CALIFORNIA
High-Speed Rail Authority

2014 Business Plan Ridership and Revenue Technical Memorandum

2014 BUSINESS PLAN

Section 4: *Ridership and Revenue Forecasts*

CAMBRIDGE SYSTEMATICS

California High-Speed Rail 2014 Business Plan

Ridership and Revenue Forecasting

technical

memorandum

prepared for

Parsons Brinckerhoff for the California High-Speed Rail Authority

prepared by

Cambridge Systematics, Inc.

April 18, 2014

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Executive Summary

Cambridge Systematics' (CS) approach to preparing forecasts for use in the Authority's 2014 Business Plan was predicated on the following concepts:

- The ridership and revenue (R&R) model produces reasonable forecasts with reasonable sensitivities to changing conditions.
- Models are not perfect, and their imperfections need to be understood and reflected in the forecasts used for business planning purposes.
- Future conditions cannot be known with certainty. The forecasts used for business planning purposes need to recognize those uncertainties and present a reasonable range.

The resulting R&R forecasting process involved the following steps. We:

- Developed a Version 2 R&R Model that incorporated desired improvements identified by CS as well as Ridership Technical Review Panel recommendations. The Version 2 model incorporated new data, a streamlined model structure, improvements in model estimation, calibration to new data, updates to regional models, extensive validation to Year 2010 and Year 2000 conditions, and extensive sensitivity testing, including a test of service characteristics similar to those in the Northeast Corridor.
- Updated the coding of the existing transportation system to reflect current conditions, planned changes, and forecast future conditions, specifically:
  - Fares, routes, parking costs, and service frequencies for conventional rail and other transit modes to reflect the 2013 State Rail Plan.
  - New auto network and loaded congested skims developed from the California Statewide Travel Demand Model (CSTDM).
  - Cost of auto travel for the 2010 network.
- Incorporated revisions to socioeconomic growth assumptions (population, housing, and employment forecasts) consistent with the CSTDM but customized for the years for which forecasts were needed for the CHSR project: 2010, 2022, 2027, 2029, and 2040, as well as developing a range of alternative forecasts for use in the risk analysis.
- Developed a risk analysis model that incorporated a range of assumptions for the factors that we believe will have the greatest influence on high-speed rail ridership and revenue. The ridership and revenue forecasts are expressed in terms of probabilities that were developed using this approach.

Summary of Ridership and Revenue Forecasts

Ridership and revenue forecast ranges with the probabilities of achieving certain values are shown in Tables E.1 and E.2, respectively. We highlight the values representing different confidence levels, from 5 percent to 95 percent. A 15 percent confidence level means that there is a 15 percent chance that the ridership/revenue will be lower than this value (or, an 85 percent chance that it will be higher). The range in revenue for Year 2022 between the 5th and 95th percentiles is $1,030 million compared to $2,249 million in Year 2040.

Table E.1 Range of Annual Ridership by HSR scenario (millions)

	System Phase			
Confidence level that ridership will be less than Stated Value	**IOS 2022**	**Bay to Basin 2027**	**Phase 1 2029**	**Phase 1 2040**
5%	5.1	9.3	14.8	17.0
15%	6.8	12.3	19.0	21.9
25%	8.2	14.2	22.0	25.4
50%	11.3	19.1	28.4	33.1
75%	15.4	25.1	37.3	44.0
85%	18.2	29.5	43.7	49.9
95%	23.8	37.4	54.4	64.8

Table E.2 Range of Annual Revenue by HSR scenario (millions, 2013 dollars)

	System Phase			
Confidence level that ridership will be less than Stated Value	**IOS 2022**	**Bay to Basin 2027**	**Phase 1 2029**	**Phase 1 2040**
5%	283.3	515.6	702.4	799.9
15%	380.1	680.6	901.7	1,030.6
25%	450.0	795.1	1,045.0	1,195.0
50%	625.0	1,055.6	1,350.4	1,559.4
75%	851.1	1,389.0	1,790.4	2,050.1
85%	1,002.9	1,632.2	2,074.6	2,349.8
95%	1,313.0	2,074.3	2,584.0	3,048.5

1.0 Introduction

1.1 Overview

Since 2007, Cambridge Systematics (CS) has been supporting the California High-Speed Rail Authority ("the Authority") producing ridership and revenue (R&R) forecasts for different high-speed rail (HSR) service options using an innovative travel demand model. The "Version 1" model was originally estimated and calibrated using data from the 2000-2001 California Statewide Household Travel Survey and a 2005 Stated-preference survey to support alternatives analyses and project level environmental work.

In 2010 and 2011, CS updated the Version 1 R&R model to provide enhanced capabilities for analysis of refined operating plan and pricing options, and to develop independent forecasts. The work, documented in a separate technical memorandum, included a new trip frequency survey, revised socioeconomic forecasts, and recalibration of the model to 2008 conditions based on an on-line survey of long-distance travel made by California residents. The enhancements culminated in R&R model runs used to support the California High Speed Rail Draft 2012 Business Plan.[1] After receipt of public comment, the Authority made changes to the HSR scenarios being considered in the draft version of the 2012 business plan, and CS updated the model assumptions and prepared forecasts in support of the revised version of the 2012 Business Plan.[2]

In 2012 and 2013, CS made additional enhancements to the R&R model to accommodate the evolving forecasting needs of the Authority. The enhanced model, known as Version 2, represents a major overhaul of all model components, incorporates new and reanalyzed data, and reflects the most current thinking about California's future. The enhancements to the Version 2 model incorporated the recommendations of the Authority's Ridership Technical Advisory Panel and considered comments from the Authority's Peer Review Group (PRG) and the General Accountability Office's report. In addition to

[1] Cambridge Systematics, Inc., "California High-Speed Rail 2012 Business Plan, Ridership, and Revenue Forecasting, Draft Technical Memorandum," prepared for Parsons Brinckerhoff for the California High-Speed Rail Authority, October 19, 2011.

[2] Cambridge Systematics, Inc., "California High-Speed Rail 2012 Business Plan, Ridership, and Revenue Forecasting, Final Technical Memorandum," prepared for Parsons Brinckerhoff for the California High-Speed Rail Authority, April 12, 2012.

model enhancements, CS used a risk analysis approach to prepare and present ridership and revenue forecasts.

This technical memorandum documents the ridership and revenue forecasts used to support the 2014 Business Plan. Section 2.0 provides a high-level overview of the model enhancements. Section 3.0 describes the business case scenarios evaluated. Section 4 documents the assumptions related to the transportation system, and Section 5 summarizes the evaluation of socioeconomic forecasts. Section 6 explains the risk analysis approach, and Section 7 documents the ridership and revenue forecasts.

1.2 Scope of Forecasts

CS developed forecasts for three potential phases of the project as specified by the Program Manager:

1. Initial Operating Segment: Merced to San Fernando Valley: 2022.
2. Bay-to-Basin: San Jose to San Fernando Valley, with a spur to Merced: 2027.
3. Phase 1: San Francisco to Los Angeles, with a spur to Merced: 2029 and 2040.

The ridership and revenue forecasts in the 2014 Business Plan recognize the following:

- **The 2014 Business Plan forecasts better represent the timing of project phasing than prior forecasts.** For the 2012 Business Plan, CS prepared forecasts for all project phases for forecast year 2030. The Authority applied growth factors to estimate annual ridership and revenue between 2022 and 2040, which is when the phases are planned to begin revenue operations. For the 2014 Business Plan, forecasts were developed for year 2022, 2027, 2029, and 2040, eliminating the factoring process.
- **The 2014 Business Plan forecasts are expressed in probabilistic terms.** The 2012 Business Plan forecasts were developed with different set of assumptions that lead to " High" and " Low" outcomes. A more comprehensive risk analysis approach was implemented for this plan using Monte Carlo simulation techniques. This technical memorandum provides the ridership and revenue forecast ranges with the probabilities of achieving different confidence levels.

Ridership and Revenue Adjustments to Account for " Ramp up"

Our ridership and revenue forecasts assume a mature high speed rail system, where potential passengers are fully aware of the system. In reality, it usually takes some years for a new system to achieve this mature state. The financial plan for the CHSR system should reduce ridership and revenue in the early years of each phase to account for the "ramp up" of ridership and revenue over time.

1.3 DISCLAIMER

The information and results presented in this memorandum are estimates and projections that involve subjective judgments, and may differ materially from the actual future ridership and revenue. This memorandum is not intended nor shall it be construed to constitute a guarantee, promise, or representation of any particular outcome(s) or result(s). Further, the material presented in this memorandum is provided for solely purposes of the Authority's business planning and should not be used for any other purpose.

2.0 Model Updates and Enhancements

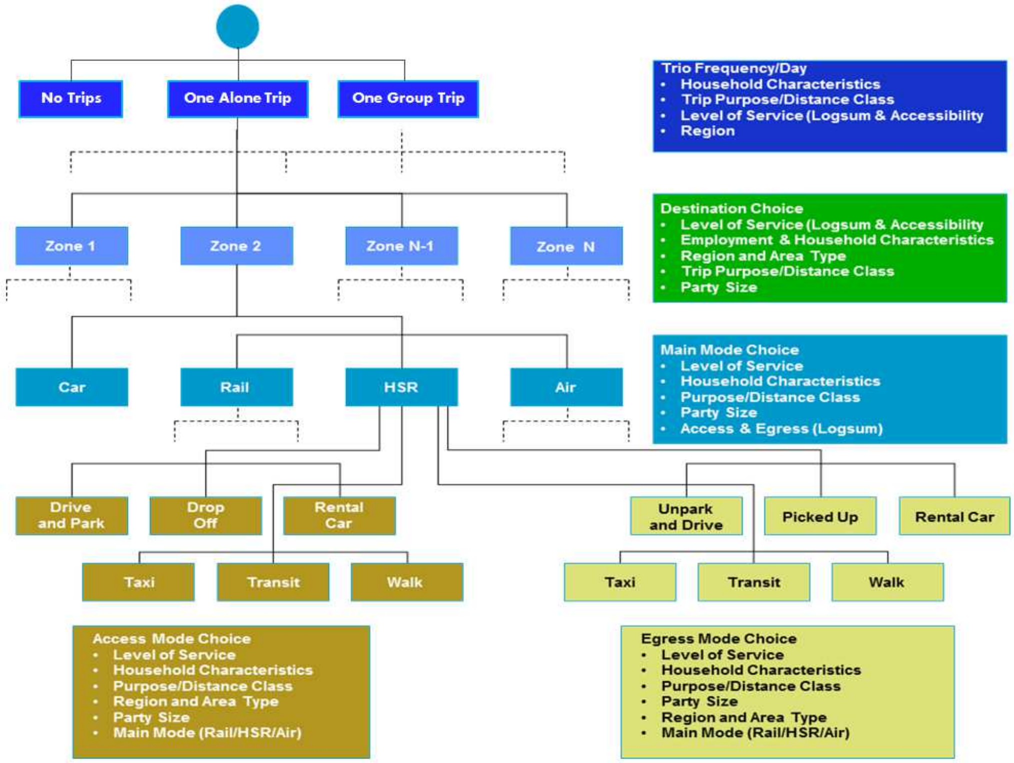
Complete details regarding updates and enhancements to the travel demand model used for ridership and revenue forecasts are contained in a separate memorandum. Below is an overview of the model structure and the improvements made since the 2012 Business Plan.

2.1 Overall Model Structure

The overall structure of the ridership and revenue model is illustrated in Figure 2.1. The primary components are:

- Trip frequency model, which estimates the number of trips made by each household on an average day.
- Destination choice model, which estimates the destinations of home-based trips.
- Mode choice models, which estimates the choice of main mode (e.g., auto, air, conventional rail, or high-speed rail) as well as access/egress mode.

Figure 2.1 Long-Distance Model Structure



Trip Frequency Model

The key structural features of the trip frequency models, in comparison to the Version 1.0 trip frequency models, includes:

1. Trip frequency for each trip purpose (business, commute, recreation, and other) is handled in separate models. Unlike Version 1.0, there is no distinction between short-and long-distance. Instead, all trips greater than 50 miles (measured as straight-line distance from TAZ centroid-to-centroid) were considered long-distance trips.

2. The choice set of Version 1.0 models was 0, 1, or 2+ trips made by a traveler on a specific day. The new models replace this specification with 0 trips, 1 travel alone trip, and 1 travel in a group trip alternatives for each individual traveler on a specific day. Since the trip frequency model will explicitly model group size, a separate group size submodel (like the one in Version 1.0) is not needed.

For each of the four trip purposes, the alternatives in the multinomial logit models are identical and include:

- No long-distance trips;

- Travel-alone long-distance trip; and
- Travel-in-group long-distance trip.

The estimated models produce the probabilities of a single person in a household making a travel-alone long-distance trip and a travel-in-group long-distance trip on a given day. The trips per person were multiplied by the household size and, then, by the number of households in the specific household size group to estimate the total person trips "generated."

Destination Choice

Compared to the Version 1.0 Model, the Short versus Long distance designation was removed from the modeling system. The Version 2.0 destination choice model choice set includes all traffic analysis zones (TAZ) located more than 50 miles away from the origin TAZ (where distance is measured as straight-line distance between TAZ centroids). One destination choice model for each purpose – Business, Commute, Recreation, and Other – was estimated and calibrated. In application, the destination choice model allocates the percentage of trips, originating in each TAZ, to each destination TAZ.

Mode Choice

Full information maximum likelihood (FIML) techniques were used to simultaneously estimate the access/egress and main mode models. This was in contrast to the earlier models, where access/egress mode choice was estimated separately, and logsum information from those models was used in the main mode choice models. This approach allowed relationships between access/egress utility coefficients and main mode utility coefficients to be consistently estimated and, if necessary, constrained in ways that would otherwise not be possible.

2.2 OVERVIEW OF MODEL UPDATES

The key properties of Version 2 Model include the following (see also Table 2.1):

- **Version 2 incorporates a significant amount of new data:**
  - Our analysis of the 2012/2013 California Household Travel Survey (CHTS) provided a valuable statewide data source for estimation and calibration.
  - A 2011 Harris web survey conducted for this project was used to develop reasonable targets for the long distance trip frequency model.
  - New data were used both in the calibration and validation of the models.
- **Version 2 has a better streamlined model structure throughout:**

  - We combined long-distance and short-distance interregional trips into one model of long distance trips (trips 50 miles or more from the trip-maker's home).
  - The distance effects are included in the utility functions of different models.
  - Travel alone or in a group is fully integrated into the trip frequency.
  - A streamlined application program has made it possible to run the long-distance model in several hours.
- **Version 2 has significant improvements to model estimation:**
  - CHTS statewide RP data were used to estimate trip frequency models, destination choice models, and joint mode and access/egress choice models.
  - Joint RP/SP mode choice model estimation was implemented.
  - Main mode choice and access/egress mode choice models are estimated simultaneously in a unified nested logit framework.
  - A limited number of constants and constraints were used throughout the various model components.
  - Long-distance skims and model inputs are updated for main mode choice and access/egress mode choice.
- **Version 2 is calibrated to new sources of data:**
  - 2010 base year reflects how the 2008 recession affected travel.
  - The statewide 2012/2013 CHTS (expanded to reflect the 2010 population) is used to calibrate all model components.
  - Final forecasts will incorporate data from the 2013 stated and revealed-preference survey (SP/RP).
- **Version 2 uses new updated regional models from SCAG and MTC:**
  - Skims in intraregional markets were developed.
  - Path building was tested and implemented in intraregional models.
  - New modeled trip tables from SCAG and MTC were used in the model.
  - Modeled SCAG and MTC intraregional trip tables were updated to be more consistent with county-to-county interchanges from the 2012/2013 CHTS.
- **Version 2 is extensively validated to 2010 and 2000 conditions:**
  - 2010 traffic counts, Amtrak and commuter rail ridership, and air passenger data have been used as independent validation checks of the models.

– The model is validated by applying to 2000 conditions, conducting an NEC-like model run, and understanding differences in results across versions.

