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Quantifying Major Travel Delay Reduction Benefits from Shifting Air Passenger Traffic to Rail

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Quantifying Major Travel Delay Reduction Benefits from Shifting Air Passenger Traffic to Rail

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16. Abstract

This study provides a method to quantify the benefits of reducing the costs from flight delays by shifting air passenger traffic to high-speed rail (HSR). We first estimate the number of flight reductions by each quarter hour for airport origin and destination pairs based on HSR ridership forecasts in the California High-Speed Rail 2020 Business Plan. Lasso models are then applied to estimate the impact of the reduced queuing delay at SFO, LAX and SAN airports on arrival delays at national Core 29 airports. Finally, these delay reductions are monetized using aircraft operating costs per hour and the value of passenger time per hour. We apply several different variations of this approach, for example, considering delay at all 29 Core airports or just major California airports, different scenarios for future airport capacity and flight schedules, and different forecasts for future HSR ridership. We estimate mid-range delay cost savings of $51-88 million (2018 dollars) in 2029 and $235-392 million (2018 dollars) in 2033. The estimated savings are similar to, but slightly lower than, those based on cost estimates to upgrade airport capacity to handle passenger traffic that could be diverted to HSR.

17. Key Words High speed rail, air travel, ridership, forecasting, mathematical models, flight delays, mathematical models, airport capacity, railroad capacity, cost analysis	**18. Distribution Statement** No restrictions.

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About the UC Institute of Transportation Studies

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Disclaimer

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Executive Summary

Executive Summary

The 2015 Interregional Transportation Strategic Plan (Caltrans, 2016) identifies high-speed rail (HSR) as the highest transportation priority for the travel corridor between the San Francisco Bay Area and Los Angeles. While HSR benefits are difficult to quantify they include reducing traffic demands on California's roads and airports. The California High-Speed Rail Authority (CHSRA) 2020 Business Plan estimates these benefits, using "equivalent capacity analysis," which compares the cost of adding to the state's existing network of highways and airports to support the equivalent intrastate people-carrying capacity of high-speed rail. The CHSRA assumes that 20 percent the state's air travelers will instead choose to take HSR when the full Phase 1 is completed and that the state could forego a total of $23.9 billion (2019 dollars) in airport capacity improvements as a result. There are two main issues with this methodology. First, it overestimates future HSR ridership by basing it on *planned* train capacity of 66.2 million passengers annually, rather than projected actual ridership demand, which we estimate will be closer to 35.6 million. Second, based on airport data from the Federal Aviation Administration (FAA) and the Bureau of Transportation Statistics, we project that the passenger reductions will be more in the range of 5-7 percent and that therefore the savings will be more on the order of $4.6 billion (2019 dollars).

In addition to revising the estimated CHSRA construction cost savings, this study provides an alternative method of quantifying benefits based on savings from reducing flight delays by shifting air passengers to HSR. We first estimate the number of flight reductions for airport origin and destination pairs based on the HSR ridership forecast provided in 2020 Business Plan and then distribute these flight reductions to quarter hours to calculate queuing delays. After that, we apply machine learning models to estimate the impact of the reducing queuing delay at San Francisco (SFO), Los Angeles (LAX) and San Diego (SAN) airports on the arrival delays at other national Core 29 airports. Finally, we estimate the value of these delay reductions using aircraft operating costs per hour and the value of passenger time per hour.

Based on our estimates of reduced flight delays at three major California airports from a middle range of projected ridership forecasts and the effect that this would have at airports across the nation, we estimate delay cost savings of $51-88 million (2018 dollars) nationally in 2029 and $235-392 million (2018 dollars) in 2033. The estimated savings are similar to, but slightly lower than, the annualized construction cost saving of $504 million (2018 dollars) per year based on the (adjusted) CHSRA analysis method, even assuming airport capacity improvements and other flight scheduling adjustments are made. Even greater delay savings from HSR can be achieved if those improvements are not made, in addition to the (adjusted) estimated savings from foregone construction costs.

