope\_emissions$) from 1990 to 2010 with lag 0.

Table A.12: Bivariate Model Parameter Estimates (Data from 1990 to 2010)

Equation	Parameter	Estimate	Standard Error	Variable
$\Delta ln\_broadscope\_emissions$	μ_1	-2.768	0.51791	1
	Λ_{11}	1.0071	0.18821	$ln\_broadscope\_emissions_{(t)}$
	Λ_{12}	-0.60412	0.1129	$ln\_narrowscope\_emissions_{(t)}$
	Γ_{11}	-0.98467	0.29891	$\Delta ln\_broadscope\_emissions_{(t-1)}$
	Γ_{12}	0.25179	0.1075	$\Delta ln\_narrowscope\_emissions_{(t-1)}$
$\Delta ln\_narrowscope\_emissions$	μ_2	-7.27	1.1675	1
	Λ_{21}	2.6434	0.42427	$ln\_broadscope\_emissions_{(t)}$
	Λ_{22}	-1.5857	0.25451	$ln\_narrowscope\_emissions_{(t)}$
	Γ_{21}	-2.2024	0.67383	$\Delta ln\_broadscope\_emissions_{(t-1)}$
	Γ_{22}	0.66588	0.24232	$\Delta ln\_narrowscope\_emissions_{(t-1)}$

A.1.6.3 Sampling with Replacement

These econometric model-based approaches to simulating the distribution of BAU GHG emissions may be seen by some as imposing excessive structure on such a short time series of data.[10] To examine the robustness of this approach, our third alternative approach is a bare bones bootstrap GHG forecast method that draws narrow scope and broad scope GHG emissions growth rates for each year from the distribution of these emissions growth rates over the sample period 1990-2010. We created 1,000 bootstrap GHG emissions paths, all starting at the observed 2010 value and then for each successive year drew with replacement from the 20 annual growth rates through 2010.[11] This approach is equivalent to assuming a bivariate random walk with drift for the logarithm of emissions as given in (A.10) with the value of the two-dimensional vector μ set equal to the sample mean growth rate of narrow scope and broad scope GHG emissions, respectively. We then constructed a total 2013-2020 covered emissions simulation for each of the 1000 simulations by summing the resulting narrow scope emissions for 2013 and 2014 with the resulting broad scope emissions for 2015-2020. This approach is likely to understate the uncertainty in the distribution of future emissions both because it ignores any serial correlation in growth rates and because it fails to account for the estimation error in μ. That is, it ignores the second source of uncertainty discussed at the beginning of this section – uncertainty in the true values of the parameters of distribution of BAU GHG emissions – but given that it assumes the parameters of the distribution are known, it does account for uncertainty in the future values of the unobservables driving the data generation process.

[10] 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 such data are representative of the information on which policy makers must make decisions on GHG emissions caps.

[11] Each draw was a pair (narrow scope growth, broad scope growth) with the two components taken from the same year so there is consistency between two series.

A.1.6.4 Results of Alternative Methods for Forecast of BAU GHG Distribution

Means of the estimated distributions of annual broad scope emissions from 2013 to 2020 for each of the four modeling approaches are shown below Figure A.1. The dotted lines are the pointwise 95% upper and lower confidence bands on the future values of annual broad scope emissions.

There is substantial agreement across the four approaches in the estimated means of annual broad scope emissions. The four approaches differ somewhat in the size of the pointwise 95% confidence intervals. The resampling model has the smallest confidence intervals, likely due to the fact that it does not account for uncertainty in the parameters of the true data generating process. The two-sample error correction model has the largest confidence intervals, likely due to the fact this model involves estimating the largest number of parameters and the contribution of uncertainty in value of these parameters is sufficiently large to relative to the uncertainty in the values of the parameters of the other three more parsimonious models.

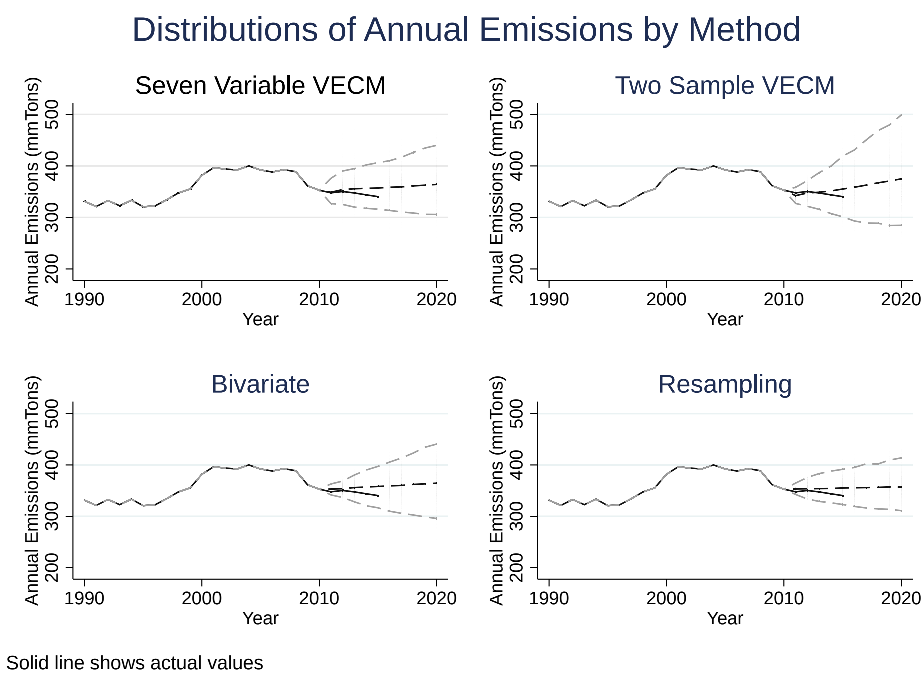

Figure A.1: Forecast Results – Annual Broad Scope Emissions

A.2 Abatement Supply

This section describes the component pieces of the abatement supply function. Abatement derives both from complementary and other policies that produce emissions reductions independent of the allowance price ("Price-Inelastic Abatement") and from abatement undertaken in response to changes in the allowance price ("Price-Elastic Abatement"). The emissions reductions resulting from these sources are summarized in Table 3 in the main text. Here we describe the assumptions behind each source of abatement.