Table 2.1 Enhanced Model Components resulting in Version 2.0

Model	Improvement	Data Source
Overall	• Replace short and long interregional with long distance (≥ 50 miles) • Improved network specification • Improved consistency through removal of "threshold" variables in network processing	
Trip Frequency	• Combined estimation of trip frequency and travel alone-group travel • Less reliance on district constants	• 2012 CHTS long distance data
Destination Choice	• Fewer constrained variables • Less reliance on district-district constants • Refined "size" variables (employment categories) • Impact of Disneyland and Yosemite on recreation travel	• 2012 CHTS long distance data • 2005 RP data
Main Mode Choice and Access / Egress Mode Choice	• Joint estimation of the access/egress and main mode choice models • Consistent perceptions of time and cost for access/egress and main mode choice • Added mode availability specification (e.g., rental car not available for egress if no rental car facilities at station) • More consistent specification of reliability variable	• 2005 RP and SP survey data • 2012 CHTS long distance data
SCAG and MTC Intraregional Models	• Consistent, underlying model forms • Networks and socioeconomic data from MTC and SCAG • Model constants calibrated according to FTA guidelines	• 2008 and 2010 model data • 2010 validation data used for regional models
Calibration, Validation, and Sensitivity Testing	• Calibration to 2010 conditions • Validation by backcasting to 2000 • Sensitivity testing via NEC-like regional HSR system alternative • Validation of the high-speed rail constant using a new RP/SP survey • Multiple model runs to determine elasticities	• Expanded 2012 CHTS data • Caltrans traffic counts • Operator boarding data

3.0 Phased Implementation Scenarios for the 2014 Business Plan

3.1 Scenario Overview

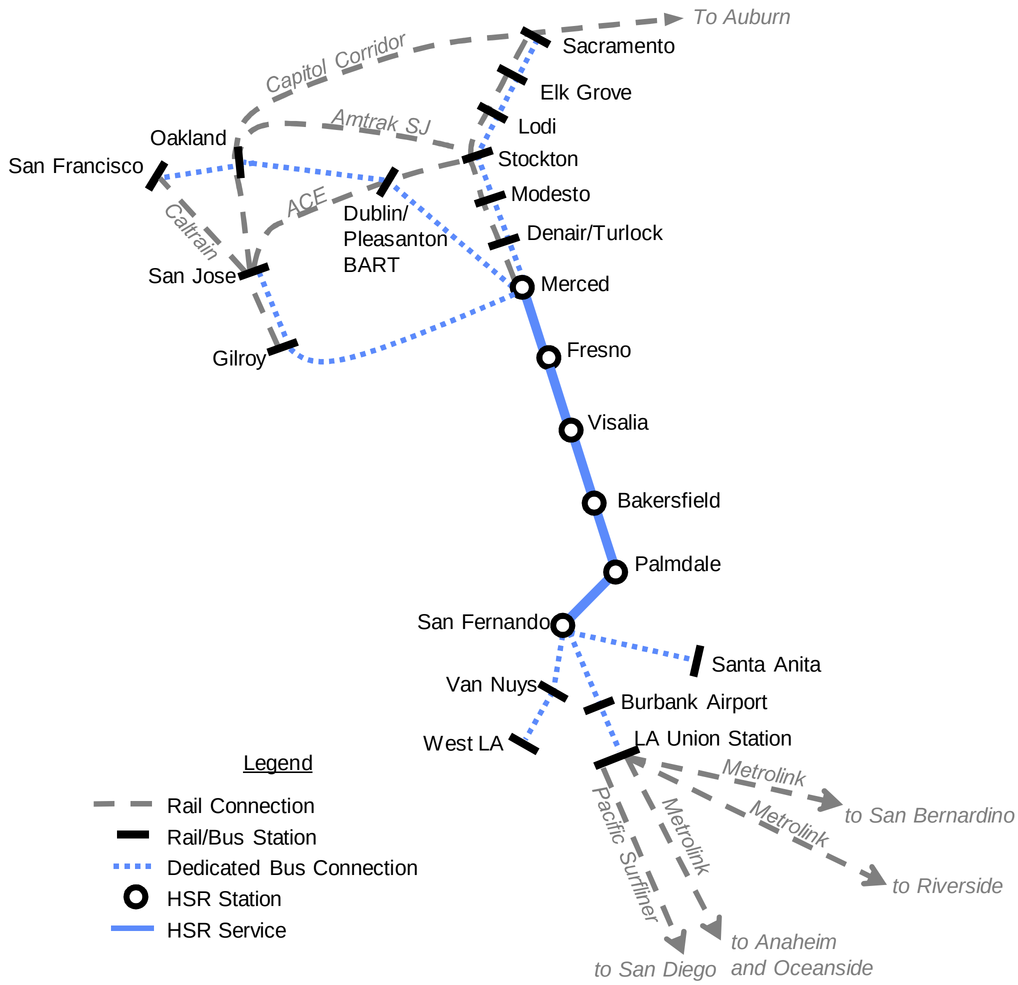
The business case evaluation assumes that the HSR project will open in phases, from 2022 through 2029, as described below. Further detail on the fares and frequencies are provided in Section 3.2.

Initial Operating Segment (IOS) – Open in 2022

The initial operating segment (IOS) is planned to begin service in 2022, characterized by:

- A north terminal at Merced and a south terminal at San Fernando (Figure 3.1).
- Dedicated coach services will be provided between the Merced station and the San Francisco Bay Area and Sacramento region, as well as between the San Fernando station and locations in the Los Angeles Basin (LA Basin).
- Connections with Amtrak at Merced to the Bay Area and Sacramento would be coordinated.

Figure 3.1 IOS



Bay to Basin – Open in 2027

An extension of the IOS phase is planned to start operations in 2027, with these service characteristics:

- In the north, the HSR system would extend to San Jose from Fresno. The terminus at Merced would remain (Figure 3.2).
- Dedicated coach services will be provided between the Merced station and the San Francisco Bay Area and Sacramento region, as well as between the San Fernando station and locations in the Los Angeles Basin (LA Basin).
- The southern HSR terminal would remain at San Fernando.
- Connections with Amtrak at Merced to the Bay Area and Sacramento would be coordinated. Caltrain feeder service at San Jose to San Francisco peninsula destinations is coordinated.

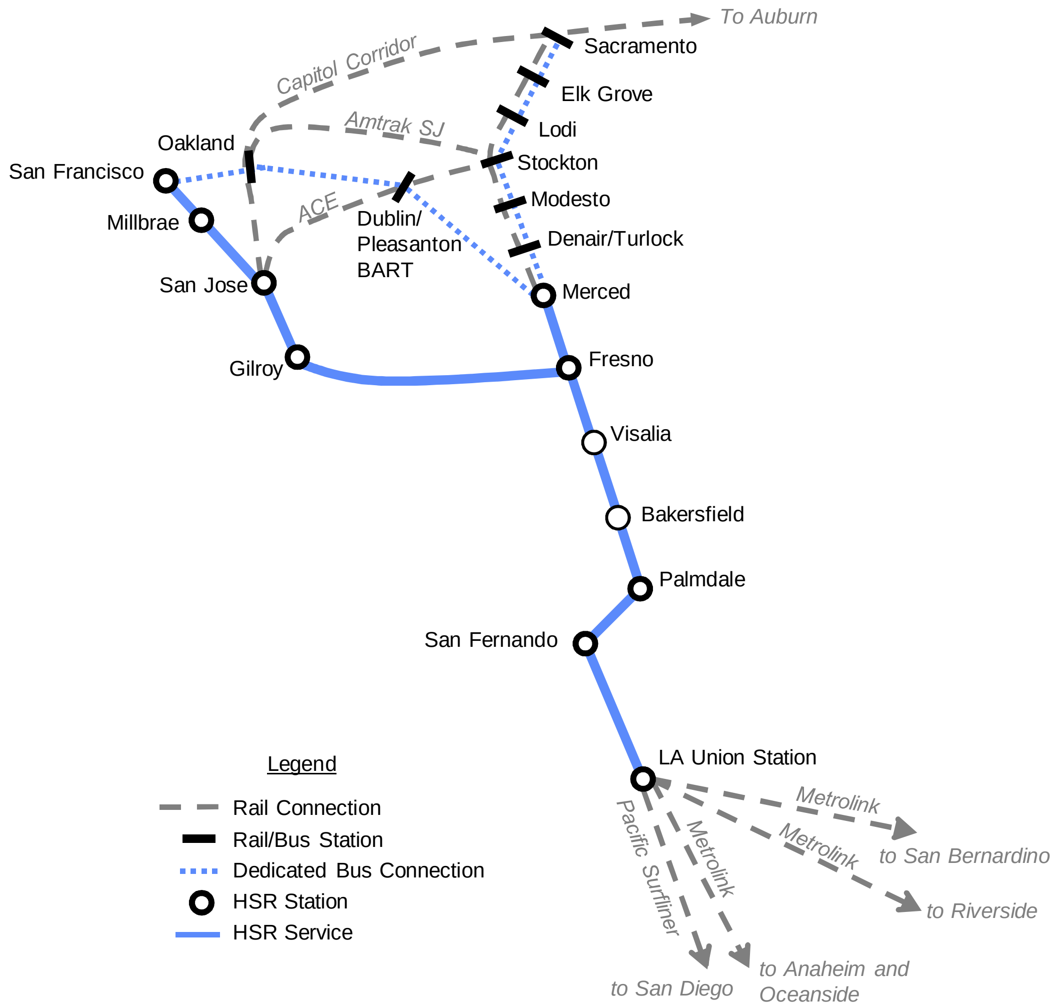
Figure 3.2 Bay to Basin

Phase 1

Scheduled to start operations in 2029, the Phase 1 scenario has the HSR North terminal at San Francisco and the south terminal at Los Angeles Union Station (Figure 3.3), with these characteristics:

- HSR service will operate on Caltrain tracks from San Jose to San Francisco, meaning that speeds would be lower than those achievable on dedicated tracks.
- Dedicated coach services would be provided from Merced to Sacramento.
- Connections with Amtrak at Merced to the Bay Area and Sacramento would be coordinated.
- Connections with Metrolink feeder service at Los Angeles Union Station to Los Angeles Basin destinations would be coordinated.

Figure 3.3 Phase 1



3.2 HSR Service Plan Assumptions

HSR fares for all 2014 Business Plan scenarios were identical to those in the 2012 Business Plan, based on the following formula, with an $86 maximum in 2013 dollars (see Table 3.1):

- $31.13 + $0.1924 per mile (in 2013 dollars) for interregional fares;
- $23.10 + $0.1604 per mile (in 2013 dollars) for intraregional fares for SCAG region; and
- $14.97 + $0.1283 per mile (in 2013 dollars) for intraregional fares for MTC and SANDAG regions.

Service assumptions varied by scenario. The details of the service frequencies are described in Table 3.2. The stopping patterns are provided in Appendix A.

Table 3.1 Assumed HSR Fares

2013 Dollars

HSR Stations	San Francisco (Transbay)	Millbrae	Redwood City	San Jose	Gilroy	Merced	Fresno	Visalia	Bakersfield	Palmdale	San Fernando	Los Angeles Union Station	Norwalk	Anaheim
San Francisco (Transbay)		$17	$18	$22	$24	$57	$68	$75	$86	$86	$86	$86	$86	$86
Millbrae			$17	$19	$23	$57	$68	$74	$86	$86	$86	$86	$86	$86
Redwood City				$18	$22	$56	$65	$72	$85	$86	$86	$86	$86	$86
San Jose					$18	$54	$61	$66	$80	$86	$86	$86	$86	$86
Gilroy						$50	$57	$63	$75	$86	$86	$86	$86	$86
Merced							$43	$50	$65	$82	$83	$86	$86	$86
Fresno								$39	$54	$71	$72	$75	$78	$81
Visalia									$49	$65	$66	$71	$73	$75
Bakersfield										$49	$50	$54	$56	$58
Palmdale											$31	$32	$33	$35
San Fernando												$26	$29	$31
Los Angeles Union Station													$26	$29
Norwalk														$26
Anaheim														

Source: Parsons Brinckerhoff.

Notes: $86 Fare constrained to $86.
$86 Fare for San Francisco Bay Area to Los Angeles Basin.

Table 3.2 HSR Service Plan Assumptions by Scenario

Business Case Scenario	North Terminus	South Terminus	HSR Service Summary[a]	Dedicated *Peak* Bus Coach Connections		Conventional Rail Connections
				North Terminus	South Terminus	
IOS	Merced	San Fernando	• 4 peak TPH from Merced and San Fernando(2 in off-peak)	• 4 BPH from Merced to Sacramento • 4 BPH from Merced to San Francisco • 4 BPH from Merced to San Jose	• 4 BPH from San Fernando to LAUS • 4BPH from San Fernando to West LA • 4BPH from San Fernando to Santa Anita	• Coordinated service with Amtrak at Merced.
Bay to Basin	San Jose and Merced	San Fernando	• 4 peak TPH from San Jose to San Fernando (3 in off-peak) • 2 peak TPH from Merced to San Fernando (1 in off-peak)	• **2** BPH from Merced to Sacramento • 2 BPH from Merced to San Francisco	• 6 BPH from San Fernando to LAUS • 6 BPH from San Fernando to West LA • 6 BPH from San Fernando to Santa Anita	• Coordinated Caltrain service from San Jose to San Francisco • Coordinated service with Amtrak at Merced.
Phase 1	San Francisco and Merced	Los Angeles	• 4 peak TPH from San Francisco to Los Angeles (same for off-peak) • 2 peak TPH from San Jose to Los Angeles (0 in off-peak) • 2 peak TPH from Merced to Los Angeles (1 in off-peak)	• 2 BPH from Sacramento to Merced.	None	• Coordinated service with Amtrak at Merced. • Metrolink connections at Los Angeles Union Station

[a] TPH – Trains per Hour.

4.0 Service Assumptions for Air, Conventional Rail, Highway, and Autos

Air Service Assumptions

For the 2012 Business Plan, CS engaged Aviation System Consulting, LLC (ASC), a California-based expert firm, to develop air service assumptions based on the latest air service patterns in the California Corridor markets. ASC analyzed the past decade of U.S. Department of Transportation data on airline service and fare levels, explained the economic factors affecting airline responses to changes in competition and capacity, and helped determine scenarios of potential airline competitive response to the introduction of HSR service. Cambridge Systematics and ASC discussed the analytical approach and assumptions developed for the 2012 BP and concluded that the analysis performed in 2011 is still relevant since no significant changes have occurred since then in the airline industry.

The baseline assumption for fares in 2030 were the same as they were in 2009. For the risk analysis, we assumed a 9 percent reduction in real fares from 2009 levels for the low values and an average increase of 16 percent over the 2009 fares for the high values. Section 6.3 provides more details on how the Low, Mid, and High fares were used in the risk analysis model.[3]

Table 4.1 Air Service Assumptions

	Airfares
Mid fare value	2009 average fares by market in constant 2005 dollars
Low fare value	9% reduction in real fares from 2009 levels
High fare value	Increase of 16% over 2009 fare levels (real fares)

Source: Aviation System Consulting.

[3] See Appendix B of "California High Speed Rail 2012 Business Plan, Ridership and Revenue Forecasting, Final Technical Memorandum, April 12, 2012" for complete details of this evaluation.

Conventional Rail Service Assumptions

Conventional rail (CVR) service, including travel times, frequency of service, and stations served were updated to reflect the latest conditions and forecasts from the 2013 California State Rail Plan (CSRP),[4] Metropolitan Planning Organization (MPO) forecasts, and the California Statewide Transportation Demand Model (CSTDM). The largest service changes from today include increased conventional rail service from Sacramento, Oakland, and San Jose to Merced to connect with High-Speed Rail, and increased service between Sacramento and Los Angeles via connected Coaster and Metrolink service. The updated CVR sources are summarized in Table 4.2 and operating frequencies are summarized in Table 4.3.

Table 4.2 Source of CVR Operating Plan Forecasts

Source of Forecast	CVR Operators
California State Rail Plan	Amtrak San Joaquin Capitol Corridor Pacific Surfliner Altamont Corridor Express Caltrain Coaster MetroRail
MPO Plans	BART SMART Metrolink
California Statewide Transportation Demand Model	Muni LRT VTA LRT Sacramento LRT SANDAG LRT Sprinter

[4] 2013 California State Rail Plan, May 2013. Available at: http://californiastaterailplan.dot.ca.gov/.

Table 4.3 CVR Operating Plan Service Frequencies

	2022-2027	2029-2040
Caltrain		
Gilroy – San Jose	8	8
Tamien/San Jose – SF (4th and King/SF Transbay)	56	56
Capitol Corridor Route:		
Auburn – Oakland	2	2
Sacramento – Oakland	6	6
Sacramento – San Jose	8	8
San Joaquin Route:		
Sacramento – Merced connection to HSR via San Joaquin Route	8	8
Sacramento – Bakersfield via San Joaquin Route		
Oakland – Bakersfield via San Joaquin Route		
Oakland – Merced connection to HSR via San Joaquin Route	10	10
Stockton – Merced connection to HSR via San Joaquin Route	1	1
Merced – Bakersfield via San Joaquin Route	6	6
Ace Route:		
San Jose – Stockton via ACE Route	4	4
San Jose – Merced connection to HSR via ACE and Union Pacific Railroad (UPRR) Route	4	4
San Jose – Merced connection to HSR via ACE and BNSF Railway (BNSF) Route	4	4
Pacific Surfliner:		
San Luis Obispo – Los Angeles	2	2
Goleta – Los Angeles	3	3
Los Angeles – San Diego	18	18
Metrolink (Ventura and Orange County Lines) and COASTER:		
East Ventura[p] – Los Angeles	20	20
Los Angeles – Irvine/Laguna Niguel	8	8
Los Angeles – Oceanside	5	5
Los Angeles – San Diego (Metrolink COASTER " through" commuter service)	5	5
Riverside – San Diego (Metrolink-COASTER " through" commuter service)	0	2
Oceanside – San Diego	34	34

Fare assumptions for all lines are consistent with on-line published fares in 2011. Consistent with previous assumptions, the peak period was assumed to be three hours during each of the a.m. and p.m. peak periods, and 10 hours for the off-peak period.