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Introduction

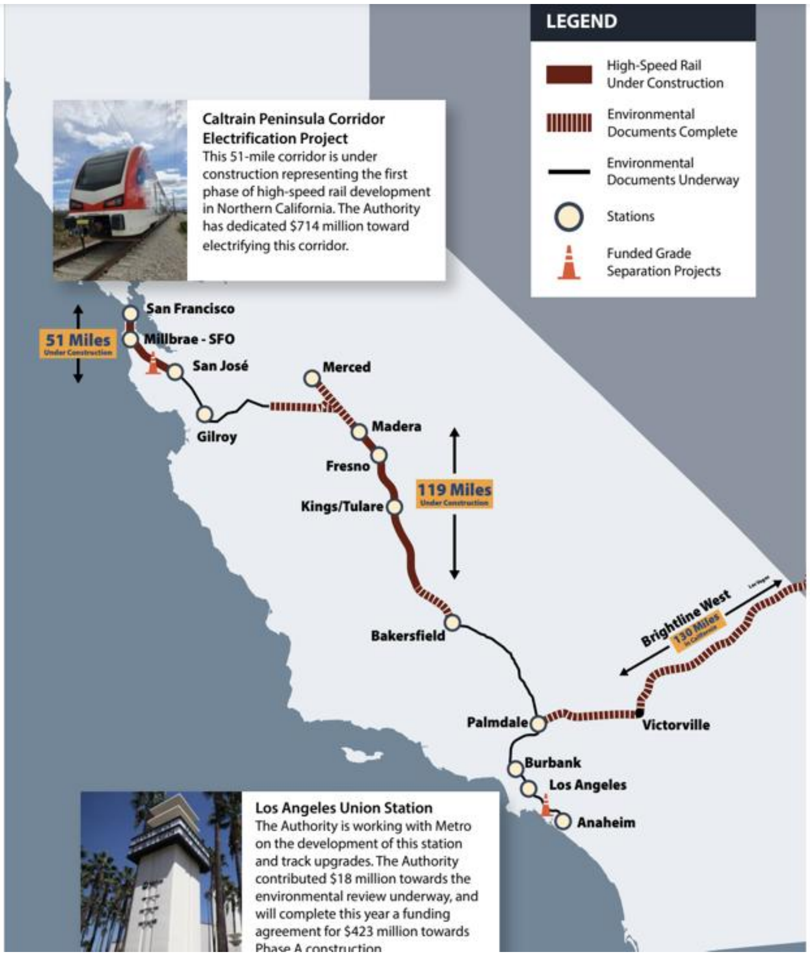

Figure 1. California HSR Development Status as of 2020

Source: CHSRA 2020 Business Plan

California High-Speed Rail (HSR) is a publicly funded high-speed rail system under construction in the state of California. Voters approved the HSR plan, or Proposition 1A, in 2008 and assigned the proceeds of a $9 billion bond to begin construction. According to the latest Business Plan 2020 by the California High-Speed Rail Authority (CHSRA) (2021), the Initial Phase is projected to provide service in the 171-mile segment from Merced to Bakersfield in the Central Valley starting from 2029. Full Phase 1 will later connect the Anaheim Regional Transportation Intermodal Center in Anaheim and Union Station in Downtown Los Angeles with the Salesforce Transit Center in San Francisco via the Central Valley in 2033. The 51-mile segment from San Francisco to San Jose and the 119-mile segment from Madera to Bakersfield are currently under development (see Figure 1). The ride between Union Station and San Francisco will cover a total distance of 380 miles and take 2 hours and 40 minutes. Future extensions (in Phase 2) are planned to connect southward to stations in San Diego County via the Inland Empire, as well as northward to Sacramento, by 2040.

Meanwhile, California has two of the ten busiest airports in the country in terms of numbers of both flights and passengers. The route from Los Angeles International Airport (LAX) to San Francisco International Airport (SFO) is the ninth busiest domestic route in the world (Official Aviation Guide, 2019). Data from the Bureau of Transportation Statistics (BTS)[1] further show that inter-regional travel between the five primary airports in the Los Angeles Basin and the three primary airports in the San Francisco Bay Area, which amounts to over 13 million people per year, is the highest in the U.S. California airports are also becoming increasingly capacity-constrained (Eno Center for Transportation, 2013; Hall, 2006) and are experiencing worsening delays. SFO, which has 23 percent of flights delayed by at least 15 minutes, ranks as the third worst delayed airport in the country.

Though there was a substantial downturn in travel demand in 2020 due to the pandemic, travel demand and operations levels are rebounding and bringing back congestion mitigation challenges. While the airports have been actively seeking solutions to increase capacity (e.g., expanding terminals, adding new gates) (CHSRA, 2019), another option is to encourage air passengers to shift to HSR as it becomes operational.