Much of California's greenhouse gas policy was in flux during 2010-2012, making it difficult to identify exactly when aspects of the complementary policies became "expected" regulations. Rather than attempting to parse exact dates or believed probabilities, we assume that the major programs set in law by 2013 – the Corporate Average Fuel Economy Standard (CAFE), energy efficiency (EE), the Low Carbon Fuel Standard (LCFS) and the 33% Renewables Portfolio Standard (RPS) – were anticipated at the time for which we simulate distributions of outcomes. While ARB forecasted GHG reductions from these complementary policies, it is unclear, especially in the out years, how ARB's baseline GHG emissions forecast, from which they estimated GHG reductions, compares to the simulations we obtain from the VAR. Thus, rather than incorporating potentially biased estimates of GHG reductions, we apply a range of adjustments to the quantity of renewable electricity generation and the emissions intensity of VMT, which approximate the range of likely impacts of these complementary policies.

As discussed at the beginning of section V of the text, we assume that abatement effects are drawn independently from BAU emissions, but there is a mechanical correlation that results from the fact that abatement in transportation and electricity generation manifests as reduced emissions intensity of these activities. We have also experimented with imposing positive correlation among the abatement paths, but these have very small impact on the probability of an interior solution. Even a correlation of 0.5 among all of the abatement paths changes the probability of an interior solution by less than 0.5 percentage points.

As is clear from the discussion below, there is significant uncertainty about the impact of the price-inelastic abatement pathways. It is important to note, however, that these uncertainties affect the distribution of emissions apart from the cap-and-trade program, but do not affect the range of abatement available from the cap-and-trade program. As a result, while any bias in our range of possible impacts from the price-inelastic abatement pathways would shift the distribution of emissions, it would not substantially change the abatement that cap-and-trade could deliver. Thus, it would not impact the slope of the abatement supply curve.

For most policies described below, we assume that abatement will fall within a specific range between a more effective abatement case and a less effective abatement case. We then sample from a symmetric $\beta(2, 2)$ distribution to create a random draw of abatement for each policy from within our assumed range. Throughout this discussion we characterize low and high abatement scenarios, with low referring to the lower bound of assumed abatement which is more likely to yield a high allowance price (e.g. less effective abatement), and high referring to the upper bound of abatement which is more likely to lead to a low allowance price (e.g. more effective abatement).

A.2.1 Price-Inelastic Abatement

This section discusses in more detail the sources of price-inelastic abatement (complementary policies and other exogenous drivers) for which we adjust the VAR output to arrive at estimated distributions of emissions quantities and prices. Policies producing non-price responsive abatement include policies targeting both in-state and imported electricity generation, automative fuel-economy standards, low-carbon fuel standards, and emissions offsets.

Table A.13: Drivers of Price-Inelastic Abatement

	Zero-Carbon Power			Transport Intensity	
Year	BAU RPS GWh	33% RPS GWh	Nuclear GWh	BAU Forecast	Raw EMFAC
2013	34300	39463	17342	0.487	0.470
2014	34300	44625	17342	0.485	0.461
2015	34300	49788	17342	0.483	0.450
2016	34300	54950	17342	0.481	0.433
2017	34300	60113	17342	0.479	0.416
2018	34300	65275	17342	0.478	0.399
2019	34300	70438	17342	0.475	0.383
2020	34300	75600	17342	0.473	0.366

A.2.1.1 In-State Electric Generation

The VAR esimation and simulation procedure described in the text and above produces a draw from the distribution of in-state electricity generation in TWh. We adjust in-state generation to account for two types of zero-carbon electricity generation, renewables and nuclear power. We subtract the assumed energy produced from these zero-carbon sources from the specific realization of in-state electricity generation before multiplying the remainder by the estimated GHG emissions intensity of thermal generation to calculate GHG emissions from in-state electric generation. Our BAU scenario assumes renewables generation meets the 20% RPS standard that was in place well in advance of the cap-and-trade program. Specific values come from the Statewide Annual Planning Renewable Net Short (RNS) update,[12] which is produced by the California Energy Commission. The 2011 RNS update provides a forecast of the amount of in-state renewable generation that would be needed to comply with the state's pre-existing 20% Renewable Portfolio Standard (RPS) commitment, including adjustments for exempted sales, energy efficiency, and imported renewable energy. The assumed BAU nuclear generation incorporates the closing of the San-Onofre Nuclear Generating Station (SONGS).[13] We assume that Diablo Canyon (the only remaining nuclear generation station in California) generates electricity equivalent to its 2001-2010 average, which we calculate from EIA data. The nuclear generation and renewable energy necessary to comply with the 20% RPS is considered part of our BAU emissions calculation. The exact output assumed for these sources is presented in Table A.13.

A.2.1.2 Renewable Electricity and Energy Efficiency

In April 2011 California adopted a 33% RPS.[14] We consider this more stringent target to be a complementary policy providing abatement beyond BAU. The state now seems very likely to exceed the 33% level by 2020, but we do not make further adjustments as it was not clear in 2012 how difficult attaining the 2020 standard would be. The 2011 RNS update (described above) forecasts that an additional 41.3 TWh of in-state

[12] See http://www.energy.ca.gov/2011publications/CEC-200-2011-001/CEC-200-2011-001-SF.pdf

[13] 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 SONGS. In January 2012, SONGS was shut down due to faulty upgrades that had been made in 2009 and 2010, and there was widespread speculation about when and whether it would reopen. In June 2013, Southern California Edison announced that the SONGS closure would be permanent. Even though the official announcement came in June 2013, this outcome was known to be the most likely outcome by mid-2012. For that reason, we assume it was known for the purposes of our analysis.