Highway Network

We used the same highway network assumptions as those used for the California Statewide Travel Demand Model (CSTDM) for each respective forecast year.[5] We averaged AM and PM peak congested travel times derived from the CSTDM for use when peak travel times were needed in the mode choice model. Similarly, we averaged midday and offpeak congested speeds for when off peak travel times were needed.

Auto terminal times represent the average time to access one' s vehicle at each end of the trip and are added to the congested travel time to get the total congested travel time skim. They are based on the area type of the trip ends and are assessed at both the origin and destination of the trip.

Travel times for the modeled forecast years were obtained by interpolating between the closest forecast years.

Auto costs are comprised of tolls and parking costs. Toll costs were imported from networks developed for the CSTDM. Tolls corresponding to single-occupancy vehicles were assumed in the auto skims. Peak and offpeak tolls were averaged where costs differed. The parking costs developed for 2010 base year scenario were used for all future year scenarios.

Automobile Operating Cost

The approach for forecasting auto operating costs for the 2014 Business Plan is consistent with the methodology used for the 2012 Business Plan, with updates to the cost projections. The range of auto operating costs used for the different forecast years are summarized in Table 4.4, with details regarding forecasts for the fuel and nonfuel components of operating cost provided below. The probability distribution used in the risk analysis model is described in Section 6.3.

Table 4.4 Range of Auto Operating Costs, 2013 dollars

Forecast Year	Range (Cents/Mile)
2022	22 to 30
2027	20 to 29
2029	19 to 28
2040	18 to 28
2050	17 to 29

Source: Cambridge Systematics, Inc.

[5] More information regarding the CSTDM model development and assumptions, see the documentation provided on the Caltrans web site: http://www.dot.ca.gov/hq/tsip/otfa/cstdm/cstdm_documentation.html.

Fuel Component of Auto Operating Costs

Forecasts of future fuel costs are a function of the cost of fuel and vehicle fuel economy. Each of these are discussed below.

Motor gasoline price forecasts. The 2012 Business Plan was based on EIA's 2011 Annual Energy Outlook (AEO). CS updated the projected motor gasoline prices in California based on the 2013 AEO, which extend through 2040. The EIA provides average motor gasoline price forecasts for three different scenarios: reference, low, and high. CS extrapolated the forecasts to 2050 using the projected average annual growth rate from 2020 to 2040. Historically, California retail gasoline prices have been higher than the U.S. average; the overall average for California prices over the U.S. average prices over the 2000 to 2012 time period has been 12 percent. CS developed a forecast of California gasoline prices by taking the forecasts from EIA and increasing them by 12 percent.

Fuel Economy Forecasts. The EIA also provides projections for fuel economy for light-duty vehicles. The 2012 Business Plan considered the adopted Corporate Average Fuel Economy (CAFE) standards for light-duty vehicles for model year 2012 to 2016 but the final fuel economy standards for model year 2017 through model year 2025 had not yet been adopted. CS updated the fuel economy projections based on the 2013 AEO forecasts, which include the adopted fuel efficiency standards for model year 2017 through model year 2025. The EIA provides forecasts for two cases:

1. **Reference Case.** The AEO2013 Reference case includes the final CAFE standards adopted in October 2012 for model years 2017 through 2025, with subsequent CAFE standards for years 2026-2040 vehicles calculated using 2025 levels. In 2010, California accepted compliance with Federal greenhouse gas (GHG) emission standards as meeting similar state standards and incorporated the national standards into their motor vehicle emissions program.[6,7] We interpret this to mean that in the future, national and California standards will be the same.
2. **Extended policy.** The Reference case assumes that the CAFE standards are held constant at model year 2025 levels in subsequent model years, although the fuel economy of new light duty vehicles would continue to rise modestly over time. The Extended case modifies the assumption assuming continued increases in CAFE standards after model year 2025. CAFE standards for new

[6] EPA (http://yosemite.epa.gov/opa/admpress.nsf/1e5ab1124055f3b28525781f0042ed40/6f34c8d6f2b11e5885257822006f60c0!OpenDocument).

[7] California Air Resources Board, Statement of the California Air Resource Board Regarding Future Passenger Vehicle Greenhouse Gas Emission Standards, May 21, 2010.

light duty vehicles are assumed to increase by an annual average rate of 1.4 percent.

The fuel economy projections for the Reference and Extended policy case are for the entire " on-the-road" fleet of vehicles (not only new vehicles). The average annual growth rate from 2035 to 2040 for the Reference case is 1.1 percent. CS extrapolated the fuel efficiency projections to year 2050 using a 1.0 percent compound annual growth rate for both scenarios

Combined Estimate of Fuel Operating Costs. While the lowest auto operating cost could be achieved by combining the high fuel efficiency with the low gasoline price, and the highest cost could be achieved by assuming the reverse, it is more reasonable to assume that high prices will coincide with high fuel economy, and low prices with low fuel economy. While fuel economy is not nearly as volatile as fuel prices, it is reasonable to assume that over a long period of time, high prices will drive the demand for better fuel economy.[8] Therefore, CS used the Extended Policy case with the High scenario of gas prices and the Reference case with the Low and Reference motor fuel price forecasts to develop auto operating costs for use in our ridership and revenue forecasting (Table 4.5).

Table 4.5 Combination of Fuel Efficiency Projections with Gasoline Price Forecast Scenarios

Fuel Efficiency Case	Gasoline Price Scenario
Extended Policy	High forecast
Reference	Reference forecast Low forecast

Non-Fuel Component of Auto Operating Costs

For the original model calibration effort in 2006-2007, nonfuel operating costs[9] were assumed to be 67 percent of the gasoline operating cost.[10] Since the nonfuel operating costs are likely to be less volatile than fuel prices, for the Version 2 model

[8] Research studies have found and press articles have reported that when gasoline prices increase, the market share of fuel-inefficient cars decrease, and the reverse occurs for fuel-efficient vehicles (Klier, Linn, 2008; Li, Timmis, Von Haefen, 2009; Busse, Knittel, Zettelmeyer, 2009; CNN, 2012; AOL Auto, 2012).

[9] Non-fuel costs include maintenance and repair, motor oil, parts, and accessories.

[10] Bay Area/California High-Speed Rail Ridership and Revenue Forecasting Study, Levels-of-Service Assumptions and Forecast Alternatives, prepared for Metropolitan Transportation Commission and California High-Speed Rail Authority, prepared by Cambridge Systematics, Inc., August 2006, Table 2-1, page 2-2.

we made them a constant amount of nine cents per mile in 2013 dollars. That nonfuel cost was used for the Low and Reference gasoline price forecasts. For the High gasoline price forecast, CS increased this to 10 cents per mile (Table 4.6).

Table 4.6 Nonfuel Costs to be Used with Gasoline Price Forecast Scenarios, 2013 dollars

Gasoline Price Scenario	2014 Business Plan
High Forecast	$0.10/mile
Reference Forecast	$0.09/mile
Low Forecast	$0.09/mile

5.0 Socioeconomic Forecast

5.1 OVERVIEW

CS updated the long-range socioeconomic projections to support the ridership and revenue risk analysis forecasts for the 2014 Business Plan. CS projections reflect our professional judgment as to reasonable range of county-level population, household, and employment levels through 2050. The projections are based upon our critical evaluation of county level socioeconomic estimates and forecasts from many sources, including:

- **Federal Agencies**: U.S. Census Bureau.
- **State Agencies:** California Department of Finance (DOF); California Employment Development Department (EDD).
- **Metropolitan Planning Organizations (MPO)**: Metropolitan Transportation Commission (MTC); Sacramento Area Council of Governments (SACOG); San Diego Association of Governments (SANDAG); Southern California Association of Governments (SCAG); and the San Joaquin Valley MPOs.
- **Third Parties within California**: California Statewide Travel Demand Model (CSTDM); California Economic Forecast Project (CEF); Center for Continuing Study of the California Economy; UCLA (Anderson School); University of Southern California (Price School).
- **Third Parties outside California**: Moody's Analytics (Economy.com); Woods & Poole, Inc.

For most sources, we assembled and reviewed forecasts from multiple publication years beginning in the early 2000s (and as early as 1965 for one source). This history allowed us to assess each source's accuracy versus actual conditions over many years. Overall, we found that the U.S. Census Bureau's population and household projections were reasonably accurate. Other sources, mostly prepared by California-based organizations, tended to over-predict population, households, and employment.

The CSTDM forecasts served as the starting point for the HSR socioeconomic forecasts because they were recently updated to reflect adopted MPO forecasts (as of early summer 2013).[11] Also, they are the only dataset that provides forecasts at the individual traffic analysis zone level. All the other forecasts are either at the state or county level.

We used the other forecasts and their underlying assumptions to explore a range of plausible population, household, and employment growth scenarios on statewide and regional bases. We considered the prior accuracy, stability (magnitude of changes of a given forecast source over time), rigor (explanation of underlying data, assumptions, and models), and robustness (internal consistency between population, housing, income, and employment components) of each source when developing and analyzing these scenarios. We also compared the scenarios to historic relationships between population, housing, and employment growth in California and the nation.

The preponderance of information suggests that CSTDM forecasts represent a likely high end of the future statewide socioeconomic growth. The CSTDM forecast assumes a statewide annual population growth rate of 1.01 percent between 2010 and 2040, which is above growth projections from nearly all other sources and observed trends over the past several years. The CSTDM forecast also assumes an average population growth rate higher than the employment growth rate, which is counter to California's trends between World War II and the recent recession.

Beyond statewide trends, the CSTDM forecasts incorporate very aggressive growth assumptions for the San Joaquin Valley.[12] These statewide and regional assumptions produce Valleywide forecasts that are 10 percent to 20 percent higher than any other source. In spite of its incorporation of recent MPO information, the CSTDM forecasts are also at odds with recent growth trends and state growth policies that aim to reduce greenhouse gas emissions by directing new socioeconomic growth into currently developed areas.

Based on this analysis, we incorporated two components of socioeconomic growth for the risk analysis and then combined them in a matrix of distributions.

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[11] CSTDM socioeconomic forecasts for the MTC, SACOG, SANDAG, and SCAG regions were generally developed and adopted by the MPOs between early 2010 and late 2012. Forecasts for the rest of California, including the San Joaquin Valley, appear to have been developed from 2003 to 2008 and adopted no later than early 2010.

[12] For this analysis, the San Joaquin Valley includes San Joaquin, Stanislaus, Merced, Madera, Fresno, Tulare, Kings, and Kern counties.

1. Statewide population, household, and employment forecasts (shown in Table 5.1 for each decade and the travel model years); and
2. Share of California population in San Joaquin Valley counties (Table 5.2):
   - Distribution 1 follows the CSTDM forecasts.
   - Distribution 2 follows the Valley-wide average distribution from recent statewide forecasts, with excess population, employment, and household-related employment shifted to the Bay Area, the Sacramento region, and Southern California.
   - Distribution 3 reflects a further shifting of population, household, and employment growth from the San Joaquin Valley to all other California regions. It assumes that the San Joaquin Valley will see 2010 to 2050 growth patterns that are closer to statewide averages (for population and households) and long-term historical patterns for jobs.

Table 5.1 Statewide Socioeconomic Forecasts for Ridership and Revenue Risk Analysis Model (millions)

	High Range Forecast			Mid Range Forecasts			Low Range Forecast		
Year	**Population**	**House-holds**	**Employ-ment**	**Population**	**House-holds**	**Employ-ment**	**Population**	**House-holds**	**Employ-ment**
2010	37.309	12.587	16.052	37.309	12.607	16.078	37.309	12.606	16.078
2020	41.560	14.153	18.677	40.790	13.891	18.331	39.756	13.510	17.867
2022	42.436	14.454	19.018	41.889	14.268	18.773	40.583	13.839	18.188
2027	44.626	15.206	19.870	43.761	14.911	19.485	41.829	14.257	18.624
2029	45.503	15.506	20.211	44.359	15.116	19.703	42.218	14.386	18.752
2034	47.693	16.258	21.063	45.506	15.512	20.097	42.742	14.549	18.876
2040	50.357	17.272	22.198	47.951	16.447	21.138	44.111	15.016	19.445
2050	54.869	18.761	24.128	51.106	17.474	22.473	46.762	15.989	20.563

Note: Ridership and revenue model forecast years are indicated by bold font in the “ year” column.

Table 5.2 Share of Statewide Socioeconomic in San Joaquin Valley Counties

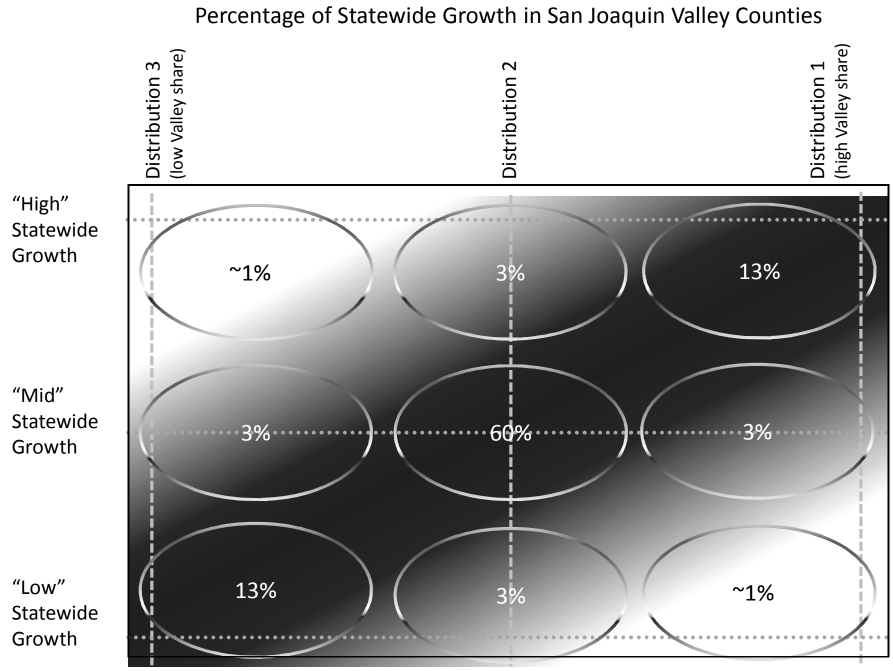
	Distribution 1 (CSTDM)			Distribution 2			Distribution 3		
Year	**Population**	**House-holds**	**Employ-ment**	**Population**	**House-holds**	**Employ-ment**	**Population**	**House-holds**	**Employ-ment**
2010	10.66%	9.66%	9.33%	10.66%	9.66%	9.33%	10.66%	9.66%	9.33%
2020	12.30%	11.34%	10.02%	11.11%	10.23%	9.57%	10.95%	10.08%	9.12%
2022	12.52%	11.53%	10.21%	11.20%	10.31%	9.62%	11.00%	10.13%	9.17%
2027	13.06%	12.00%	10.69%	11.42%	10.49%	9.96%	11.15%	10.24%	9.31%
2029	13.27%	12.19%	10.88%	11.51%	10.57%	10.09%	11.20%	10.29%	9.37%
2034	13.81%	12.66%	11.36%	11.73%	10.75%	10.43%	11.35%	10.40%	9.53%
2040	14.37%	13.38%	12.13%	12.00%	11.17%	11.07%	11.52%	10.72%	9.65%
2050	16.10%	15.24%	13.31%	12.45%	11.78%	11.67%	11.80%	11.18%	9.87%

Note: Ridership and revenue model forecast years are indicated by bold font in the "year" column.

We combined, and assigned probabilities to the outcomes (Figure 5.1). This figure shows statewide growth levels along the y-axis (side), and the San Joaquin Valley growth share along the x-axis (top). The oval and numeric overlays show our assumed likelihood of different *ranges* of statewide growth and San Joaquin Valley share. The rationale for these distributions is as follows:

- We assigned the highest probability to the middle combination of mid-level statewide growth and "Distribution 2." This combination shows more modest statewide and San Joaquin Valley growth at rates that are consistent with the more recently published third-party sources and are in line with historical trends.
- The highest probability is along the bottom-left to top-right diagonal because of how total growth and distribution match up. This diagonal reflects a general principal found in all of the third-party sources – namely, any departure from "average" statewide socioeconomic growth will depend on the fortunes of the San Joaquin Valley. If the growth levels assumed in the CSTDM were to occur, it is likely that the distribution associated with the CSTDM – high growth share in the San Joaquin Valley – would occur. Similarly, lower statewide growth levels would more likely occur along with a distribution that has less relative growth in the San Joaquin Valley.
- The probability of a statewide growth and regional distribution combination decreases somewhat rapidly as we depart from the diagonal line mentioned above.

Figure 5.1 Likelihood of Statewide and San Joaquin Valley Socioeconomic Growth Combinations



Source: Cambridge Systematics, Inc., 2013.

Note: Darker colors indicate higher probability combinations.