According to the state's 2015 Interregional Transportation Strategic Plan (California Department of Transportation, 2016), HSR is the highest priority for transportation development for the travel corridor between the San Francisco Bay Area and Los Angeles to reduce traffic demands on California roads and airports. The need to better understand and quantify the benefits of shifting traffic demands from other modes to HSR has attracted increasing research attention in recent years.

The current approach to evaluating the public benefits of HSR used by the CHSRA in its latest 2020 Business Plan, called "*Equivalent Capacity Analysis (ECA)*," monetizes the value of reducing the need for expensive airport capital improvements (new gates, terminals, runways, etc.) by diverting some travelers away from taking airplanes, and using HSR instead. The details of ECA will be presented in Section 2. It should be noted, however, that some California airports are close to their maximum passenger limits and cannot be expanded further. There are several issues with this approach, including the fact that it bases its projections of HSR ridership on the planned capacity of the trains rather than projections of actual future passenger demand, which can vary widely. It also ignores additional savings from reducing flight delays and cancellations that can be attributed to some air passengers switching to HSR.

This study corrects these errors in the ECA method and provides an alternative and complementary method to quantify the benefits to air traffic induced by HSR operations based on reducing the frequency and duration of flight delays. The contributions of this study are:

(1) It uses a range of HSR demand forecasts instead of planned HSR capacity to project ridership, which is less likely to overestimate future benefits;

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[1] Air Carrier Statistics database, T-100 Domestic Segment. US Department of Transportation, Bureau of Transportation Statistics

(2) It is the first work to apply queuing theory and machine learning models to quantify the potential impacts of HSR on air transportation, using a wide range of datasets;

(3) It is unique in measuring flight delay reductions based on the estimate cost savings of diverting air passengers to HSR;

(4) It captures benefits both within and beyond California by modeling flight delays for individual airports and the nation, while controlling for other factors including terminal conditions, en route weather, wind, traffic volume, and special events;

(5) It is entirely based on open-source data and is easily adaptable when more detailed and accurate ridership forecasts, airport capacity, and flight schedule information become available; and

(6) It develops methods for forecasting air demand and capacity by the quarter-hour, with and without considering HSR impact, which can be adapted to support other research endeavors that require detailed future demand and capacity forecasts.

This research report is organized as follows. Section 2 gives a review of current studies on HSR benefit analysis, with a special focus on the ECA method used by the CHSRA. Section 3 introduces the various data sources used in this study and Section 4 provides details about how we fuse them together to forecast future air travel capacity and demand, with and without HSR, to determine the impact of HSR on reducing the need to construct expensive new airport improvements, and the value of the cost savings. Section 5 introduces the methodology used to evaluate the impact of airline passengers shifting to HSR on the frequency of airport delays for California airports as well as national airports and Section 6 provides cost estimates for these delays. Finally, we discuss the pros and cons of our proposed approach and compare its results with those obtained from the CHRSA's equivalent capacity analysis in Section 7.

Existing Benefit-Cost Methodology Overestimates Airport Construction Savings from HSR

A widely used method to quantify the benefits of HSR in practice is Cost-Benefit Analysis, which evaluates the potential social and economic impacts of the proposed project (Tuleda et al., 2006). The costs considered usually include infrastructure costs, operating costs, and external costs (e.g., land resumption, barrier effects, noise), while the benefits usually include ticket revenues, travel time savings, pollution reduction, reliability improvement, safety improvement, and regional economic development (Derus and Inglada, 1997; Tao et al., 2011; Levinson et al., 1996; D'Alfonso et al., 2015). Many methods have been applied to assess these costs and benefits, including but not limited to game engineering methodology (Adler et al., 2010), multinomial and mixed logit models (Behrens and Pels, 2012), and optimization problem formalization (Yang and Zhang, 2012).

In this study, we focus on the benefits received by air transportation from HSR operation. A few papers have studied the complementary effects between HSR and air travel. Albalate et al. (2015) provided evidence that HSR can provide feede services to long-haul air services in hub airports, based on an empirical analysis of the European market. López-Pita and Robusté (2003) examined the possible effects of High-Speed Rail in reducing slots needed at Madrid Airport by comparing them to other studies carried out in Paris-Charles de Gaulle airport and Frankfurt airport. Zhang et al. (2018) found that air-HSR integration has significantly positive impacts on airport enplanement at primary hub airports in East Asian regions. Li and Rong (2019) assessed the impact of the HSR network on the resilience of the air transport network against random failure and malicious attack.