[14] In 2015, California adopted a new target of 50% by 2030, but this did not change the target for 2020.

renewable generation would be needed to comply with the 33% RPS. We assume that the State will meet the 33% RPS target by incrementally increasing renewables by an equal quantity each year during the 2013-2020 time period. To account for uncertainty in load growth and other factors that could contribute to the State exceeding or failing to meet this target, we draw random scaling factors from a $\beta(2,2)$ distribution with a lower bound of 0.9 and an upper bound of 1.1, which we multiply by cumulative expected GHG abatement. More formally, realization-specific abatement from the 33% RPS in year $T+k$ can be expressed as:

$$Abatement_{m,T+k} = \beta_m(RPS\_TWH_{T+k} \cdot EI_{m,T+k}),$$

where β_m is the random draw from the $\beta(2,2)$ distribution (which is applied in each of the eight years) associated with simulation draw m, RPS_TWH is the value of (additional to BAU) renewable TWH described in year $T+k$ and $EI_{m,T+k}$ is the realization of emissions intensity for thermal generation in California for simulation draw m.

We make no further adjustments to the VAR forecast to account for increased energy efficiency. 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, 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 BAU forecasts.

A.2.1.3 CAFE and LCFS

We incorporate the impacts of these complementary policies by calibrating model-year-specific VMT emissions intensities (essentially miles per gallon) and emissions factors for transportation fuel over the period 2013-2020, using EMFAC (2011), ARB's tool for forecasting fleet composition and activity in the transportation sector.[15] EMFAC estimates VMT and GHG emissions intensity for each on-road vehicle-class by model year and calendar year. Thus, the advantage of explicitly modeling on-road vehicle fleet composition and activity is that we can more precisely simulate the impact of complementary policies that are designed to directly target specific segments of the vehicle fleet.

To account for CAFE, a policy that proposes to drive the average emissions intensity of new light-duty cars and trucks from 26.5 miles per gallon (MPG) in 2011 to 54.5MPG in 2020, we force the EMFAC forecasts of emissions factors for new light-duty vehicles in model-years 2013-2020 to match the fuel-economy standards established by CAFE. We then calculate fleet-wide annual emissions factors for calendar years 2013-2020, by taking the VMT-weighted sum over the set of all model-year by vehicle-class emissions factors.

We model the implementation of the LCFS as a linear decline in EMFAC's GHG emission factors for on-road gasoline and diesel.[16] In recognition of the ethanol blend wall, we fix the share of biofuel in gasoline at 11% from 2013 through 2020. For diesel, the share of preexisting biofuels is quite small, so we model the penetration of biodiesel as beginning at 2% in 2013 and increasing linearly to 10% in 2020.

[15] EMFAC 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. The model uses historical data on fleet composition, emissions factors, VMT, and turnover to forecast future motor vehicle emissions. Emissions are calculated for forty-two different vehicle classes composed of passenger cars, various types of trucks and buses, motorcycles, and motor homes.

[16] This approach stems from an important difference between the cap-and-trade program and EMFAC methods of accounting for GHG emissions from biofuels. While the cap-and-trade program does not assign a compliance obligation to emissions from ethanol or biodiesel, EMFAC includes combustion emissions from fossil and bio-fuels in it's measures 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 pre-existing levels of biofuels in California transportation fuel.

In order to reflect the underlying random aspects of vehicle emissions, even with successfully implemented complementary policies, we model the effect of these policies by taking random draws from a $\beta(2,2)$ distribution, where the adjusted EMFAC emissions intensity of VMT is the lower bound and the average VMT emissions intensity from our VAR estimates is the upper bound. Abatement is the product of the specific forecast of VMT from the VAR and the difference between the specific forecast of VMT emissions intensity from the VAR and a random draw from the $\beta(2,2)$ distribution, bounded below by zero.[17] More formally, realization-specific abatement from transport sector complementary policies can be expressed as:

$$Abatement_{m,T+k} = VMT_{m,T+k} \cdot max\{0, (EI_{m,T+k} - \beta_{T+k})\},$$

where $VMT_{m,T+k}$ and $EI_{m,T+k}$ are VMT and emissions intensity from simulation draw m of the VAR during year $T+k$, respectively, and β_{T+k} is the transport emissions intensity drawn from the $\beta(2,2)$ distribution in year $T+k$. The row labeled 'Fuel Economy & LCFS' in Table 3 summarizes the distribution of resulting abatement from these standards as well as from the Low Carbon Fuel Standard.

A.2.1.4 Other Exogenous Drivers of Abatement

In addition to the direct effects of regulation, the cost of implementing these complementary policies and other exogenous (to cap-and-trade) factors will likely cause electricity and transportation fuel prices to rise for all customers over the years of our forecast, which will reduce consumption.

To account for the impact of exogenous (to cap-and-trade) drivers on the quantity of electricity demanded we take an average statewide retail electricity price of \$135.3/MWh in 2012,[18] and assume that this price will increase by 2.15% (real) per year.[19] We incorporate uncertainty by drawing a random elasticity estimate from a $\beta(2,2)$ distribution. For the analysis with complementary policies, we assume an elasticity of -0.1 to -0.2, which combined with a marginal CO_2e intensity of 0.428 MT/MWh, yields a reduction of 6.4 to 12.8 MMT over the life of the program. For the analysis without complementary policies, we assume a -0.3 to -0.5 elasticity range, which yields the reduction of 19.1 to 31.5 MMT.[20] The row labeled 'Exogenous Electricity Rate Effects' in Table 3 summarizes the distribution of abatement under these assumptions.

Another exogenous driver of higher transportation fuel prices is the LCFS, which could end up significantly raising gasoline prices. Discussions with market participants and regulators suggest that the impact is likely to be capped at \$0.20 per gallon, and could be much smaller if regulations are relaxed. Reflecting that this price change is the greatest source of uncertainty, we estimate abatement by drawing random a price impact from a $\beta(2,2)$ distribution with a lower bound of \$0.00 and an upper bound of \$0.20, applying an elasticity of -0.2 throughout.[21] The effects of LCFS price impacts are combined with those of the fuel economy standards and reported in Table 3.