6.0 Risk Analysis

6.1 Approach

CS employed a risk analysis approach to produce our 2014 Business Plan ridership and revenue forecasts. This approach was predicated on the following concepts:

- The ridership and revenue (R&R) model produces reasonable forecasts with reasonable sensitivities to changing conditions.
- Models are abstractions used to represent the real world; methods to account for the impacts of the abstractions need to be employed for forecasts used for business planning purposes.
- Future conditions cannot be known with certainty. The forecasts used for business planning purposes need to recognize those uncertainties and present a reasonable range.

In the 2012 Business Plan, we dealt with uncertainty by developing a baseline forecast and then creating assumptions to develop a high and low forecast. While informative, this approach does not provide any context regarding the likelihood of the high and low case.

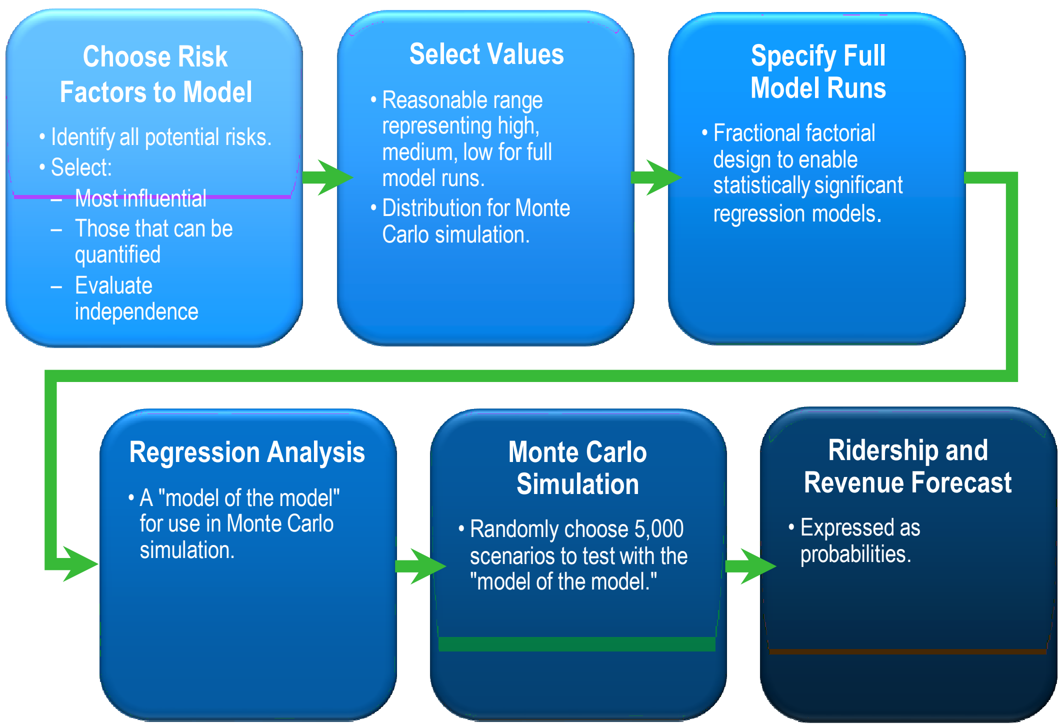
To better illustrate the uncertainties inherent in predicting ridership and revenue, we developed a more robust approach that allowed us to express forecasts as the probability of achieving different outcomes. Developing these probabilities in a statistically reliable way requires running numerous – thousands – of scenarios. However running thousands of scenarios with the ridership and revenue model is simply not practical, since it takes over an hour to run an individual scenario.

We developed an approach that used a much lower number of model runs to create statistical relationships of changes in individual inputs and combinations of inputs on ridership and revenue. We used this "model of the model" to transform 47 scenarios using the complete ridership and revenue model into 5,000 unique scenarios. By evaluating the frequency of different levels of ridership and revenue outcomes of these 5,000 scenarios selected through Monte Carlo simulation, we can state, in a statistically valid way, the likelihoods of different outcomes.

Our approach to uncertainty is a bottoms-up approach-addressing the combined influence of likely risk factors on ridership and revenue outcomes.[13] An complementary approach would be to develop a reference case based on the past history of forecast outcomes for similar projects. The HSRA may wish to evaluate our range of forecasts from the perspective of past forecast outcomes on other projects. However, they should be careful to recognize that our approach results in a broad band of potential outcomes, which might incorporate many of the uncertainties meant to be covered in a reference case forecast.

Our probabilistic approach to the ridership and revenue forecasts illustrated in Figure 6.1, and described in the subsections below. Appendix B provides additional details of the risk analysis approach, and Section 7.0 has the resulting forecasts.

Figure 6.1 Risk Analysis Approach



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13 Bent Flyvbjerg, Mette K. Skamris Holm, and Søren L. Buhl, "How (In)accurate Are Demand Forecasts in Public Works Projects?," Journal of the American Planning Association, Spring 2005, Vol. 71, No. 2.

6.2 Choosing Risk Factors to Model

We compiled a comprehensive list of factors that could affect high-speed rail ridership and then selected the six factors we thought would have the greatest potential variability and/or influence on total high-speed rail ridership. Our rationale for selecting the factors is described below.

Potential Risk Factors

There are two major risk categories:

1. **Future Expectations Risks –** These are risks that have to do with our expectations regarding the future (i.e., model inputs). Travel demand models are based on snapshots of travel patterns and traveler behavior today and typically assume that travelers' responses to future travel options will be the same as they were when the snapshot was taken. While this may suffice for short-term forecasts, when considering long term forecasts this simple approach ignores the likelihood of significant changes in traveler behavior resulting from structural changes in society and the economy. Examples from the past of such changes include:
   - Increasing workforce participation by women in the 60s, 70s, and 80s of last century.
   - Introduction of new work options such as telecommuting, shared jobs, and web-based conference calls (e.g., GoToMeeting™).
   - Demographic shifts, such as the aging of the baby boomers, accompanied with increasing longevity and activity.
   - Globalization of markets.
   - Technological advances such as the Internet, cell phones, and smart phones.

   While we cannot know for certain what new changes will occur in society, we can speculate on what some of those changes might be and incorporate some of that speculation into our forecasts for the risk analysis.
2. **Model Related Risks** – These are risks that have to do with the inner workings of the model that reflect traveler behavior (i.e., model coefficients and constants).

While these two categories are not entirely independent, it is a useful way to think about the factors that influence potential long distance travel in California. Appendix B has a long list of potential risk factors along with how we proposed addressing them in our analysis. As we considered more risks, we knew that the amount of computation time and analysis necessary to include those risks in the Monte Carlo simulation would increase significantly. Therefore, we kept the risks to the handful that we judged would have the largest impacts on ridership and revenue. We judged some of the risks to be so speculative or difficult to address that we did not include them but simply identified them in this technical memorandum. There was also a middle ground of risks that we chose to address through sensitivity test model runs.

In all cases, we tried to select risk factors as independent of each other as possible to reduce the complications caused by correlation of the factors. A high level of correlation between the risk factors could lead to invalid results; many statistical software packages fail to execute when a high level of correlation between independent variables exists.

Selected Risk Factors

We included six risk factors that we thought would have the greatest impact on high-speed rail ridership and revenue:

1. Total California population, households, and employment;
2. Spatial distribution of population and employment;
3. Auto operating cost;
4. Airline fares;
5. High speed rail main mode choice constants; and
6. Trip frequency model constants.

6.3 SELECT RISK FACTOR VALUES

To conduct the risk analysis, each factor must be quantified so it can be treated as a continuous independent variable within a regression model represented as a distribution of values. The middle value often (but not always) has the greatest likelihood of occurring. The shape of the distribution can be triangular, normal, uniform, or another form. The shape of this distribution determines the likelihood of an independent variable's value under random sampling.

For each risk factor, we developed low, middle, and high values for each forecast year that we used in full model runs. We then developed a distribution around these values based on best available research and analysis for use in the Monte Carlo simulation (see Table 6.1). The distributions are described in more detail in the following subsections.

Table 6.1 Risk Factor Values and Distributions

Risk Factor				Inputs for Model Runs				Distribution for Monte Carlo Simulation
Description	Measure	Level	Description	2022	2027	2029	2040	
Overall Population and Employment Growth	Ratio of future year households to observed year 2010 households	High	California Statewide Travel Demand Model Forecast – High household and employment growth rate	1.148	1.208	1.232	1.372	Correlated with Regional Spatial Distribution as shown in Figure 5.1
		Mid	Mid-level household and employment growth rate	1.132	1.183	1.199	1.305	
		Low	Low household and employment growth rate	1.098	1.131	1.141	1.191	
Regional Spatial Distribution	Ratio of San Joaquin Valley population to rest of California	High	California Statewide Travel Demand Model Forecast – High growth rate in San Joaquin Valley	0.115	0.120	0.122	0.134	Correlated with Regional Spatial Distribution as shown in Table 5.2
		Mid	Mid-level growth rate in San Joaquin Valley	0.103	0.105	0.106	0.112	
		Low	Low growth rate in San Joaquin Valley	0.101	0.102	0.103	0.107	
Auto Operating Cost[a]	$/mile (2005$)	High	Based on high fuel forecasts and low fuel efficiency	$0.26	$0.24	$0.24	$0.24	Triangular, with Low set to 15 percent probability of occurrence and High at 85 percent probability of occurrence
		Mid	Reference/Base	$0.21	$0.20	$0.19	$0.20	
		Low	Based on low fuel forecasts and high fuel efficiency	$0.18	$0.17	$0.16	$0.15	
Airline Fares	Air fare skim factor	High	16 percent increase, as used in 2012 Business Plan airline competitive response scenario	1.16	1.16	1.16	1.16	Triangular, with Low set to 15 percent probability of occurrence and High at 85 percent probability of occurrence
		Mid	Base scenario, consistent with 2012 Business Plan runs	1.00	1.00	1.00	1.00	
		Low	9 percent reduction, as used in 2012 Business Plan airline competitive response scenario	0.91	0.91	0.91	0.91	
High Speed Rail Main Mode Choice Model Constants[b]	Change in HSR constant units from Base	High	Equivalent to 60 fewer minutes of IVTT for business/commercial (90 for recreation/other)	0.61	0.61	0.61	0.61	Normal distribution with Mean = 0 and Standard Deviation = 0.48
		Mid	Average of Offset Approach for CVR and Air Offset Method	0	0	0	0	
		Low	Equivalent to 60 more minutes of IVTT for business/commercial (90 for recreation/other)	-0.61	-0.61	-0.61	-0.61	
Trip Frequency Model Constants	Annual average roundtrips per capita	High	Increase from Mid scenario of 1.75 round trips per person	9.11	9.11	9.11	9.11	Truncated Normal distribution with Mean = 7.36 and Standard Deviation = 0.85
		Mid	Constants calibrated to CHTS trip rates that produce average of 7.36 round trips per person	7.36	7.36	7.36	7.36	
		Low	Decrease from Mid scenario of 1.75 round trips per person	5.61	5.61	5.61	5.61	

[a] See memorandum, “ Revised forecasts of gasoline prices and fuel efficiency for use in 2014 Business Plan Model Runs and Forecasts” dated September 30, 2013.

[b] See memorandum, “ Version 2 Model High Speed Rail Alternative Specific Constants” dated January 8, 2014.

Socioeconomic Risk Factors (Overall Population and Employment Growth and Regional Spatial Distribution)

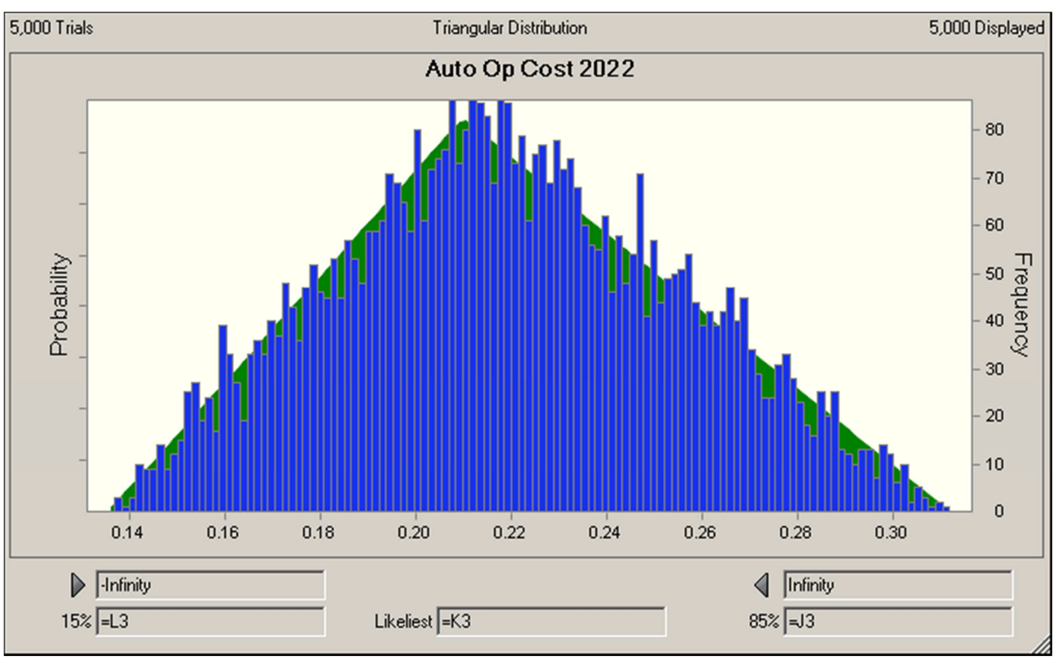
See Section 5.0 for details, including the distribution.

Auto Operating Cost

CS updated the range of gasoline prices and fuel efficiency forecasts in California with the latest U.S. Energy Information Administration (EIA) projections (See Section 4.0). The low, middle, and high estimates were used as the respective values for the auto operating cost risk factor. The low and high values were set at the 15 percent and 85 percent percentile, respectively, along a triangular distribution. This means that 30 percent of the scenarios in the Monte Carlo simulation were likely to have values lower or higher than these levels – 15 percent of the observations on either side.

For year 2022, the range of values used in the risk analysis was actually broader than $0.18 to $0.26 per mile values specified as the " low" and " high" values for auto operating cost. The highest probability of occurrence was at the middle value of $0.21/mile in 2005 dollars (Figure 6.2). Similar assumptions were made for other forecast years with the low and high values for the 15th and 85th percentiles, and the mid values as specified in Table 6.1.

Figure 6.2 Auto Operating Cost Distribution – Year 2022 ($/mile in 2005 dollars)

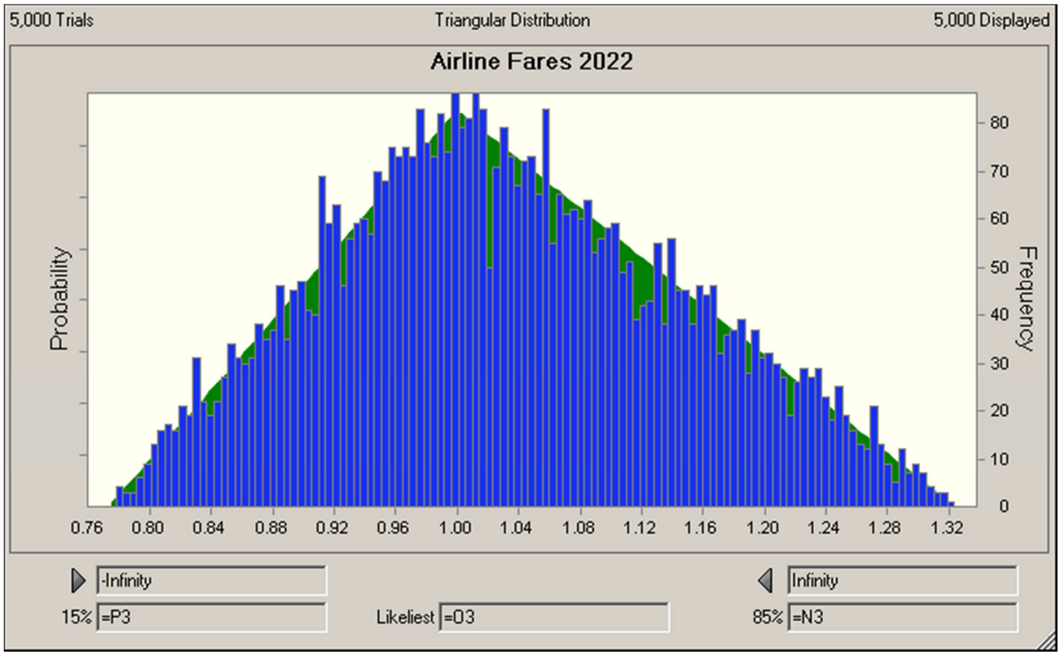


Air Fares

In the 2012 business plan, we assumed that the baseline assumption for fares in 2030 be the same as they were in 2009. Forecast year mid-level air fares remain consistent with the 2012 Business Plan, which were developed in 2011 by Cambridge Systematics and Aviation System Consulting (Section 4.0). As part of sensitivity analysis for the 2012 Business Plan ridership and revenue forecasting, Cambridge Systematics, in partnership with Aviation System Consulting, developed airline competitive response scenarios. The low-fare scenario was a 9 percent reduction in real fares from 2009 levels and the high-fare scenario increased real fares over 2009 levels by an average of 16 percent across all markets.