The current method for monetizing highway and airport traffic reduction benefits of California HSR used in the CHSRA 2020 Business Plan (CHSRA, 2021) is based on the Authority's 2019 Equivalent Capacity Analysis (ECA) Report (CHSRA, 2019).[2] This analysis compares the cost of adding capacity to the state's existing network of highways and airports that would otherwise be required to accommodate the growth in passenger traffic that is forecast to be diverted to high-speed rail. We focus here solely on the impact on air travel. Detailed steps of the CHRSA analysis are as follows:

[2] The discussion in this section, including the reproduced tables, is taken from the CHSRA 2019 Equivalent Capacity Analysis Report.

1. Estimate high-speed rail's total "people-carrying" capacity once completed using the following equation:

$$C_{hsr} = n_t \times s_t \times l_t$$

Where C_{hsr} is high-speed rail's total "people-carrying" capacity, which is 7,560 per hour in each direction; n_t is the potential frequency of trains, which is 12 trains per hour in each direction; s_t is the number of seats per train, which is 900; and l_t is the average load factor per train, which is 70 percent.

2. Assume that 20 percent of high-speed rail's capacity would be served by air travel if HSR were not built:

$$C_{air} = C_{hsr} \times p_{air}$$

Where C_{air} is the capacity to be served by air travel if HSR were not built, which is 1,512 passengers per hour per direction; p_{air} is the percentage of HSR's capacity to be served by air travel if HSR were not built, which is 20 percent.[3]

3. Distribute the required air capacity between the airports according to the estimates presented in the Travel Demand Model used in the 2018 Business Plan and overall flight patterns in California:

$$N_{pax} = C_{air} \times 4$$

$$N_i = N_{pax} \times \gamma_i$$

$$n_{f,i} = N_i/(s_f \times l_f)$$

Where N_{pax} is the total number of passengers accommodated, the multiplicator of 4 captures both directions and that each trip affects two airports, N_{pax} = 6,000 passengers per hour; N_i is the number of passengers accommodated at airport i; γ_i is the share of airport i in California; $n_{f,i}$ is the number of flights at airport i; s_f is the number of seats per flight, which is 125; l_f is the average load factor per flight, which is 74 percent.

4. Derive the needed number of gates and parking at each airport based on the assumptions of aircraft seating capacity, load factor, gate capacity, and runway capacity:

$$n_{g,i} = N_i/\delta_g$$

$$n_{p,i} = N_i/\delta_p$$

Where $n_{g,i}$ is the number of gates needed at airport i; δ_g is the gate capacity factor, which is 500,000 passengers per year per gate; $n_{p,i}$ is the number of parking spaces needed at airport i; δ_p is the parking space supply factor, which is 500 to 1,350 parking spaces per 1,000,000 passengers. The report does not specify

[3] The 20 percent diversion rate is based on the Travel Demand Model (TDM) used in the 2018 Business Plan to forecast ridership and revenue.

how the number of required runways is calculated but does summarize projected airport capacity needs, as shown in Table 1. Note that neither LAX nor SFO appear in the table as there is no further potential to add capacity once current and planned improvements are completed.

Table 1. Summary of Projected Airport Capacity Needs Using the Equivalent Capacity Analysis Method

Airport	% of Regional Travel	Passengers/Hours	Gates Needed	Runway Needed?
Los Angeles Basin — 43% of Total Diverted Air Travel by Region				
Burbank	29%	700	11	No
Ontario	19%	500	7	No
Long Beach	17%	450	7	No
Orange County	35%	900	13	No
Bay Area – 41% of Total Diverted Air Travel by Region				
Oakland	53%	1,300	19	Yes
San Jose	47%	1,200	17	Yes
San Diego – 6% of Total Diverted Air Travel by Region				
San Diego	100%	400	6	No
San Joaquin Valley – 3% of Total Diverted Air Travel by Region				
Fresno	92%	200	3	No
Bakersfield	8%	10	1	No
Sacramento – 5% of Total Diverted Air Travel by Region				
Sacramento	100%	300	5	No
Monterey – 2% of Total Diverted Air Travel by Region				
Monterey	100%	100	2	No
Total[27]		6,000	91	2

5. Calculate the airport expansion cost including the construction cost of runways, gates and parking, as well as any auxiliary costs. The summary of all estimated airport costs can be found in Table 2.