[17] We impose a zero lower bound on abatement to account for instances when the specific VAR realization of VMT emissions intensity is below the $\beta(2,2)$ random draw of VMT emissions intensity. Failing to include this lower bound would result in some instances of negative abatement, which seem implausible because the complementary policies are both minimum standards.

[18] See 2012 EIA Electric Power Annual, Table 2.10

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

[20] Ito (2014) estimates a medium-long run price elasticity for residential electricity demand of -0.09, suggesting that a lower elasticity might be more relevant under the no complementary policies case when we assume 100% pass-through to all types of customers.

[21] While some estimates of the elasticity of demand for transportation fuels are somewhat higher than this, these estimates generally include changes in vehicle choice behavior. Abatement from such changes in fleet composition is already reflected in the auto fuel economy adjustments discussed above.

A.2.1.5 Offsets

Offsets were expected to be a relatively low-cost (though not free[22] means for a covered entity to meet a portion of its compliance obligation.[23] 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. Additionally, ARB has authorized the use of approximately 5.3 MMT of offsets that were listed under a voluntary early action offset program. However, the total 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 the four original 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.[24] ARB subsequently added additional offset protocols, such as rice cultivation and mine methane capture and destruction. It was estimated that the addition of these two protocols would more than double the number of offsets available between 2013 and 2020.[25] To account for the high degree of uncertainty as to offset availability we model offset use as random draw from a $\beta(2, 2)$ distribution with a lower bound of 66 MMT and an upper bound of 130 MMT.[26]

A.2.1.6 Electricity Imports and Reshuffling

As discussed in the main text, 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. However, since it is not possible to physically track the source of electricity supplied in California, importers are instead required to self-report the generation source from which they are procuring the electricity. Electricity importers therefore have an incentive to engage in a variety of practices that lower the reported GHG emissions 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. ARB has tried to limit reshuffling, focusing on avoiding reshuffling of imports from coal plants partially owned by California utilities.

According to the CEC Energy Almanac, over the last two decades there have been approximately 95 TWh of net electricity imported into California each year on average. Supposing imported electricity remains at this level through 2020, this implies 760 TWh will be imported over the 8 years of the cap. Before the market opened, electric utilities reported to the CEC that they planned to procure 109 TWh of imported electricity under long-term contracts with coal-fired power plants over the 8-year period. To account for ARB's focus on avoiding reshuffling of imports from coal-fired power plants, we hold this quantity fixed at forecasted levels and consider a range of emission intensities for the remaining 651 TWh of imports. We consider a high-intensity case where the remaining imports report an average emissions intensity of 0.284 MT/MWh, two-thirds of the California cap-and-trade market's administratively set default emissions rate applied to any imports that do not claim a specific generation source for the power, and a low-intensity

[22]Most estimates of the price at which offsets would be available put their cost at below or just above the auction reserve price. 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/MT. We group these with the abatement available at or slightly above the auction reserve price.

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

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

[25]Ibid.

[26]We assume a single 8-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.

Table A.14: Electricity Import Emissions Calculation

	Electricity Import Emissions				Abatement from Baseline	
Year	Baseline MMT	Coal MMT	Non-Coal (low) MMT	Non-Coal (High) GWh	low Forecast	High Forecast
2013	40.17	18.42	11.14	22.29	10.61	0.00
2014	40.17	18.20	11.17	22.34	10.80	0.00
2015	40.17	14.62	11.64	23.28	13.91	2.27
2016	40.17	14.62	11.64	23.28	13.91	2.27
2017	40.17	14.62	11.64	23.28	13.91	2.27
2018	40.17	12.96	11.86	23.71	15.35	3.49
2019	40.17	12.96	11.86	23.71	15.35	3.49
2020	40.17	12.96	11.86	23.71	15.35	3.49
Total	321.36	119.37	92.80	185.61	109.19	16.38

case where the remaining imports report an average emissions intensity of 0.142 MT/MWh, one-third of the default emissions rate. We incorporate uncertainty by drawing a random intensity estimate from a $\beta(2,2)$ distribution bounded by our high- and low-intensity cases.

To calculate emissions reductions from imports we multiply 651 TWh – the quantity of imports net of coal – by the difference between 0.326 MT/MWh – the emissions intensity implied by our BAU estimate of emissions from imports – and a random draw from our $\beta(2,2)$ distribution.[27] More formally, realization-specific abatement from reshuffling can be expressed as:

$$Abatement_{m,T+k} = 81.37 \cdot (0.326 - \beta_m).$$

To summarize the results of this calculation, we consider reductions from an 8 year BAU of 321 MMT. Under the high emissions scenario, emissions from electricity imports would be 305, producing an 8-year reduction of 16. Under the low emissions scenario, emissions would be 212, yielding an 8-year reduction of 109 MMT. Annual emissions from electricity imports under these assumptions are summarized in Table A.14.

A.2.2 Price-Elastic Abatement

In order to assess the impact of the change in the GHG emissions price on the quantity demanded in the allowance market, we first analyze price-elastic demand for emissions 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 lowest tier of the APCR, and at the price to access the highest tier of the APCR.[28] We also consider responses of industrial emissions to allowance prices.

For this analysis, we assume full pass-through of the GHG allowance price to end-use consumers. To the extent that some pass-through is reduced through other policies, this will overstate the degree of price-

[27] Our BAU assumes annual emissions from imported electricity will be 40.17 MMT. Subtracting 13.63 MMT for specified imports from coal-fired plants, and supposing 81.37 TWh of annual imports from other sources (i.e., total net imports less specified coal) the average emission factor for non-coal-fired imports would be 0.326 MT/MWh (about 23% below the default emissions factor).