There have been no significant structural changes in the airline industry to warrant changing this range of assumptions, so we maintained this range, and express it in terms of a triangular distribution. Therefore, the 9 percent reduction in fares is set as the low value at the 15th percentile, and the 16 percent increase in fares is set as the high value at the 85th percentile. It should be noted that the fares in the 2012 Business Plan high-fare scenario differed by market for an average of a 16 percent increase. However, varying the fares by market segment would significantly increase the effort needed to produce each full model run. Thus, the risk factor for the 2014 Business Plan, applies a factor to the entire mid fare matrix (Figure 6.3). The highest probability of occurrence is at the mid value, having factor of 1.00. The 15 percent percentile is at a factor of 0.91 and the 85 percent percentile is at a factor of 1.16.

Figure 6.3 Distribution of Factor Applied to Air Fare Mid-Level Matrix



High-Speed Rail Main Mode Choice Constants

An important part of any mode choice model is a modal constant that explains factors that are not quantifiable by the stated and revealed-preference (RP) surveys. When dealing with existing modes such as auto, conventional rail (CVR), and air, we can calibrate this constant by comparing the model outcomes to observed behavior. With a new mode like HSR, this is impossible, so there is uncertainty in the specified constant.

Uncertainty in the HSR constants comes from the distributional assumptions of the model itself and the data used to estimate the model. The former is relatively straightforward, in that the logit model may not be an accurate representation of how individuals actually make mode choices. The latter refers to the uncertainties associated with how the stated-preference (SP) data were collected, the survey instrument, respondents perceptions based on " public opinion" at time of the survey, and other related issues. This uncertainty is driven by the following:

1. HSR currently does not exist in California, and thus we are unable to calibrate the HSR constant to observed mode shares.
2. HSR does not exist in the United States. Americans have very little experience with HSR, so we cannot use oberved data or experiences from other parts of the country to guide our knowledge in assessing Californian' s willingness to use HSR. In addition, while we have gained some insights

from SP surveys on the attractiveness of HSR between destinations within California, these results have a degree of error and uncertainty due to the lack of actual experience on HSR. In many travel-related SP surveys, individuals are asked to assess a new mode with which they are familiar, such as a new bus, toll road, or urban rail system, even if it does not provide service for the travel being considered.

3. Uncertainty exists in the HSR system itself. The HSR constant captures all unobserved attributes and variables that affect an individual's decision to use HSR that are not captured by other variables within the model. This includes wait and terminal times, the existence or nonexistence of security checkpoints, attractiveness of the HSR stations, and amenities on trains such as food options, wireless Internet, etc.
4. Uncertainty exists in the mode choice model and the methodology used to calculate the HSR constant. Inherent uncertainty exists in all parts of model estimation including, but not limted to, the estimated variables within the mode choice model, sampling error associated with the data summarized from the SP survey, sampling error with the observed data collected for calibration of the existing model, and the method used to specify the mid-level HSR constants.

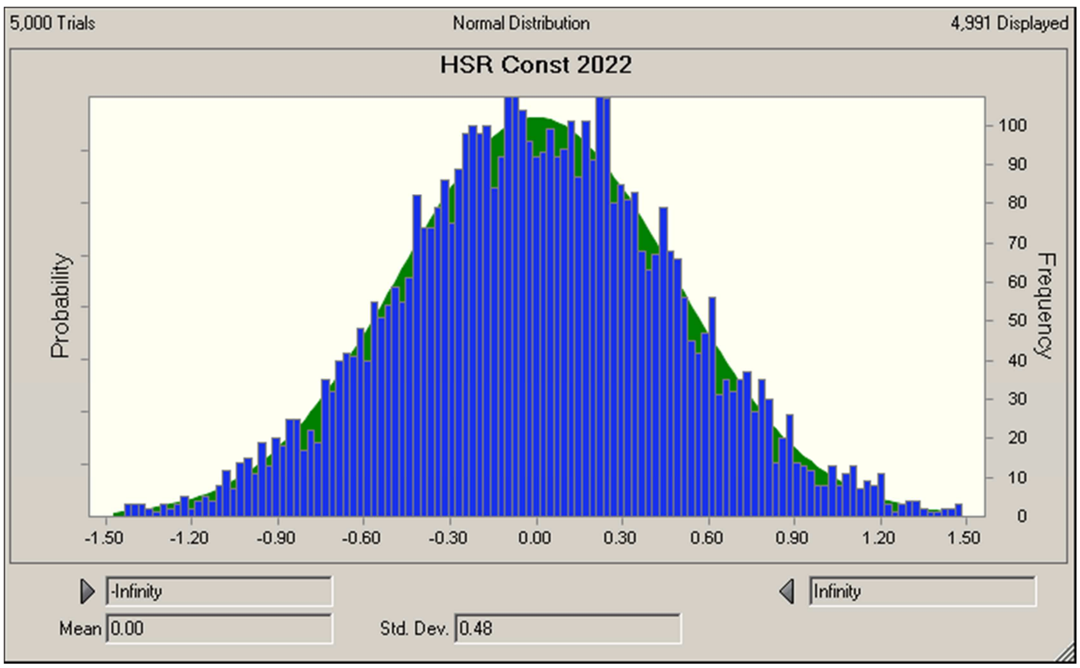
Mid-level HSR constants were specified based on the relationships of the air, CVR, and HSR constants estimated using SP data, and the air and CVR constants after calibration to match observed 2010 travel. We chose a normal distribution to represent the uncertainty in the HSR constants because the distribution of all coefficients in the estimated mode choice models should be normal. Further, to avoid overcomplicating the risk analysis model, the distribution of the HSR constant was not varied by trip purpose. The risk factor used in the risk analysis regression equation was the HSR constant unit change from the mid-level (specified) HSR constant. The mid-level risk factor value for the HSR constant is set to 0.0 (i.e., 0.0 change from the specified constant). A 0.1 unit change in the risk factor value would correspond to a 0.1 unit increase in the HSR constant for each purpose. Note that an increase in the constant means an increase in the desirability of the mode.

To develop the variance for the HSR constant distribution, we started by considering a value for the absolute minimum HSR constant. Since there was no apparent reason that any of the unobserved characteristics for the HSR mode should be any worse than those for the CVR mode, we thought the CVR constant should represent this minimum value for the HSR constant. As mentioned above, a single distribution was applied for all trip purposes due to the constraints in our application of the risk analysis procedure. Because recreation/other was, by far, the most prevalent long-distance trip purpose (about 75 percent of all long distance trips), we focused on the relationship between the recreation/other mode choice model CVR and HSR constants. The

CVR constant was -1.25 units lower than the HSR constant for the recreation/other trip purposes; thus, -1.25 was selected as the lower bound for the unit offset for the distribution. Since the normal distribution was used for the risk analysis, we chose the 0.5th percentile value of the distribution to correspond to the offset value of -1.25. Thus, 0.5 percent of the time (1 in 200), the HSR constant used in the risk analysis for recreation/other would be less than the CVR constant.

The above led to the specification that the deviation in the HSR constant used in the risk analysis would follow a normal distribution with mean zero and standard deviation 0.48. Figure 6.4 shows the distribution of HSR constant offsets used for 2022.

Figure 6.4 Distribution of HSR Constant Units from Mid Scenario – Year 2022



Trip Frequency Model Constants

Similar to the uncertainty found in the HSR constants, uncertainty also exists in the constants calibrated for the trip frequency model. The trip frequency model estimates the total number long-distance trips (greater than or equal to a straight-line distance of 50 miles from the trip maker' s home) made per person per day. The data used for the trip frequency model estimation was from the long-distance travel portion of the 2012-2013 California Household Travel Survey (CHTS). The data used for calibration was based on 2012-2013 CHTS data weighted (expanded) to match 2010 California population characteristics.

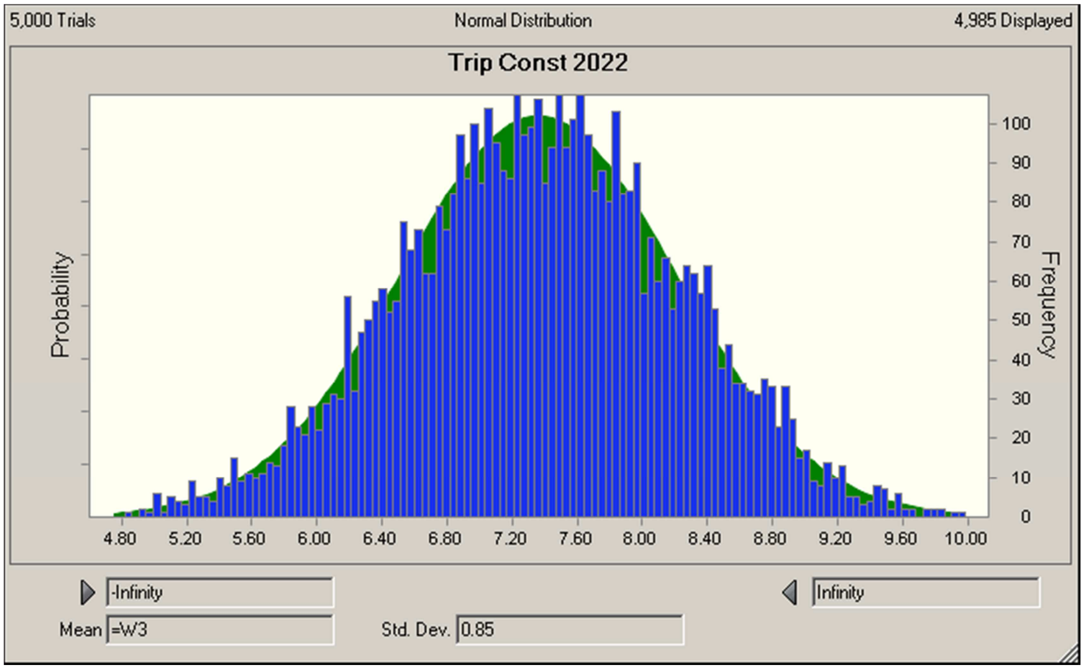
Based on the weighted 2012-2013 CHTS data, California residents made an annual average of 8.2 intra-California long distance trips (50 miles or more) per person in 2010. For long distance trips over 100 miles in length, the overall average annual trips per capita estimated using the weighted 2012-2013 CHTS was close to the midpoint of national data collected in the 1995 American Travel Survey and the 2001 National Household Travel Survey. Thus, we were confident that the HSR ridership and revenue trip frequency model calibrated to match 2010 trip making estimated using the 2012-2013 CHTS data should be used to set the midpoint trip rates for the risk analysis.

The annual intra-California long distance trips per person estimated using data from the 2011 Harris panel long distance survey performed for the CAHSRA was 6.0 trips per person per year. We believed there was a very high probability that the true number of annual trips per person per year was above the reported Harris Survey number. Thus, we considered 2.2 annual trips below the annual average long distance trips per person forecast using the calibrated trip frequency model as the lower bound in the distribution.

The calibrated trip frequency model constants resulted in averages of 7.36 annual long-distance trips per person for each of the forecast years.[14] These values represented the mid-level values in the distribution for the risk analysis. We used a normal distribution, with a standard deviation of 0.85. This resulted in 2.2 annual trips less per person than the mid-level value to fall at the 0.5th percentile. Figure 6.5 shows the distribution for 2022. The 15th and 85th percentiles are at 1.75 annual trips per household below and above the midpoint, respectively.

[14] The difference in annual long-distance trips from the weighted CHTS is, in part, due to the elimination of long-distance bus trips from the dataset.

Figure 6.5 Distribution of Average Annual Roundtrips/person – Year 2022



Note: The solid green shape represents the input distributions provided to the Monte Carlo simulation model. The blue bars represents the distribution of values selected by the Monte Carlo simulation model.

Specify Full Model Runs

Once the risk factors and their distributions were defined, the full ridership and revenue model was run to obtain input into the Risk Analysis regression equations. We began by running a " mid-level" model run with all risk factors set at the mid value for each forecast year. To limit the number of model runs to a reasonable level we used a fractional 2-level factorial design for running the full model (where the two levels correspond to High and Low from Table 6.1). Thirty-two runs were used to estimate all the main effects and two-factor interactions resulting from varying the input data. Fourteen additional runs with data points between the mid level and low level, and between the mid-level and high-level values of each risk factor distribution were added to provide information regarding the nonlinearity of the forecast distributions and to ensure that the regression models represented the middle values within the distributions, and not just the extremes. These additional runs were important since the regression models, discussed in the next section, were exponential rather than linear.

Regression Analysis

Ridership versus Revenue

We began the analysis by testing the relationship between ridership and revenue resulting from the Version 2 Model runs. Revenue and ridership were closely correlated with a R^2 of more than 0.999 for each year. Since revenue and ridership were highly correlated, we developed regression equations for revenue only and used the above relationships between revenue and ridership to calculate the corresponding ridership forecasts for the risk analysis.

Revenue Regression Models

Using the results from the ridership and revenue forecasts from each of the 47 full model runs,[15] we estimated relationships between the revenue forecasts and the input risk factor levels. The Monte Carlo method, described in the next section, made it feasible to quickly produce the thousands of revenue forecasts based on varying levels of the input risk factor variables that were necessary to estimate probabilities of specific outcomes. The revenue forecasts produced using the Monte Carlo method were predicated on deterministic equations (in our case, the regression models). Therefore, special attention was given to the construction of the deterministic equations. We analyzed both linear and nonlinear transformations of model variables, and found that exponential relationship between revenue and risk factors resulted in the best model fits, with all forecast years having R^2 above 0.99. The differences between predicted revenues and estimated revenues from the full model runs was between +/- 5 percent.

Monte Carlo Simulation

Crystal Ball add-on software to Excel provided us the capability to run a randomized series of scenarios (Monte Carlo simulation). We defined the scenarios by varying the six risk factor values throughout their associated distributions for each forecast year. The revenue regression equation for each forecast year was used to estimate the associated revenue for each scenario and the relationship between revenue and ridership for each forecast year was used to estimate the ridership. Crystal Ball was used to automate the simulation process by selecting combinations of input values for the risk factors that were used to construct individual scenarios Crystal Ball automatically calculated and recorded the results of thousands of runs for the randomly selected input values. For each 2014 Business Plan forecast year, we ran a series of 5,000 Monte Carlo

[15] 1 Base Run + 32 2-level Factorial Runs + 14 additional Runs.

simulations using Crystal Ball to obtain revenue probability distributions. The results are presented in the next section.

6.4 Additional Risks not Quantified

Our approach winnowed a wide variety of potential risks down to a manageable set of six factors that we believed would have the most influence on ridership and revenue outcomes. The following risks were not specifically evaluated because we judged them to have less impact on ridership and revenue or were too speculative to try to estimate.

- Changes in household income, household size;
- Changes in spatial distribution of growth within metropolitan regions;
- Changes in the types of jobs available in California;
- Changes in major attractions in California (such as Disney);
- Changes in highway capacity;
- Changes to security screening practices at rail stations or airports; and
- Changes to the automobile travel experience, such as self-driving cars.

In addition, this evaluation assumes that the HSRA will be able to deliver the type and quality of service indicated by the business plan. We did not test the implications of slower, less frequent, or less reliable service.

7.0 Ridership and Revenue Forecast Results for Business Plan Scenarios

7.1 SUMMARY OF ASSUMPTIONS

Each of the HSR service scenarios were evaluated using assumptions that generated ridership and revenue outcomes expressed in probabilistic terms for each forecast year. Table 7.1 summarizes the input assumptions for each HSR scenario. The fundamental differences between the multiple model runs within each HSR scenario involve:

- Auto operating costs (described in Section 4.0);
- Air fares (described in Section 4.0);
- Socioeconomic factors (described in Section 5.0):
  - Total population, households and employment; and
  - Spatial distribution of population, households and employment.
- HSR mode choice constant (described in Section 6.4); and
- Trip Frequency model constant (described in Section 6.5).