6. Consider the accuracy range of the cost estimation by assuming the potential cost increases of up to 30 percent and cost decreases of up to 20 percent.

Table 2. Summary of Estimated Airport Costs Using the Equivalent Capacity Analysis Method (Millions, 2018$ and Year of Expenditure$)

Airports	Per Unit	BUR	ONT	LGB	SJC	OAK	SNA	SAN	MRY	FAT	BFL	SMF	Total[36]
Gates	—	11	7	7	17	19	13	6	2	3	1	5	**91**
New Runways	—	0	0	0	1	1	0	0	0	0	0	0	**2**
Passenger Terminal Facilities Cost/Unit	6,976 $/m²	—	—	—	—	—	—	—	—	—	—	—	**—**
Passenger Terminal Facilities	—	139	171	131	341	195	219	97	29	25	15	58	**1,425**
Apron Cost/Unit	$1.2M ea	—	—	—	—	—	—	—	—	—	—	—	**—**
Aprons Total	—	14	10	8	22	25	18	7	2	4	1	6	**118**
Cost/Jetway	$0.6M/ea	—	—	—	—	—	—	—	—	—	—	—	**—**
Jetway Tota	—	8	5	5	12	14	10	4	1	2	1	3	**65**
Cost/Parking Space	$45,000/ea	—	—	—	—	—	—	—	—	—	—	—	**—**
Parking Total	—	175	114	106	272	308	159	32	11	29	1	71	**1277**
Cost/Runway	$36M/ea												
Runway Total	—	0	0	0	36	36	36	0	0	0	0	0	**109**
Developed Land Clearing	—	0	0	0	4,554	513	3,416	1,072	1	0	0	0	**9,556**
Utility Cos	—	0	0	0	236	6	106	23	0	0	0	0	**397**
ROW Cost	—	0	0	0	1,851	93	436	141	15	0	0	0	**2,562**
Env. Mitigation	—	10	9	8	165	33	119	37	1	2	1	4	**388**
Prog. Implementation	—	88	79	67	1,917	312	1,159	360	16	16	5	36	**4,054**
Contingency	—	87	77	66	1,879	306	1,136	353	15	15	5	35	**3,974**
Total – 2018 $	—	521	465	395	11,312	1,840	6,840	2,127	92	93	27	213	**23,924**
Total – YOE $	—	567	532	452	12,956	2,107	7,834	2,435	105	106	31	244	**27,400**

Note: For the purposes of this analysis, costs for equivalent highway and airport capacity were assumed to have the same timing as the capital costs for high-speed rail. As such, YOE costs were estimated using the same escalation rate, over the same time horizon used for high-speed rail Phase 1 system costs in the 2020 Business Plan, which assumed a 2033 completion date.

[36] Totals may not match sum due to rounding.

The results of this analysis indicate that a comparable airport infrastructure investment would require the construction of additional 91 gates and two runways across the state along with auxiliary facilities, with a total projected cost of $23.9 billion (2018 dollars) (CHSRA, 2019, Appendix B) and assuming a completion date of 2033 (same as Phase1 for rail).

Despite being simple and easy to understand, the ECA method does not consider some important factors. First, the ECA uses *planned* HSR capacity, instead of *forecasted* HSR demand, to estimate benefits. As a result, the benefits listed in the 2020 Business Plan are highly likely to be overestimated because the true demand is expected to be less than the planned design capacity (which includes excess capacity). Second, the current method only considers the benefits of air passengers shifting to HSR in terms of cost savings from comparable highway and airport capacity upgrades. It fails to capture a broader scope of benefits of HSR for passengers and society, for example, the fact that HSR is more punctual and reliable than air (Pagliara et al., 2012); that HSR has fewer accidents and fatalities, generates less noise and congestion, as well as improving air quality (Levinson et al., 1996); and that HSR can also increase accessibility of the region in general (Cao et al., 2013). Third, it ignores the potential benefits to the aviation industry, and the National Airspace System (NAS) on a broader scale. HSR will attract some current air passengers and may lead to a reduction in flight operations and relieve congested airspace and airport runways, bringing delay cost savings to the airlines and air passengers. This study improves the ECA method on the first and third points by using the CHSRA projected HSR ridership demand to calculate the potential number of passengers diverted from air to rail and by quantifying the additional savings from reducing flight delays attributable to those diversions. Our detailed methodology to quantify the air traffic delay reduction benefits induced by HSR operations will be introduced in Sections 4 and 5. In the next section we identify our data sources.