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

response of GHG abatement. We recognize that output-based free allocation of allowances to some trade exposed industries will dampen the effect of allowance prices on the final product prices, but even in these industries, process improvements to lower GHG emissions will still be incentivized by the full price of the allowance.[29]

A.2.2.1 Allowance Price Trajectory

The price of allowances at any point in time will reflect a weighted average of the probabilities of different equilibrium outcomes. So, price will evolve over time as new information becomes available, eventually ending at the aggregated equilibrium price. A full dynamic model of this process would be a large and complex undertaking, which we do not attempt here. Instead, for each of the 1000 random draws, we assume a linear price path from the start of the program to the end of 2020.[30] The trajectories are illustrated in Figure A.2.

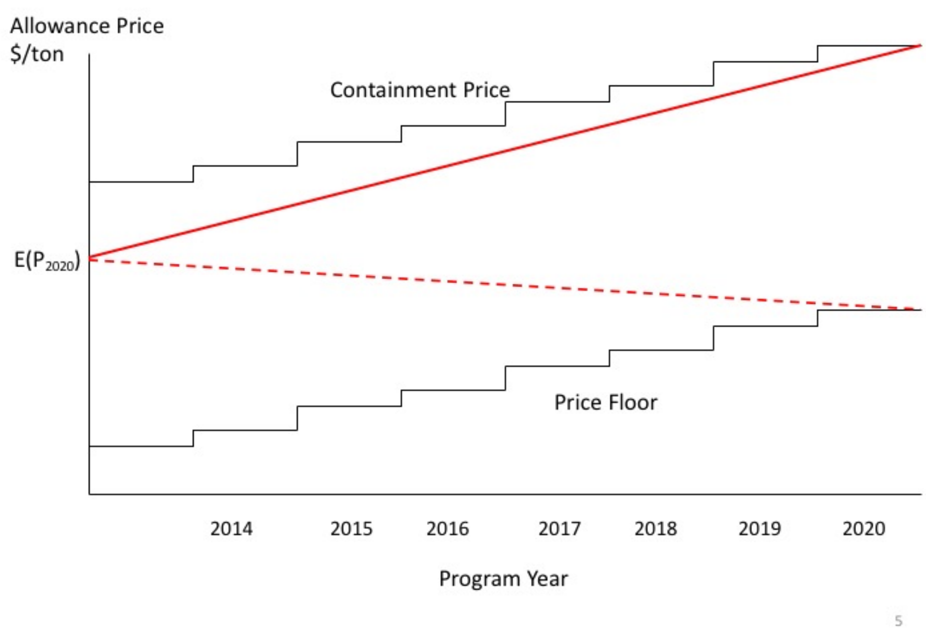

Figure A.2: Assumed Trajectories of Allowance Prices Conditional on Endpoints

The details of this approximation are as follows: We begin by creating a probability distribution of the aggregate market equilibrium under the assumption that for each draw the GHG price to which demand will respond in every year is the 2020 equilibrium price associated with that draw, discounted back to each year at a 5% real discount rate. From this price distribution we create a price for 2013 that is the probability-weighted average of the (discounted) 2020 possible price outcomes. For each draw, we then assume that the

[29]For transportation fuels, we assume full pass-through of the GHG emissions cost of tailpipe emissions, but no pass-through of GHG cost from refinery emissions to final fuel prices due to output-based free allocation.

[30]And similarly for the analysis of the program extension to 2030, we assume a linear price path from 2018 to 2030. We start in 2018, because the extension legislation was not passed until July 2017 and the implementation rules for the extension were still uncertain as of late 2017.

price to which demand responds follows a linear path from this 2013 price to whatever equilibrium price results from that draw. This creates a new distribution of probabilities for prices in 2020, which in turn creates a new discounted price in 2013 that reflects the probability-weighted average 2020 outcomes. We then recalculate the linear price paths for each draw. This iterative process converges quickly so that the price-responsive abatements in response to these price paths create a distribution of 2020 equilibrium prices that, after discounting, is within $0.01 of the 2013 price that we assume begins the linear price path. This implies that all price paths to 2020 begin at the same 2013 level, with some increasing to the highest tier of the APCR,[31] others decreasing to the price floor, and others ending at some price in between the floor and highest APCR tier. Assuming that the price follows such a linear path has a small effect on the mean level of price-responsive abatement, but substantially reduces the variance of price-responsive abatement compared to assuming that the price in every year is the (discounted) final year price.

A.2.2.2 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,[32] 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 vehicles with fuel economy as great or greater than 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 smaller. Similarly, if urban planning policies are undertaken to reduce auto usage independent of the allowance price, then price-responsive changes to transportation demand will be muted. Short-run estimates of the price elasticity are generally -0.2 or smaller.[33] Long-run elasticities are generally between -0.3 and -0.5.[34] 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.[35]

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. We assume 100% pass-through of allowance prices on tailpipe emissions to the cost of gasoline. Many studies on pass-through of fuel taxes and crude oil price changes, including Borenstein, Cameron and Gilbert (1997), Lewis (2011), and Marion and Muehlegger (2011), have found pass-through to retail price equal or very close to 100%.

Using an allowance price trajectory, as described above, reaching the highest price in the price containment reserve in 2020 which (in 2015 real dollars) is $72.12,[36] and assuming a -0.1 price elasticity of demand, yields a reduction of 6.4 MMT over the life of the program from reduced use of gasoline. For diesel, the same

[31] Even though there was no firm price ceiling at the time the market was launched, we assume that market participants believed the price would not be allowed to go higher than the highest step of the APCR.

[32] See, for instance, Archsmith et. al. (2017).

[33] See Hughes, Knittel and Sperling, 2008. Levin, Lewis and Wolak, 2017, suggests that medium run elasticities are more likely to be in the range of -0.3.

[34] See Dahl, 2012

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

[36] This translates to an increase of about $0.57 per gallon of gasoline at the pump in 2015 dollars (after accounting for 10% biofuels).

allowance price trajectory,[37] yields a reduction of 1.8 MMT over the life of the program.