Table 7.1 Summary of HSR Assumptions for each Modeled Business Plan Scenario

	Year 2022	Year 2027	Year 2029	Year 2040
HSR Phase	IOS-S	Bay-to-Basin	Phase 1	Phase 1
Highway Network	Year 2022 (1)	Year 2027 (1)	Year 2029 (1)	Year 2040 (1)
Auto Travel Time	Year 2022 (2)	Year 2027 (2)	Year 2029 (2)	Year 2040 (2)
Auto Parking	Year 2010	Year 2010	Year 2010	Year 2010
AIR Travel Time	Year 2011 (3)	Year 2011 (3)	Year 2011 (3)	Year 2011 (3)
AIR Service Frequency	Year 2030 (3)	Year 2030 (3)	Year 2030 (3)	Year 2030 (3)
AIR Reliability	Year 2010 (4)	Year 2010 (4)	Year 2010 (4)	Year 2010 (4)
Parking Cost at Airport	Year 2010	Year 2010	Year 2010	Year 2010
CVR Service Plans	SRP Year 2025 Build HSR (5)	SRP Year 2025 Build HSR (5)	SRP Year 2040 Build HSR (5)	SRP Year 2040 Build HSR (5)
CVR Fares	Year 2010	Year 2010	Year 2010	Year 2010
CVR Reliability	Year 2010 (6)	Year 2010 (6)	Year 2010 (6)	Year 2010 (6)
Parking Cost at CVR Station	Year 2010	Year 2010	Year 2010	Year 2010
HSR Service Plan	2012 BP for IOS-S.	2012 BP for B2B.	2012 BP for Ph1.	2012 BP for Ph1
HSR Fares	2012 BP (85% of airfare)	2012 BP (85% of airfare)	2012 BP (85% of airfare)	2012 BP (85% of airfare)
HSR Reliability	2012 BP (99%)	2012 BP (99%)	2012 BP (99%)	2012 BP (99%)
HSR Parking Cost	2012 BP (May 09 – High)	2012 BP (May 09 – High)	2012 BP (May 09 – High)	2012 BP (May 09 – High)
Urban/Light Rail Service Plans	Year 2020 (7)	Year 2020 (7)	Year 2035 (7)	Year 2035 (7)
Other Transit Lines	Year 2010	Year 2010	Year 2010	Year 2010
Socioeconomic Data	Probability Distribution	Probability Distribution	Probability Distribution	Probability Distribution
Auto Operating Cost	Probability Distribution	Probability Distribution	Probability Distribution	Probability Distribution
Air Fares	Probability Distribution	Probability Distribution	Probability Distribution	Probability Distribution
HSR Constant	Probability Distribution	Probability Distribution	Probability Distribution	Probability Distribution
Trip Frequency Constant	Probability Distribution	Probability Distribution	Probability Distribution	Probability Distribution

(1) The HSR master highway network was developed based on the California Statewide Travel Demand Model (CSTDM) highway network for each respective forecast year. Thus, the highway " build" assumptions are consistent with those used for the CSTDM.

(2) The auto travel times for peak and offpeak were developed by loading the CSDTM AM peak and offpeak congested speeds for year 2020 and 2040 on to the corresponding year HSR highway network and then skimming the HSR network to obtain peak and offpeak travel times. Travel times for the modeled forecast years were obtained by interpolating between the closest forecast years.

(3) Air service frequency and travel times remain consistent with the 2012 Business Plan, which were developed in 2011 by Cambridge Systematics and Aviation System Consulting.

(4) Air reliability remains consistent with Year 2010 Bureau of Transportation Statistics published data (http://www.transtats.bts.gov/OT_Delay/OT_DelayCause1.asp?pn=1)

(5) The conventional rail (CVR) service plan, including travel times, frequency of service, and stations served, are based on the 2013 California State Rail Plan (SRP). Assumptions for CVR operators not specifically mentioned in the SRP are based on Metropolitan Planning Organization (MPO) forecasts.

(6) CVR reliability remains consistent with Year 2010 reliability assumptions developed from information published by each CVR operator.

7.2 SUMMARY OF RIDERSHIP AND REVENUE FORECASTS

Ridership and revenue forecast ranges with the probabilities of achieving certain values are shown in Tables 7.2 and 7.3, respectively. We highlight the values representing different confidence levels, from 5 percent to 95 percent. A 15 percent confidence level means that there is a 15 percent chance that the ridership/revenue will be lower than this value (or, an 85 percent chance that it will be higher). The range in revenue for Year 2022 between the 5th and 95th percentiles is $1,030 million compared to $2,249 million in Year 2040.

Table 7.2 Range of Annual Ridership by HSR scenario (millions)

Confidence level that ridership will be less than Stated Value	System Phase			
	IOS 2022	Bay to Basin 2027	Phase 1 2029	Phase 1 2040
5%	5.1	9.3	14.8	17.0
15%	6.8	12.3	19.0	21.9
25%	8.2	14.2	22.0	25.4
50%	11.3	19.1	28.4	33.1
75%	15.4	25.1	37.3	44.0
85%	18.2	29.5	43.7	49.9
95%	23.8	37.4	54.4	64.8

Source: Cambridge Systematics, Inc

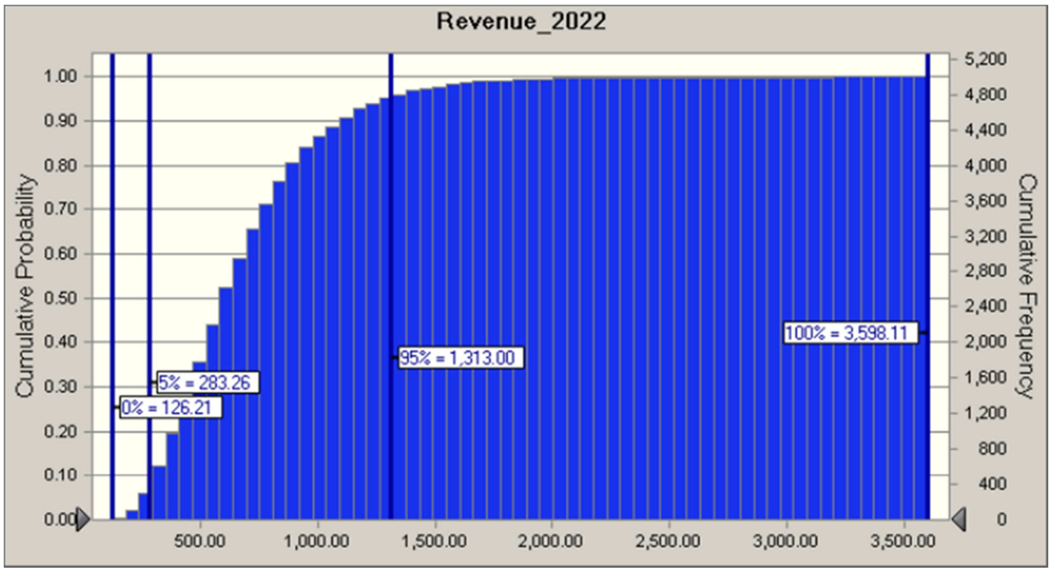
Table 7.3 Range of Annual Revenue by HSR scenario (millions)
2013 Dollars

Confidence level that ridership will be less than Stated Value	System Phase			
	IOS 2022	Bay to Basin 2027	Phase 1 2029	Phase 1 2040
5%	283.3	515.6	702.4	799.9
15%	380.1	680.6	901.7	1,030.6
25%	450.0	795.1	1,045.0	1,195.0
50%	625.0	1,055.6	1,350.4	1,559.4
75%	851.1	1,389.0	1,790.4	2,050.1
85%	1,002.9	1,632.2	2,074.6	2,349.8
95%	1,313.0	2,074.3	2,584.0	3,048.5

Source: Cambridge Systematics, Inc

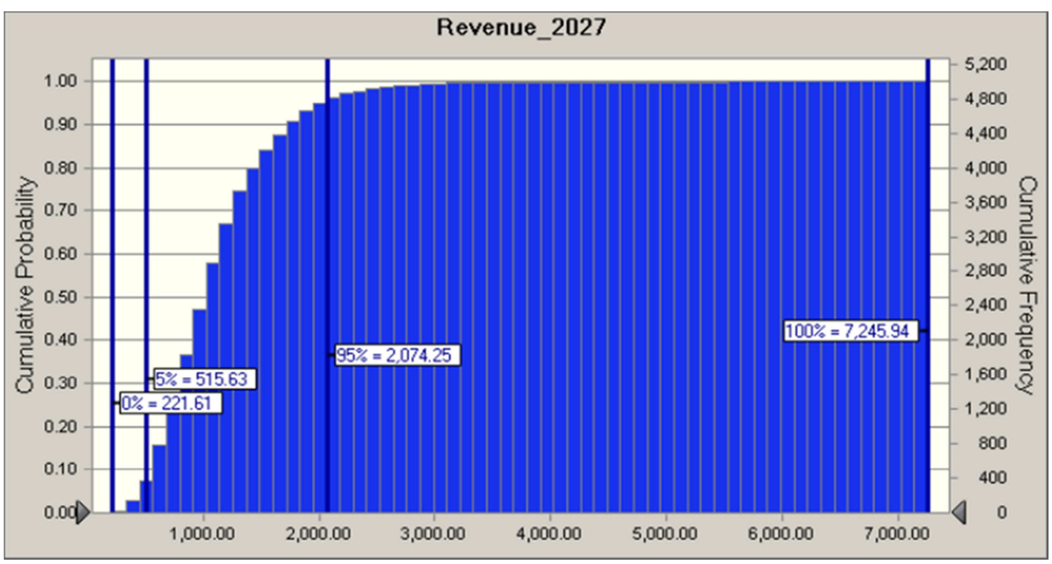
Figures 7.1 through 7.4 display the cumulative probabilities of achieving specified revenue levels for the various forecast years. The distributions are skewed to the right, indicating that the values where there is 99 percent confidence that revenue will be lower than the specified values are further away from the median (or 50th percentile) than the revenues for the 1 percent confidence level. This is a result of the right skewed risk factor input distributions for auto operating cost and airfare.

Figure 7.1 Forecast Annual Revenue: Cumulative Probability Distribution for Year 2022 – IOS (millions)



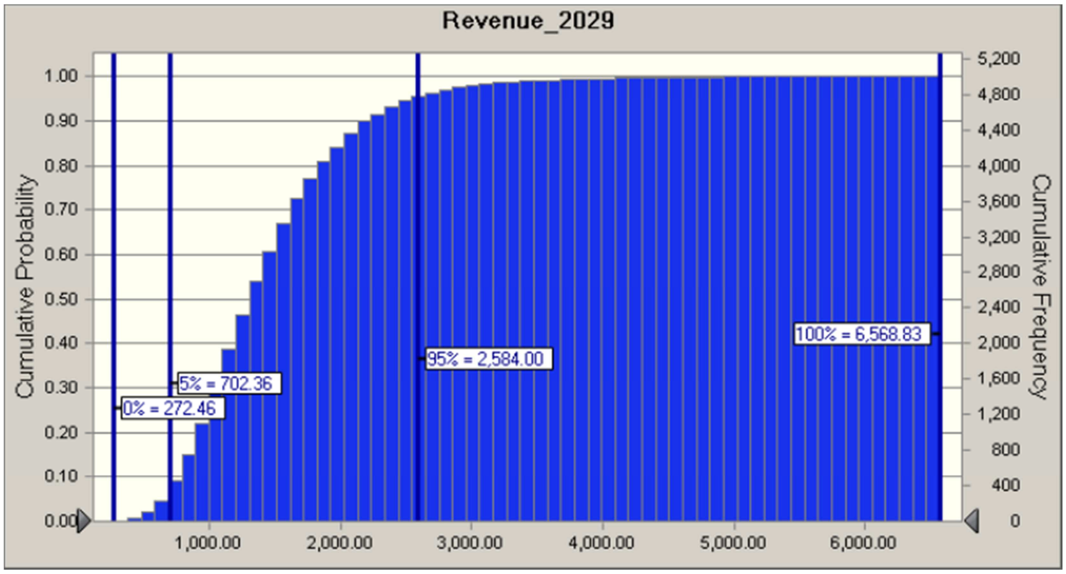
Source: Cambridge Systematics, Inc

Figure 7.2 Forecast Annual Revenue: Cumulative Probability Distribution for Year 2027 – Bay-to-Basin (millions)



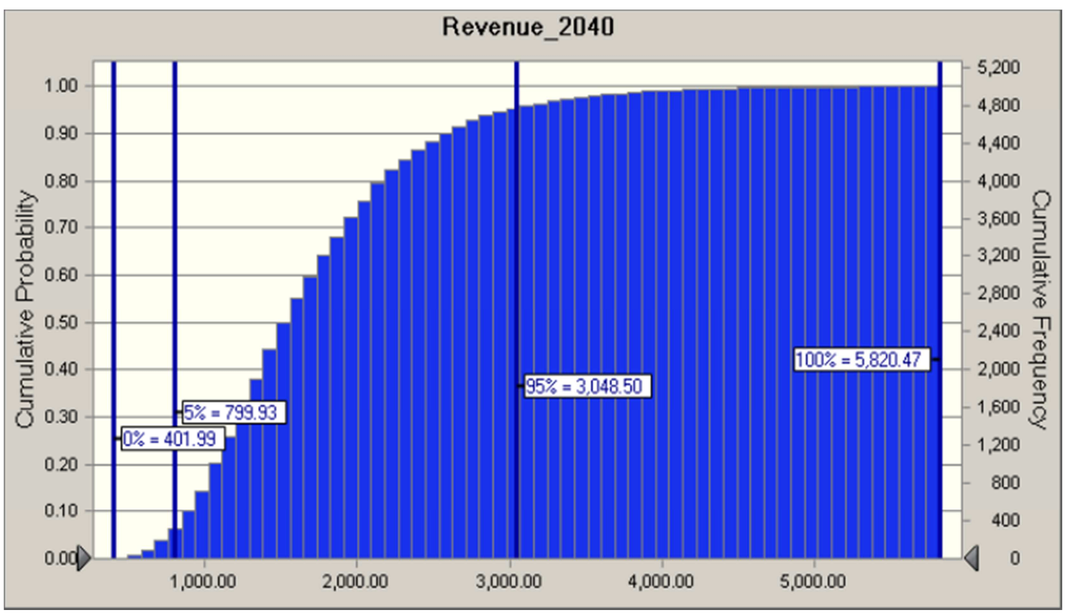
Source: Cambridge Systematics, Inc

Figure 7.3 Forecast Annual Revenue: Cumulative Probability Distribution for Year 2029 – Phase 1 (millions)



Source: Cambridge Systematics, Inc

Figure 7.4 Forecast Annual Ridership: Cumulative Probability Distribution for Year 2040 – Phase 1 (millions)



Source: Cambridge Systematics, Inc

7.3 Ridership and Revenue Forecast Comparisons by Project Phase and Year

A comparison of Year 2022 IOS, Year 2027 Bay-to-Basin, Year 2029 Phase 1, and Year 2040 Phase 1 annual trips by major market is shown in Table 7.4. These values are shown for illustrative purposes, to provide a sense of how ridership and revenue varies by project phase for particular region pairs and at particular stations. We prepared these comparisons for a model run that represents the median values for all of the factors that were used in the risk analysis. These values are likely to be close to, but not necessarily identical to those that represent the 50th percentile confidence level forecast. Also, these values represent a mature system that we have not reduced to account for the time it takes for customers to become fully familiar with the new service.

The IOS scenario provides limited HSR service compared to the other scenarios. The IOS scenario provides four peak trains per hour (TPH) but only runs between Merced and San Fernando. Although dedicated coach services are provided at the terminals, the lack of express service in the Bay Area and in the LA Basin results in longer travel times in the peninsula and in the Basin.

The HSR extension to San Jose (Bay to Basin scenario) and improvements in the frequency of service to 6 peak TPH increases systemwide trips, especially within the longer distance markets of MTC to SCAG and MTC to SANDAG where the share of HSR doubles. Similarly, extending the HSR service in the Bay Area to San Francisco and south to LA Union Station (Phase 1 scenario) provides more access to the populous regions in these markets. The HSR mode share increases by one-third between MTC and SCAG and by one-half between MTC and SANDAG from the Bay-to-Basin to Phase 1 scenario. The extension of HSR service in the Bay Area significantly increases HSR travel between the Bay Area and points south since passengers would not have to transfer using Caltrain.