Data Sources for Estimating Air Travel Demand

In this study, we combine a wide range of data sources, mainly from two groups. The first group is the flight operation datasets used for air passenger capacity/demand forecasting and delay estimates. These sources are:

- The Aviation System Performance Metrics (ASPM) dataset from the Federal Aviation Administration (FAA),[4] which provides historical airport scheduled arrivals and departures for each quarter-hour, as well as capacity information determined by visibility, winds, and fleet mix. We collected more than 20 million quarter-hour observations over the analyzed airports (including the Core 30 airports[5] except for Honolulu International Airport) from 2010 to 2019. We also collected the ASPM flight-level dataset in order to calculate the traffic share between airport Origin-Destination (OD) pairs in California.
- The FAA Terminal Area Forecast (TAF),[6] which contains both historical records and future forecasts of the annual number of flight operations for the airports that we analyzed.
- The FAA Airport Capacity Profile,[7] which gives the model-estimated future hourly rate of arrivals and departures under certain runway configurations, flight rules, and separation standards. This dataset is available for the Core 29 airports only.
- The on-time performance dataset from the Bureau of Transportation Statistics (BTS) TranStats data library, which contains the positive arrival delay against schedule (in minutes), information on canceled and diverted flights, and the diverted arrival delay against schedule (in minutes) of each aircraft. Our flight delay metric – daily average arrival delay (in minutes per flight) — is computed based on Dai et al.'s (2021) work using this dataset. Only positive delay against schedule (not greater than 10 hours) is considered, where early arrivals are counted as zero delay. A flight cancellation is counted as a 120-minute delay and the diverted arrival delay against schedule time is used for diverted flights. Flights are assigned to days based on their scheduled arrival time.

The second group of datasets includes HSR ridership forecasts, historical mode share information, and air carrier data, which are used to forecast the flight reductions resulting from passengers shifting to HSR. These are:

- The CHSRA 2020 Business Plan Ridership and Revenue Forecasting Technical Report,[8] which gives annual HSR ridership forecasts for each major regional market in the state for the year 2029 (the completion year of the Central Valley segment) and 2033 (the completion year of the full Phase 1),

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[4] Aviation System Performance Metrics (ASPM) – ASPMHelp.
https://aspm.faa.gov/aspmhelp/index/Aviation_System_Performance_Metrics_(ASPM).html

[5] FAA Operations & Performance Data. Federal Aviation Administration.

[6] Terminal Area Forecast (TAF). https://www.faa.gov/data_research/aviation/taf/

[7] Airport Capacity Profiles - Airports. https://www.faa.gov/airports/planning_capacity/profiles/

[8] Table 5.3 Comparison of Annual Ridership and Revenue by Major Market

as shown in the third and the fourth columns of Table 3. These point estimates, which will be referred as “base run” results in the following sections, are ridership estimates using the base input values (HSR train frequency, ticket price, etc.). The CHSRA Ridership and Revenue Model Documentation (2016) also give range estimates, i.e., different quantiles (minimum, 1%, 10%, 25%, median, 75%, 90%, 99%, maximum) of ridership based on a Monte Carlo simulation (Table 4). Overall, the CHSRA projected between 8.6 million and 109.8 million HSR passengers in 2033 with a median estimate of 35.6 million, compared to the CHSRA’s ECA estimate of 66.2 million.

The CHSRA Ridership and Revenue Model Documentation (2016),[9] which includes results from the 2012-2013 California Household Travel Survey for before-HSR-time mode share of auto, air, and conventional rail for the major markets. These numbers are shown in the fifth through seventh columns of Table 3.