Assuming an elasticity of -0.2 about doubles the reduction from transportation fuels to 16.3 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 24.3 MMT, 32.2 MMT, and 40.1 MMT, respectively. Note that transportation fuels are 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 the -0.3 to -0.5 elasticity range 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 impact of the LCFS on gasoline prices and gasoline quantity consumed, as discussed above.

A.2.2.3 Demand for Electricity

In California, 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, because a rising GHG price has relatively little impact of the ordering of marginal production costs among in-state fossil fuel generation.[38] The three large regulated investor-owned utilities (IOUs) that serve about 85% 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 could 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, but some share were to be distributed to residential customers lump sum. Publicly-owned utilities that serve the remainder of demand were not obligated to sell their allowances, and were free to decide how much of the value of the free allowances would be used to offset retail rate increases that would result from higher wholesale electricity prices.

Based on a resolution from the CPUC in December 2012,[39] a best guess at the outset of the program seemed to be that the revenues from utility sales of allowances would be used first to assure that the cap-and-trade program causes no price increase to residential consumers. In addition, the revenues would 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 would 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 would see more than 100% pass-through of energy price increases due to allowance costs.[40] BBWZ (2016) discusses the possible interpretations of the CPUC decision and how it would allocate a disproportionate share of the wholesale cost increase from cap-and-trade to industrial and commercial customers and protect residential customers from rate increases. For the purpose of our analysis, however, imposing a more-than-100% pass-through on a subset of customers to cover the remaining (residential) customers who see no increase has nearly the same effect on total consumption as assuming 100% pass-through to all customers.[41] So, for simplicity, we simply

[37] This translates to an increase of about \$0.73 per gallon of diesel at the pump in 2015 dollars

[38] Bushnell, Chen, and Zaragoza-Watkins (2014).

[39] 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.

[40] 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.

[41] This would not be the case if residential customer demand were clearly more or less elastic than demand from commercial and industrial customers. There is not, however, consistent evidence in either direction.

assume 100% pass-through of increased electricity costs to all retail customers.

With a statewide *average* GHG intensity of 0.326 metric tonnes (MT) per MWh (based on the 2012 GHG inventory), this means that the cost of electricity generation per MWh would increase $0.326 \cdot$ allowance price. At an allowance price of \$50/MT, this raises average rates by \$16.30/MWh and at \$70.36/MT by \$22.94/MWh.[42] We apply these increases to the state average retail rates of all customer classes, based on EIA data, to get a weighted average percentage price response.

The choice of an elasticity for incorporating price-responsive changes in electricity usage due to the carbon price again confronts the issue of short-run versus long-run decision-making by customers. As with transportation fuels, other regulations that improve energy efficiency – such as building codes and regulation of appliance efficiency – are likely to lower the demand response to increased electricity prices. There have been many studies of residential electricity demand, which suggest a short-run elasticity below -0.2 and a long-run elasticity mostly in the range of -0.3 to -0.5.[43] Commercial and industrial electricity demand elasticity estimates are few in number and not at all consistent. Kamerschen and Porter (2004) estimates a long-run industrial price elasticity of demand of -0.35 when controlling for heating and cooling degree-days. Based on these estimates, we use a range of -0.1 to -0.2 for the price elasticity of demand in the presence of complementary policies, and -0.3 to -0.5 for longer run elasticity, assuming no damping effect of complementary policies.

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 MT/MWh – to calculate the reduction in emissions at different prices.[44] The result is a reduction of 7.7 MMT when the price equilibrates at the auction reserve by the end of the program, 26.9 MMT when price ends at the lowest step of the APCR, and 32.9 MMT when price is at the highest step of the APCR in 2020.[45]

A.2.2.4 Demand for Natural Gas

In 2012, it appeared that ARB policy would give free allowances to natural gas distribution companies (which are nearly all investor-owned regulated utilities in California) equal to their obligation associated with their 2011 supply to non-covered entities (less than 25,000 MT of CO2e per year), but then declining at the cap decline factor. The utilities receiving the free allowances would then consign them to the quarterly auctions and receive revenues. The utility would then be responsible for procuring allowances equal to the GHG emissions associated with all its sales of natural gas including to the non-covered entities. Importantly, however, the CPUC had decided that the revenues from the free allowances should be returned to customers on a non-volumetric basis.[46] As a result, the marginal cost of procuring and selling natural gas would rise by the associated allowance cost for GHGs.[47] Thus, we assume 100% pass-through of GHG allowance costs to volumetric natural gas prices of utilities.

[42] The 0.326 MT/MWh figure is arrived at by taking total 2012 GHG electricity emissions measured for in-state (44.9 MMT) and for imports (39.8 MMT) and dividing by total consumption (259.5 MMWh). This assumes 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.

[43] See Ito (2014) and Fell et al (2014) for two recent estimates and references to the earlier literature.

[44] 0.428 MT/MWh is the default rate assigned to "unspecified" source of electricity under the cap-and-trade program. The marginal GHG intensity of 0.428 is based roughly on the efficiency of 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.

[45] The baseline price from which all price increases are calculated is the average price of electricity, assumed constant in real terms over 2013-2020.

[46] Since this time, there have been lengthy legal proceedings at the CPUC and protests about the non-volumetric basis for refunds, but that opinion has prevailed thus far.

[47] For a history of this policy discussion, see http://docs.cpuc.ca.gov/PublishedDocs/Efile/G000/M197/K205/197205891.PDF.

Large industrial natural gas consumers were not as a class allocated free allowances either directly if they procured their own gas or indirectly to the utility if they purchased through the utility. As discussed in the text, some industrial customers were allocated free allowances through output-based allocation in order to reduce leakage. This effectively lowered their marginal cost of producing their output, and reduced the pass-through of GHG costs to their final goods customers. However, these customers still had an incentive to reduce natural gas consumption in their production processes. For simplicity, we assume that the output-based allocation did not materially reduce price responsiveness of demand for allowances from large industrial natural gas customers.