Table 7.4 Comparison of Annual Ridership (millions) and Revenue (millions, 2013 dollars) by Major Market for Mid-Level Forecast Year Scenarios

		Year 2022 IOS Mid-Level			Year 2027 B2B Mid-Level			Year 2029 Ph1B Mid-Level			Year 2040 Ph1B Mid-Level		
	Market	HSR Rider.	HSR Rev.	HSR Share	HSR Rider.	HSR Rev.	HSR Share	HSR Rider.	HSR Rev.	HSR Share	HSR Rider.	HSR Rev.	HSR Share
SACOG	SACOG	–	–	0.00%	–	–	0.00%	–	$0.00	0.00%	–	$0.00	0.00%
SACOG	SANDAG	0	$2.70	3.70%	0	$3.10	3.50%	0	$3.00	3.20%	0	$3.30	3.10%
SACOG	MTC	–	–	0.00%	0	$0.70	0.10%	1.3	$24.00	2.10%	1.6	$29.20	2.20%
SACOG	SCAG	0.5	$41.30	7.50%	0.6	$49.10	7.90%	0.5	$40.70	6.20%	0.5	$46.00	6.20%
SACOG	San Joaquin Valley	0.2	$9.70	1.50%	0.2	$10.30	1.50%	0.3	$11.20	1.80%	0.3	$13.00	1.50%
SACOG	Other Regions	0	$1.50	0.10%	0.1	$3.50	0.80%	0.2	$4.20	0.90%	0.2	$4.90	0.80%
SANDAG	SANDAG	0	$0.00	0.10%	0	$0.00	0.10%	–	$–	0.00%	–	–	0.00%
SANDAG	MTC	0.1	$10.30	3.70%	0.3	$26.40	8.50%	0.5	$42.40	13.30%	0.6	$48.30	13.90%
SANDAG	SCAG	0.3	$9.10	0.30%	0.3	$10.00	0.30%	0.9	$24.60	0.70%	0.9	$24.10	0.70%
SANDAG	San Joaquin Valley	0.2	$14.40	6.70%	0.2	$15.40	6.80%	0.3	$18.60	7.70%	0.3	$21.60	7.30%
SANDAG	Other Regions	0.1	$4.40	2.40%	0.1	$7.40	3.50%	0.1	$8.80	4.60%	0.1	$9.90	4.60%
MTC	MTC	–	–	0.00%	0.3	$5.60	0.80%	2.2	$43.20	5.60%	2.5	$51.40	6.10%
MTC	SCAG	1.5	$121.40	6.80%	3.6	$305.60	15.40%	4.6	$397.30	19.70%	5.5	$472.80	21.60%
MTC	San Joaquin Valley	0.6	$31.60	1.40%	1.8	$109.70	3.90%	3.5	$168.30	7.40%	5	$236.50	8.40%
MTC	Other Regions	0.1	$3.40	0.10%	1.5	$34.10	3.10%	2.7	$62.70	5.30%	3.3	$79.00	5.80%
SCAG	SCAG	2.7	$82.70	1.70%	3.6	$108.90	2.10%	5	$141.90	2.80%	5.4	$153.80	2.70%
SCAG	San Joaquin Valley	2.8	$169.40	7.70%	3.4	$202.80	8.80%	3.1	$192.10	7.90%	3.7	$228.80	7.70%
SCAG	Other Regions	0.7	$51.60	2.40%	1.2	$87.50	3.70%	1.5	$93.30	4.60%	1.6	$104.50	4.80%
San Joaquin Valley	San Joaquin Valley	1.1	$55.20	5.10%	1.1	$55.60	4.80%	1.1	$56.00	4.80%	1.4	$71.00	4.30%
San Joaquin Valley	Other Regions	0.5	$22.40	1.80%	0.7	$39.00	2.90%	0.8	$39.40	3.00%	0.9	$46.50	2.80%
Other Regions	Other Regions	0	$2.30	0.20%	0.1	$5.50	0.80%	0.2	$6.10	0.80%	0.2	$7.30	0.80%
Long-Distance Total		**11.4**	**633.5**	**1.70%**	**19.3**	**1,080.00**	**2.70%**	**28.6**	**1,368.60**	**4.00%**	**34.2**	**1,641.80**	**4.10%**
MTC (< 50 miles)	MTC (< 50 miles)	–	–	0.00%	0	$0.20	0.00%	0.4	$7.40	0.00%	0.5	$8.60	0.00%
SCAG (< 50 miles)	SCAG (< 50 miles)	–	$0.00	0.00%	–	$0.00	0.00%	0.1	$1.70	0.00%	0.1	$1.60	0.00%
Short-Distance Total**		**–**	**0**	0.00%	**0**	**0.2**	0.00%	**0.5**	**9.1**	0.00%	**0.5**	**10.2**	0.00%
Total		**11.4**	**$633.50**	**0.00%**	**19.3**	**$1,080.20**	**0.10%**	**29.1**	**1,377.70**	**0.10%**	**34.7**	**$1,652.00**	**0.10%**

*With the exception of the SCAG and MTC regions, only long distance trips (trips made to locations 50 or more miles from a traveler's home) are shown in the table. In the SCAG and MTC regions, separate summaries of intraregional trips made to locations less than 50 miles from the travelers' homes are also shown.

**Only short-distance auto, hsr, and cvr modes are shown in this table.

Daily Station Boardings for Mid-Level Forecast Year Scenarios

The busiest stations in the IOS scenario are expected to be the two end-of-line stations – Merced (with 6,900 daily boardings) and San Fernando (with 11,500) – see Table 7.5. Palmdale is also expected to be a busy station, with 5,400 daily boardings.

Table 7.5 Forecast of Daily Station Boarding – IOS – 2022

Station	Between Regions	Within SCAG	Total
Merced	6,900		6,900
Fresno	3,000		3,000
Visalia	1,300		1,300
Bakersfield	3,200		3,200
Palmdale	5,400		5,400
San Fernando	11,500		11,500
Daily	31,300		31,300
Annual (Millions)	11.4		11.4

Source: Cambridge Systematics, Inc

The busiest stations in 2027 – besides the two end-of-line stations – are Fresno and Palmdale (Table 7.6). Daily boardings in Fresno are estimated to increase from 3,000 in 2022 to 4,200 in 2027, an increase of 40 percent. Daily boardings at Palmdale are estimated at 7,300, an increase of 35 percent from 2022 levels.

Table 7.6 Forecast of Daily Station Boardings – Bay to Basin: 2027

Station	Between Regions	Within SCAG	Within MTC	Total
San Jose	11,100	–	–	11,100
Gilroy	4,300	–	–	4,300
Merced	4,100	–	–	4,100
Fresno	4,200	–	–	4,200
Visalia	1,100	–	–	1,100
Bakersfield	3,800	–	–	3,800
Palmdale	7,300	–	–	7,300
San Fernando	17,100	–	–	17,100
Daily	53,000	–	–	53,000
Annual (Millions)	19.3	–	0.0	19.3

Source: Cambridge Systematics, Inc

With Los Angeles Union Station at the south end of the line, boardings at the San Fernando station (8,700 daily boardings) are expected to be significantly less than with the Bay to Basin Scenario – 17,100 (Table 7.7). Similarly, the station boardings at San Jose under this scenario – 8,000 are considerably less than the 11,100 forecast under the Bay to Basin Scenario. Nearly 5 percent of the daily boardings at San Francisco and 9 percent of the daily boardings at Millbrae are expected to be for trips within the Bay Area region. In 2040, daily station boardings at the San Francisco station are expected to be 18,900, an increase of 29 percent compared to the same service in year 2029 (Table 7.8). Boardings at the Los Angeles Union station are expected to increase by 13 percent compared to the boardings in year 2029.

Table 7.7 Forecast of Daily Station Boardings – Phase 1: 2029

Station	Between Regions	Within SCAG	Within MTC	Total
San Francisco (Transbay)	14,700	–	700	15,400
Millbrae	6,300	–	600	6,900
San Jose	8,000	–	200	8,200
Gilroy	4,500	–	–	4,500
Merced	3,400	–	–	3,400
Fresno	4,500	–	–	4,500
Visalia	1,200	–	–	1,200
Bakersfield	3,600	–	–	3,600
Palmdale	3,900	–	–	3,900
San Fernando	8,700	100	–	8,800
Los Angeles Union Station	19,600	100	–	19,700
Daily	78,400	200	1,500	80,100
Annual (Millions)	28.6	0.1	0.4	29.1

Source: Cambridge Systematics, Inc.

Table 7.8 Forecast of Daily Station Boardings – Phase 1:2040

Station	Between Regions	Within SCAG	Within MTC	Total
San Francisco (Transbay)	18,900	–	800	19,700
Millbrae	7,800	–	700	8,500
San Jose	10,000	–	200	10,200
Gilroy	5,700	–	–	5,700
Merced	3,900	–	–	3,900
Fresno	5,400	–	–	5,400
Visalia	1,600	–	–	1,600
Bakersfield	4,400	–	–	4,400
Palmdale	4,600	–	–	4,600
San Fernando	9,400	100	–	9,500
Los Angeles Union Station	22,100	100	–	22,200
Daily	93,800	200	1,700	95,700
Annual (Millions)	34.2	0.1	0.5	34.7

A. HSR Operating Plans

Initial Operating Service (IOS) – 2022

Dedicated Bus Connections – North

6 Peak Hours

Pattern#	1	2	3
Frequency of service (mins)	15	15	15
San Francisco	0		
Oakland	40		
Dublin Pleasanton BART	80		
Sacramento		0	
Elk Grove		10	
Lodi		35	
Stockton		60	
Modesto		120	
Denair/Turlock		155	
San Jose			0
Gilroy			40
Merced	200	200	150
# of buses	24	24	24
Transfer Time @ Merced	15	15	15

10 Off Peak Hours

Pattern#	1	2	3
Frequency of service (mins)	30	30	30
San Francisco	0		
Oakland	40		
Dublin Pleasanton BART	80		
Sacramento		0	
Elk Grove		10	
Lodi		35	
Stockton		60	
Modesto		120	
Denair/Turlock		155	
San Jose			0
Gilroy			40
Merced	200	200	150
# of buses	20	20	20
Transfer Time @ Merced	15	15	15

HSR Patterns

6 Peak Hours

	62	70	22	42
Frequency	60	60	60	60
Run times from start in minutes				
Merced	0	0	0	0
Fresno	19	25	25	19
Visalia	38	44	35	29
Bakersfield	69	69	66	60
Palmdale	100	106	97	97
San Fernando	126	132	123	123
# of Trains	6	6	6	6

10 Off Peak Hours

	67	27
Frequency	60	60
Run times from start in minutes		
Merced	0	0
Fresno	25	25
Visalia	44	35
Bakersfield	75	66
Palmdale	112	97
San Fernando	138	123
# of Trains	10	10

Dedicated Bus Connections – South

Pattern#	1	2	3
Transfer Time @ San Fernando	15	15	15
Frequency of service (mins)	15	15	15
San Fernando (bus)	0	0	0
Burbank Airport (bus)	12		
Los Angeles Union Station (bus)	37		
Van Nuys (bus)		12	
West Los Angeles (bus)		32	
Santa Anita (bus)			40
# of buses	24	24	24

Pattern#	1	2	3
Transfer Time @ San Fernando	15	15	15
Frequency of service (mins)	30	30	15
San Fernando (bus)	0	0	0
Burbank Airport (bus)	12		
Los Angeles Union Station (bus)	37		
Van Nuys (bus)		17	
West Los Angeles (bus)		37	
Santa Anita (bus)			40
# of buses	20	20	20

Bay-to-Basin – 2027

Dedicated Bus Connections – North

Peak Period
6 Peak Hours

Pattern#	1	2
Frequency of service (mins)	30	30
San Francisco	0	
Oakland	40	
Dublin Pleasanton BART	80	
Sacramento		0
Elk Grove		10
Lodi		35
Stockton		60
Modesto		120
Denair/Turlock		155
Merced	200	200
# of buses	12	12
Transfer Time @ Merced	15	15

Off-peak
10 Off Peak Hours

Pattern#	1	2
Frequency of service (mins)	60	60
San Francisco	0	
Oakland	40	
Dublin Pleasanton BART	80	
Sacramento		0
Elk Grove		10
Lodi		35
Stockton		60
Modesto		120
Denair/Turlock		155
Merced	200	200
# of buses	10	10
Transfer Time @ Merced	15	15

HSR Patterns

High Speed Rail - Peak

Pattern	30	40	50	60	70	80
Frequency	60	60	60	60	60	60
San Jose	0	0	0	0		
Gilroy	15	18	18	18		
Merced					0	0
Fresno	59	56	62	56	19	25
Visalia	69	72	72	66	29	44
Bakersfield	100	97	97	97	54	75
Palmdale	131	134	134	128	91	106
San Fernando	154	157	157	151	114	129
# of Trains	6	6	6	6	6	6

High Speed Rail - Off-peak

Pattern	25	35	40	85
Frequency	60	60	60	60
San Jose	0	0	0	
Gilroy	15	18	18	
Merced				0
Fresno	59	62	56	25
Visalia	69	72	72	35
Bakersfield	100	103	97	66
Palmdale	137	134	134	103
San Fernando	160	157	157	126
# of Trains	10	10	10	10

Dedicated Bus Connections – South

Pattern#	1	2	3
Frequency of service (mins)	10	10	10
San Fernando (bus)	0	0	0
Burbank Airport (bus)	12		
Los Angeles Union Station (bus)	37		
Van Nuys (bus)		17	
West Los Angeles (bus)		37	
Santa Anita (bus)			40
# of buses	36	36	36

Pattern#	1	2	3
Frequency of service (mins)	15	15	15
San Fernando (bus)	0	0	0
Burbank Airport (bus)	12		
Los Angeles Union Station (bus)	37		
Van Nuys (bus)		17	
West Los Angeles (bus)		37	
Santa Anita (bus)			40
# of buses	40	40	40

Phase 1– 2029

Dedicated Bus Connections – North

Dedicated Coach - Peak Period

Frequency	30
Sacramento	0
Elk Grove	10
Lodi	35
Stockton	60
Modesto	120
Denair/Turlock	155
Merced	200
# of buses	12
Transfer Time @ Merced	15

Dedicated Coach - Off-peak Period

Frequency	60
Sacramento	0
Elk Grove	10
Lodi	35
Stockton	60
Modesto	120
Denair/Turlock	155
Merced	200
# of buses	10
Transfer Time @ Merced	15

HSR Patterns

High Speed Rail - Peak

Pattern	10	20	30	40	50	60	70	80
Frequency	60	60	60	60	60	60	60	60
San Francisco Transbay	0	0	0	0				
Millbrae	16	16	16	16				
San Jose	42	42	48	48	0	0		
Gilroy	53	57	63	66	18	15		
Merced							0	0
Fresno	89	101	107	104	62	53	19	25
Visalia	98	111	117	120	72	63	29	44
Bakersfield	122	142	148	145	97	94	54	75
Palmdale	151	179	179	182	134	125	91	106
San Fernando	170	199	199	208	154	145	111	132
Los Angeles	180	210	210	219	165	156	122	143
# of Trains	6	6	6	6	6	6	6	6

High Speed Rail - Off-peak

Pattern	10	25	35	40	85
Frequency	60	60	60	60	60
San Francisco Transbay	0	0	0	0	
Millbrae	16	16	16	16	
San Jose	42	48	48	48	
Gilroy	53	63	66	66	
Merced					0
Fresno	89	107	110	104	25
Visalia	98	117	120	120	35
Bakersfield	122	148	151	145	66
Palmdale	151	185	182	182	103
San Fernando	170	205	202	208	129
Los Angeles	180	216	213	219	140
# of Trains	10	10	10	10	10

Phase 1 – 2040

Dedicated Bus Connections – North

Dedicated Coach - Peak Period

Frequency	30
Sacramento	0
Elk Grove	10
Lodi	35
Stockton	60
Modesto	120
Denair/Turlock	155
Merced	200
# of buses	12
Transfer Time @ Merced	15

Dedicated Coach - Off-peak Period

Frequency	60
Sacramento	0
Elk Grove	10
Lodi	35
Stockton	60
Modesto	120
Denair/Turlock	155
Merced	200
# of buses	10
Transfer Time @ Merced	15

HSR Patterns

High Speed Rail - Peak

Pattern	10	20	30	40	50	60	70	80
Frequency	60	60	60	60	60	60	60	60
San Francisco Transbay	0	0	0	0				
Millbrae	16	16	16	16				
San Jose	42	42	48	48	0	0		
Gilroy	53	57	63	66	18	15		
Merced							0	0
Fresno	89	101	107	104	62	53	19	25
Visalia	98	111	117	120	72	63	29	44
Bakersfield	122	142	148	145	97	94	54	75
Palmdale	151	179	179	182	134	125	91	106
San Fernando	170	199	199	208	154	145	111	132
Los Angeles	180	210	210	219	165	156	122	143
# of Trains	6	6	6	6	6	6	6	6

High Speed Rail - Off-peak

Pattern	10	25	35	40	85
Frequency	60	60	60	60	60
San Francisco Transbay	0	0	0	0	
Millbrae	16	16	16	16	
San Jose	42	48	48	48	
Gilroy	53	63	66	66	
Merced					0
Fresno	89	107	110	104	25
Visalia	98	117	120	120	35
Bakersfield	122	148	151	145	66
Palmdale	151	185	182	182	103
San Fernando	170	205	202	208	129
Los Angeles	180	216	213	219	140
# of Trains	10	10	10	10	10

B. Risk Factors and Model Approach

This section provides additional details related to the risk analysis. It covers:

- The potential risk factors and implications for forecasting; and
- The full model runs and regression analysis.

B.1 Potential Risk Factors and Implications for Forecasting

Cambridge Systematics considered a broad range of factors that could influence ridership and revenue on the California High Speed Rail system. Our evaluation of these risk factors and how they were handled in our analysis is provided on the pages that follow.