As explained in the text, in the first compliance period (2013-2014), only large industrial customers incurred a compliance obligation from natural gas combustion (whether they purchased the gas directly or through the gas utility). These customers comprised approximately 59% of gas demand, so as discussed above we calculate abatement in those years assuming only 59% is covered. During 2015-2020, all gas consumption was to be covered by the program, and we calculate price-response of abatement accordingly.

If the cost of natural gas emissions were fully passed through to customers, then it would would raise the price of natural gas by \$0.0543 per MMBTU for every dollar per tonne of allowance price. Based on Auffhammer and Rubin (2018) and Bernstein and Griffin (2006), we assume a demand elasticity of -0.1 to -0.3 for analysis of price-responsive abatement in the presence of complementary policies, slightly higher than most of the short-run elasticity estimates. It is worth noting that much of the natural gas combustion (other than for electricity generation) is used for heating buildings and water and California's Title 24 imposes the most aggressive energy efficiency standards in the country for building design, insulation and other energy use.[48] California also has many programs to subsidize energy efficiency upgrades for both residential and commercial/industrial customers. For the absence of complementary policies – including building standards – we assume a demand elasticity range of -0.3 to -0.5, reflecting longer-run elasticity estimates.[49] We then draw realized elasticities from a $\beta(2, 2)$ distribution with this support.

For the first compliance period, when only industrial customers are covered, we use the baseline retail price of \$5.77, EIA's reported average price of natural gas for industrial customers in 2012, and the 2012 industrial consumption for the baseline quantity. For later years, we use the volume-weighted average retail price across industrial, commercial, and residential customers and the total consumption from these three sectors.[50]

A.2.2.5 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 emissions 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 analysis of non-price responsive abatement discussed above.

A.2.2.6 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

[48] See, for instance, http://www.energy.ca.gov/title24/2008standards/residential_manual.html .

[49] As with the previous energy demands, there are estimates of higher elasticities in the literature, but they generally include switching to other fossil fuel energy sources.

[50] See EIA Natural Gas Annual, 2012.

Table A.15: Summary of Potential for Price-Responsive Emissions Abatement

	Scenarios with Complementary Policies					
Price-responsive Allowance Demand Reduction	Elasticities		Range of Energy Price Changes At Different Allowance Price Trajectories 2013-2020 ($2015)		Cumulative Abatement from Trajectory to APCR (MMT) 2013-2020	
Allowance Price Trajectory ($/tonne)			$12.50/$15.44	$12.50/$72.12		
Sector	Low	High	Trajectory to ARP	Trajectory to APCR	Low Elas	High Elas
Electricity ($/MWh)	-0.1	-0.2	$4.08/$5.04	$4.08/$23.54	6.5	12.9
Transportation ($/Gallon)	-0.1	-0.2	$0.11/$0.13	$0.25/$0.60	8.2	16.3
Natural Gas ($/MMBTU)	-0.1	-0.3	$0.68/$0.84	$0.68/$3.92	16.1	46.7
	Scenarios with No Complementary Policies					
Price-responsive Allowance Demand Reduction	Elasticities		Range of Energy Price Changes At Different Allowance Price Trajectories 2013-2020 ($2015)		Cumulative Abatement from Trajectory to APCR (MMT) 2013-2020	
Sector	Low	High	Trajectory to ARP	Trajectory to APCR	Low Elas	High Elas
Electricity ($/MWh)	-0.3	-0.5	$4.08/$5.04	$4.08/$23.54	19.2	31.7
Transportation ($/Gallon)	-0.3	-0.5	$0.11/$0.13	$0.25/$0.60	24.3	40.1
Natural Gas ($/MMBTU)	-0.3	-0.5	$0.68/$0.84	$0.68/$3.92	46.7	75.3

Notes: All energy price changes assume 100% pass-through.
ARP: Auction Reserve Price APCR: Highest tier of Allowance Price Containment Reserve
Range of price changes for Transportation are for 2015-2020 only
Range of Transportation price changes based on weighted average of gasoline and diesel
Range of price changes for Electricity and Natural Gas are for 2013-2020
Transportation abatement is for tailpipe emissions only, does not include associated upstream emissions
Transportation abatement is for 2015-2020 only
Natural Gas abatement is sum of large users for 2013-2020 and small users for 2015-2020

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.[51] 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.

[51] 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.

A.2.2.7 Summary of Potential for Price-Responsive Abatement

Table A.15 summarizes the potential impact of allowance prices on energy prices and the potential resulting price-responsive abatement along different trajectories, to the Auction Reserve Price and to the highest tier of the Allowance Price Containment Reserve. Even with the much higher elasticities that we assume when there are no complementary policies, the aggregate abatement is likely to be small compared to the uncertainty in BAU emissions and other exogenous sources of abatement.

A.3 Alternative Allowance Price Results

In the text and in section A.1 we describe alternative approaches to modeling BAU emissions and supply of abatement. In this section we summarize results for these alternative approaches.

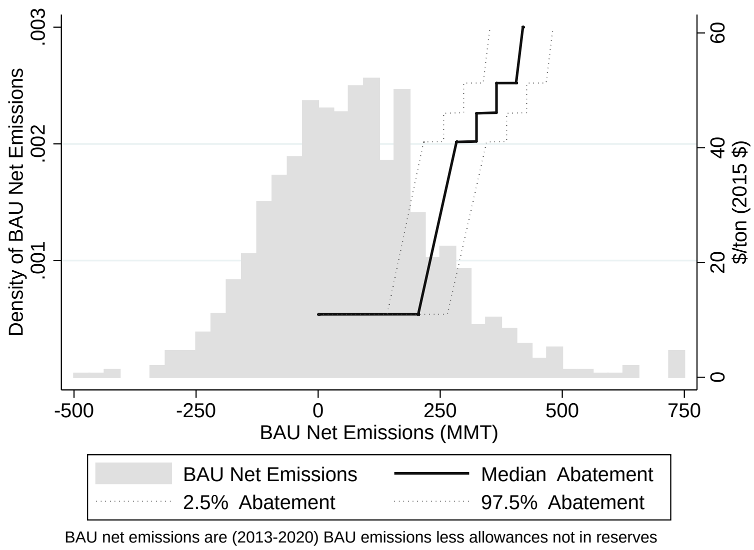

Figure A.3: Net Emissions and Abatement Supply with No Complementary Policies (2013-2020)