Table B.1 California High Speed Rail Ridership and Revenue Forecasts for 2014 Business Plan Potential Risk Factors and Implications for Forecasting

Risk Factor	Discussion
Future Expectations Risks	
State Growth and Fiscal Changes: (relative to CSTDM projections):	
Overall Growth: 1) Increase or decrease in overall expected level of households and/or employment; 2) Variation in growth rates over time.	CS has documented substantial variation in long-range population and employment forecasts over the last 10 years. While current forecasts from different sources show similarities in the 2040/2050 timeframe, the sources differ as to growth rates in intervening years. This is a significant uncertainty, and likely to be included in the risk analysis.
Household Income: Changes in the number of high/middle/low income households throughout the State or in certain regions.	This is an important consideration since interregional trip rates vary by household income levels. Latest SANDAG forecasts show overall shift to poorer households. Other demographers are projecting increase in unskilled immigration combined with increased domestic out-migration of skilled labor. The current CSTDM socioeconomic projections may be the most optimistic scenario in terms of household income. Capturing the range of potential permutations here, especially at the regional level would be an enormous effort. We suggest that we keep this analysis at the state level, and evaluate uniform changes first in a sensitivity evaluation, and then determine if inclusion in the Monte Carlo simulation is warranted.
Household Size: Changes in number of residents or workers per household.	This is an important consideration since interregional trip rates vary between household size and workers/household. There is high uncertainty in household size characteristics given current state growth policies, aging population, and large reductions in fertility rates among immigrant populations. We also need to explore the extent to which household size is correlated with household income. After we review alternative socioeconomic forecasts, we will develop sensitivity tests to evaluate the impacts of these factors, and then decide whether to include them in the Monte Carlo simulation.

Risk Factor	Discussion
Regional Spatial Distribution: Changes in planned development densities and/or housing types within major metropolitan areas.	California MPOs are projecting increased development density and "jobs-housing balance" as a result of SB-375. Much new growth is being assumed in areas well-served by transit and in proximity to HSR stations. Both assumptions represent a departure from trend conditions. We suggest one scenario as a sensitivity test that assumes continuation of trend development patterns rather than increased development density and jobs/housing balance throughout the State. This will provide a sense of scale of the impact on potential high-speed rail ridership.
Statewide Spatial Distribution: Different household and employment allocation between San Diego, SCAG, San Joaquin Valley, Bay Area, and Sacramento regions.	As noted above, state policy is trying to encourage more jobs-housing balance, particularly for the San Joaquin Valley and Inland Empire. This policy shift seems to be playing out in the MPO employment forecasts (instead of households). We suggest handling this factor as part of "regional spatial distribution" alternate scenario.
Job Types: Changes in job growth rates in key industries.	This is more subtle, and more difficult to evaluate in the risk analysis. If deemed important, can handle with sensitivity tests.
Changes in large California attractions: • Beaches wiped out due to climate change or manmade disaster (e.g., oil spill) • Yosemite and other natural parks eliminated (or less attractive) due to Federal budget cuts or climate change • Disneyland closes • Googleland and Facebookland open to public in Silicon Valley	Over the course of a generation or two, it is reasonable to expect that people's tastes will change, and long-time popular attractions could go out of business or reduce in size. Witness the rise and fall and rise of Atlantic City, New Jersey. While not impossible, we believe these risks are so speculative that they can be ignored in the risk analysis, but can be suggested as considerations in our report.
Transportation System Changes:	
Automobile fuel cost	The cost of auto fuel is volatile both in short term and over the long term, subject to the uncertainties of geology, global economics and geopolitics, environmental concerns and others. Our previous analysis showed considerable sensitivity to this variable. Therefore, we suggest that this variable be incorporated directly into the risk analysis.

Risk Factor	Discussion
Highway capacity	Highway capacity assumptions in key urban and interregional corridors could be different than planned for any number of reasons, but in particular, more or less funding than implied by adopted plans, increased O&M costs which will leave less funding for new capacity, and policy shifts for or against highway expansion. Highway capacity assumptions affect peak and off-peak travel speeds, which in turn affects each model step. Alternate highway capacities should be evaluated as a sensitivity test. Changing the highway network is a labor intensive exercise that then requires rerunning highway skims. In the past, we have tested the effect of changing highway travel times by factoring up or down the travel time skims. We will test the implications of differences in skims first in a sensitivity test, and then with further tests if found to be significant.
Security/screening changes resulting in longer or shorter terminal times for air, high speed rail, or conventional rail.	Security screening on HSR could increase terminal times. It could also change the mode specific constant (due to increased inconvenience in relation to air and conventional rail). Since HSR security screening is outside of the HSRA's control, we should include this in the risk analysis. We believe the most important risk relates to potential screening for high speed rail. Since the impact of terminal time is rolled into the constant, we will incorporate this risk analysis into the overall testing of the high speed rail constant described under model-related risks.
Airline ticket prices and frequency of service: • Increase or decrease in ticket prices due to factors such as fuel cost or competitive response. • Increase or decrease in frequency due to competitive response • Changes in pricing policies, such as elimination of baggage and other fees, or increases in such fees (relative to today's levels).	Since airlines compete directly with HSR service, and price is an important factor we suggest a range of airline cost levels is appropriate in the risk analysis. Similarly, airlines could choose to reduce or eliminate air service in certain markets in response to rail competition. It's also possible that nonstop service could be introduced between additional California city pairs as a competitive response. We will use the range of airline ticket prices developed for the last Business Plan by Geoff Gosling as a basis for this business plan. This variable should be incorporated directly into the risk analysis.

Risk Factor	Discussion
Changes to the automobile travel experience, such as: • Readily available real time traveler information • Driverless cars (e.g., Google Cars)	Real time traveler information has become common in the last few years. Although it will help people make choices about when they might drive, we do not expect it to be a big factor in choosing driving over traveling by rail. Driverless cars, on the other hand, would significantly change the driving experience, creating, in essence, a new travel mode. We have not included driverless cars in our stated-preference surveying efforts, so incorporating this new mode into our analysis would not be possible for the 2014 Business Plan. However, we should point this out as a potential risk factor in our documentation (as we did for the 2012 Business Plan), and consider sensitivity tests that change the attractiveness of automobile travel.
Changes in HSR service characteristics, such as frequency, price, or travel time, or introduction of airport style security lines.	There could be a variety of reasons why the HSR service might not be delivered as proposed in the 2014 Business Plan. While these are real risks, our analysis will be cleaner and easier to understand if we assume the service levels proposed by the HSRA and handle any variations in these service levels as system alternatives that could be handled with sensitivity tests. However, some of the recent criticisms about the California High Speed Rail project focus on disbelief that the HSRA can achieve the service characteristics proposed. A separate analysis of the implications of less favorable characteristics would be reasonable.
Model Related Risks	
Overall amount of long distance travel. This aspect of model-related risk is related almost exclusively to the trip frequency model.	This could be reflected in the trip frequency values, and would be an appropriate value to test in the risk analysis. It could be reflected by a modification of the alternative specific constants for "make a trip."
Amount of travel by trip purpose. This aspect of model-related risk is also associated almost exclusively with the trip frequency model.	Home-based long distance travel is forecast for four different trip purposes: business, commute, recreation, and other. The variability in the percentage of trips for each trip purpose found by different surveys suggests that either the "true" distribution of trips by purpose are not adequately captured, or that the distribution of trips by purpose varies over time. The existence of this variability within the surveys, suggests that the proportion of trips by purpose would be a good candidate for adjusting within the risk analysis model by adjusting the calibrated constants.

Risk Factor	Discussion
Amount of travel induced by the introduction of HSR. This aspect of model-related risk is related to both the trip frequency and destination choice models	There are two components of induced travel on HSR: 1) new travel resulting from increased accessibility afforded by HSR (we'll call this) and 2) new travel on HSR resulting from changes in destination choice due to the increased accessibility afforded by HSR (we'll call this). We'll call the first type of induced travel "raw induced travel" and the second type "destination induced travel." We'll call the sum of the two, "total induced travel." While the amount of total induced travel can have high variability within the forecasts, we expect that raw induced travel will comprise a small percentage of overall HSR ridership. The impacts of raw induced travel can be accounted for in the total amount of long distance travel analyzed through changes in trip frequency. The destination induced travel impacts are probably greater. However, these impacts can probably be taken into account through the analysis of different land use patterns. Alternatively, they might be analyzed through varying the logsum coefficients in the destination choice models. A sensitivity test might be warranted.
Share of travel that can be captured by HSR. This aspect of model-related risk is related exclusively to the main mode choice model.	Since HSR does not exist in the United States, the only basis for estimating the relative attractiveness of HSR to other modes comes from the stated-preference survey. We cannot calibrate the HSR constant to actual HSR service. Some variation in this value would be appropriate in the risk analysis.

B.2 Model Runs Used in Ridership and Revenue Forecasting

Once the risk factors and their distributions were defined, the full ridership and revenue model was run to obtain input into the Risk Analysis regression equations. We began by running a "mid-level" model run with all six factors set at the mid value (see Experiment Number 1 in Table B.2) for each forecast year. To limit the number of model runs to a reasonable level we pursued a fractional 2-level factorial design for running the full model. Thirty-two runs (Experiment Numbers 2-33 in Table B.2) were used to estimate all the main effects and two-factor interactions resulting from varying the input data. This design, which was only one-half of the 64 runs required for a full 2-level factorial design for 6 factors, saved run time but could not be used to estimate interactions between three or more factors. However, we do not have reason to believe there would be large high-order interactions among the risk factors we selected. Additional runs with data points between the mid level and low level, and between the mid-level and high-level values of each risk factor distribution were added to provide information regarding the nonlinearity of the forecast distributions and to ensure that the regression models represented the middle values within the distributions, and not just the extremes (Experiment Numbers 34-47 in Table B.2). These additional runs were important since the regression models, discussed in the next section, were exponential rather than linear.

Table B.2 Ridership and Revenue Version 2.0 Model Run Experiments for each Forecast Year

Experiment Number	Overall Growth	Regional Spatial Distribution	Auto Operating Cost	Airline Fares	HSR Mode Choice Constant	Trip Frequency Constant
1	Mid	Mid	Mid	Mid	Mid	Mid
2	Low	Low	Low	Low	Low	Low
3	Low	Low	Low	Low	High	High
4	Low	Low	Low	High	Low	High
5	Low	Low	Low	High	High	Low
6	Low	Low	High	Low	Low	High
7	Low	Low	High	Low	High	Low
8	Low	Low	High	High	Low	Low
9	Low	Low	High	High	High	High
10	Low	High	Low	Low	Low	High
11	Low	High	Low	Low	High	Low
12	Low	High	Low	High	Low	Low
13	Low	High	Low	High	High	High
14	Low	High	High	Low	Low	Low
15	Low	High	High	Low	High	High
16	Low	High	High	High	Low	High
17	Low	High	High	High	High	Low
18	High	Low	Low	Low	Low	High
19	High	Low	Low	Low	High	Low
20	High	Low	Low	High	Low	Low
21	High	Low	Low	High	High	High
22	High	Low	High	Low	Low	Low
23	High	Low	High	Low	High	High
24	High	Low	High	High	Low	High
25	High	Low	High	High	High	Low
26	High	High	Low	Low	Low	Low
27	High	High	Low	Low	High	High
28	High	High	Low	High	Low	High
29	High	High	Low	High	High	Low
30	High	High	High	Low	Low	High
31	High	High	High	Low	High	Low
32	High	High	High	High	Low	Low
33	High	High	High	High	High	High
34	High	High	Mid	Mid	Mid	Mid
35	Mid	High	Mid	Mid	Mid	Mid
36	Mid	Mid	Mid	MidHigh	MidLow	MidLow
37	Mid	Mid	MidHigh	Mid	MidLow	MidLow
38	Mid	Mid	Mid	MidLow	MidLow	MidHigh
39	Mid	Mid	MidHigh	Mid	MidLow	MidHigh
40	Mid	Mid	MidLow	Mid	MidHigh	MidHigh
41	Mid	Mid	Mid	Mid	MidHigh	MidLow
42	Mid	Mid	MidLow	MidLow	MidHigh	MidHigh
43	Mid	Mid	Mid	MidHigh	MidHigh	MidLow
44	Mid	Mid	Mid	Mid	Low	Mid
45	Mid	Mid	Mid	Mid	MidLow	Mid
46	Mid	Mid	Mid	Mid	MidHigh	Mid
47	Mid	Mid	Mid	Mid	High	Mid

B.3 REGRESSION MODELS FOR RIDERSHIP AND REVENUE

Ridership versus Revenue

We began the analysis by testing the relationship between ridership and revenue resulting from the Version 2 Model runs. Revenue and ridership were closely correlated with a R^2 of more than 0.999 for each year. The relationship between ridership and revenue for each forecast year was as follows:

- Year 2022 Revenue = 55.147 * Ridership
- Year 2027 Revenue = 55.401 * Ridership
- Year 2029 Revenue = 47.467 * Ridership
- Year 2040 Revenue = 47.049 * Ridership

For all the 47 runs in each model year, the predicted revenues from the above equations were compared with the actual revenues, and the results show the differences between predicted revenue based on ridership versus actual revenue was between -9 percent and 5 percent.

Since revenue and ridership were highly correlated, we developed regression equations for revenue only and used the above relationships between revenue and ridership to calculate the corresponding ridership forecasts for the risk analysis.

Revenue Regression Models

Using the results from the ridership and revenue forecasts from each of the 47 full model runs, we estimated relationships between the revenue forecasts and the input risk factor levels. The Monte Carlo method, described in the next section, made it feasible to quickly produce the thousands of revenue forecasts based on varying levels of the input risk factor variables that were necessary to estimate probabilities of specific outcomes. The revenue forecasts produced using the Monte Carlo method were predicated on deterministic equations (in our case, the regression models). Therefore, special attention was given to the construction of the deterministic equations. We analyzed both linear and nonlinear transformations of model variables, and found that exponential relationship between revenue and risk factors resulted in the best model fits, with all forecast years having R^2 above 0.99. The differences between predicted revenues and estimated revenues from the full model runs was between ±5 percent. For each of the forecast years, the regression models had the following functional form:

*Revenue = exp (Intercept + a * Overall Growth + b * Regional Spatial Distribution + c * Auto operating cost + d * Airline fares + e * HSR Mode Choice Constant + f * Trip Frequency Constant)*

The coefficients and related statistical measures for each forecast year are shown in Tables B.3 through B.6. The standardized estimates show the estimated changes in revenue (in standard deviation units) when the specified input variable is increased by one standard deviation. For all years, the HSR mode choice constant has the highest standardized estimate, followed by the annual round trips per person and the auto operating cost.

Table B.3 Regression Equation for Year 2022 IOS

	Parameter Estimate	Standard Error	t Value	Pr > |t|	Standardized Estimate
Intercept	16.961	0.186	91.25	<.0001	0.000
Growth in Households	1.411	0.151	9.32	<.0001	0.059
Regional Spatial Distribution	2.491	0.506	4.93	<.0001	0.031
Auto Operating Cost	1.569	0.096	16.31	<.0001	0.102
Airline Fares	0.085	0.031	2.76	0.0088	0.017
HSR Mode Choice Constant	0.895	0.006	145.27	<.0001	0.912
Annual Round Trips/Person	0.137	0.002	62.88	<.0001	0.395
Adjusted R-square	0.998				

Table B.4 Regression Equation for Year 2027 Bay-to-Basin

	Parameter Estimate	Standard Error	t Value	Pr > |t|	Standardized Estimate
Intercept	17.580	0.152	115.75	<.0001	0.000
Growth in Households	1.343	0.111	12.04	<.0001	0.091
Regional Spatial Distribution	1.461	0.450	3.25	0.0024	0.024
Auto Operating Cost	1.692	0.109	15.59	<.0001	0.117
Airline Fares	0.098	0.034	2.87	0.0065	0.021
HSR Mode Choice Constant	0.827	0.007	120.50	<.0001	0.898
Annual Round Trips/Person	0.137	0.002	56.46	<.0001	0.421
Adjusted R-square	0.997				

Table B.5 Regression Equation for Year 2029 Phase 1

	Parameter Estimate	Standard Error	t Value	Pr > |t|	Standardized Estimate
Intercept	17.961	0.135	133.54	<.0001	0.000
Growth in Households	1.302	0.095	13.68	<.0001	0.107
Regional Spatial Distribution	0.876	0.413	2.12	0.0400	0.016
Auto Operating Cost	1.631	0.103	15.87	<.0001	0.124
Airline Fares	0.093	0.034	2.74	0.0091	0.021
HSR Mode Choice Constant	0.791	0.007	116.32	<.0001	0.891
Annual Round Trips/Person	0.136	0.002	56.56	<.0001	0.433
Adjusted R-square	0.997				

Table B.6 Regression Equation for Year 2040 Phase 1

	Parameter Estimate	Standard Error	t Value	Pr > |t|	Standardized Estimate
Intercept	18.010	0.090	200.32	<.0001	0.000
Growth in Households	1.232	0.052	23.78	<.0001	0.198
Regional Spatial Distribution	1.022	0.328	3.12	0.0034	0.026
Auto Operating Cost	1.767	0.106	16.71	<.0001	0.140
Airline Fares	0.106	0.039	2.74	0.0092	0.023
HSR Mode Choice Constant	0.785	0.008	103.79	<.0001	0.869
Annual Round Trips/Person	0.136	0.003	51.06	<.0001	0.426
Adjusted R-square	0.997				