A.3.1 No Complementary Policies

In section III we summarize how we adjust for several complementary policies that provide a horizontal shift to the abatement supply curve. These complementary policies also impact the elasticity of response to allowance prices, rotating the slope of the abatement supply curve, as discussed in subsection V.A of the main text. When we remove the fuel economy regulations, we assume this increases the price elasticity of gasoline demand and consequently the elasticity of transportation emissions to the price of allowances. The logic of this assumption is that customers would choose to purchase more fuel efficient vehicles under high gasoline and allowance price outcomes, whereas under the fuel economy standards they would be required to purchase fuel efficient vehicles under any scenario. Therefore we increase the elasticity of demand for diesel and gasoline from a range of -0.1 to -0.2 to a range from -0.3 to -0.5. Similarly we assume that the removal of energy efficiency programs and other customer-facing complementary policies increase the elasticity of demand for natural gas and electricity also increase to -0.3 to -0.5.

Figure A.3 presents the equivalent of Figure 4 from the text under the assumptions of adopted in the section V.A with no complementary policies. Abatement supply is more price elastic under this set of assumptions and the upward sloping portion of the abatement supply curve – above the Auction Reserve Price, but below the steps of the Allowance Price Containment Reserve – now falls in a higher-probability region of the BAU probability density function. Still, as reported in the text, the probability of the equilibrium outcome falling in this range is only 8.3%.

A.3.2 Alternative BAU Estimates

In subsection A.1.6 we described three alternative approaches for estimating the distribution of future BAU emissions. In this subsection we present potential implications of those approaches for the distribution of market equilibria.

In order to get to the market equilibria, however, one needs estimates of the distribution of abatement supply. Recall that for our primary analysis, estimates of the abatement supply from complementary policies came in part from the estimation of the seven-variable vector auto regression. In particular, estimates of the GHG reduction from transportation and in-state thermal electricity generation were derived from the estimated paths of VMT and GHG intensity of transportation in one case, and in-state thermal electricity generation and the GHG intensity of that generation in the other case. It is not straightforward to derive similar estimates from the two-sample error correction model, because of the separate estimation for the two samples, and the bivariate vector autoregression and sampling from past growth rates with replacement do not yield any estimates of abatement supply. For this reason, and to present a comparison that is not driven by different abatement supply estimates, we present results for all four approaches using the abatement supply from our primary analysis. The difference in the outcomes is driven entirely by differences in estimates of BAU emissions.

Figure A.4 presents our primary results alongside the results from the three alternative approaches. The upper left graph replicates our primary results from Figure 4 from the text. The other three graphs show the equivalent presentation of results from the three alternative approaches. In all cases, the probability of an interior solution is quite small. In our primary results, it was estimated to be 1.2%. Using the two-sample error correction model, it is estimated to be 2.2%, while the estimates are 4% with the cointegrated bivariate vector autoregression, and less than 1% using the simplest model of just sampling growth rates (with replacement) from the 20 years of GHG data.

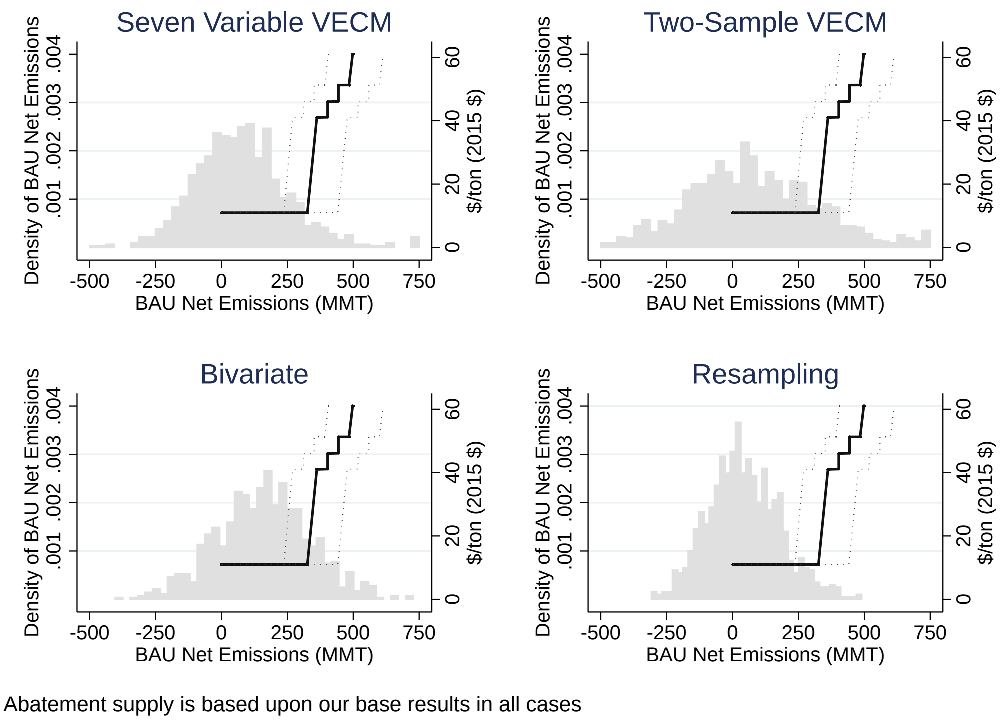

Figure A.4: Net Emissions and Abatement Supply Under Alternative Approaches to BAU Estimation

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