Air Carriers: T-100 Domestic Market (All Carriers) data[10] from the BTS website, which is used to identify the airport share of each market. The BTS Air Carriers T-100 Domestic Segment (All Carriers) data,[11] which is used to calculate the average passenger load for each airport OD pair and transform the number of diverted passengers as shown in the last two columns of Table 3. (These numbers are converted into the number of flights that could potentially be eliminated by HSR, as discussed in Section 4 below.) For both datasets, the 2019 full year data is used since it excludes the abnormal pandemic effects and should therefore be more reliable. The airports that are expected to have passenger and flight reductions are summarized in Table 5.

[9] Table 6.11 Calibration Targets and Results for Region-to-Region Pairs
[10] OST_R | BTS | Transtats. https://www.transtats.bts.gov/Fields.asp?gnoyr_VQ=GED
[11] OST_R | BTS | Transtats. https://www.transtats.bts.gov/Fields.asp?gnoyr_VQ=GEE

Table 3. Annual Diverted Passengers from Air to HSR by Market

Market[a]		Annual HSR Ridership Forecast (Millions)		Before-HSR-Time Mode Share			Number of Diverted Passengers from Air to HSR (Thousands)	
		2029	2033	Auto	Air	CVR	2029	2033
SACOG	SACOG	0.0	0	100%	0%	0%	0	0
SACOG	SANDAG	0.0	0.1	73%	27%	0%	0	27
SACOG	MTC	0.6	0.9	98%	0%	2%	0	0
SACOG	SCAG	0.3	0.8	75%	24%	0%	72	192
SACOG	SJV	0.2	0.2	99%	0%	1%	0	0
SACOG	Others	0.1	0.1	100%	0%	0%	0	0
SANDAG	SANDAG	0.0	0	100%	0%	0%	0	0
SANDAG	MTC	0.2	0.7	49%	49%	2%	98	343
SANDAG	SCAG	0.0	2.8	98%	0%	2%	0	0
SANDAG	SJV	0.1	0.4	96%	3%	1%	3	12
SANDAG	Others	0.0	0.1	90%	5%	5%	0	5
MTC	MTC	1.8	2.2	99%	0%	1%	0	0
MTC	SCAG	2.4	6.4	69%	30%	1%	720	1920
MTC	SJV	4.3	4.6	99%	0%	1%	0	0
MTC	Others	2.3	2.7	99%	0%	1%	0	0
SCAG	SCAG	0.0	4.6	99%	0%	1%	0	0
SCAG	SJV	0.9	4.6	99%	1%	0%	9	46
SCAG	Others	0.4	1.2	96%	1%	2%	4	12
SJV	SJV	1.6	1.8	98%	0%	2%	0	0
SJV	Others	0.6	0.7	100%	0%	0%	0	0
Others	Others	0.1	0.5	99%	0%	0%	0	0
Total		16.2	35.6				906	2557

a. Full names and locations of the markets are given in Table 5.

Table 4. Range of Annual Ridership by Implementation Step (Millions)

Confidence Level That Ridership Will Be Less Than Stated Value	Implementation Step — Silicon Valley to Central Valley line 2029	Implementation Step — Phase 1 2033
Minimum	3.7	8.6
1%	6.5	14.6
10%	9.6	21.1
25%	12.4	27.0
Median	16.5	35.6
75%	21.7	46.1
90%	27.1	56.8
99%	37.3	76.0
Maximum	53.4	109.8
Base Run	16.2	35.6

Source: Cambridge Systematics (2016). California High-Speed Rail Ridership and Revenue Model Documentation. Table ES.1

Table 5. Counties and Airports of the Major Regions in the State

MPO	Full Name	Counties	Major Airports	Minor Airports
SACOG	Sacramento Area Council of Governments	El Dorado, Placer, Sacramento, Sutter, Yolo, Yuba	Sacramento (SMF)	
SANDAG	San Diego Association of Governments	San Diego	San Diego (SAN)	
MTC	San Francisco Metropolitan Transportation Commission	San Francisco, Alameda, Santa Clara, Contra Costa, San Mateo, Marin, Sonoma, Solano, and Napa	San Francisco (SFO), San Jose (SJC), Oakland (OAK)	
SCAG	Southern California Association of Governments	Imperial, Los Angeles, Orange, Riverside, San Bernardino, and Ventura	Los Angeles (LAX), John Wayne (SNA), Burbank (BUR), Ontario (ONT), Long Beach (LGB)	Oxnard (OXR), Palm Springs (PSP)
SJV	San Joaquin Valley Counties	San Joaquin, Kings, Stanislaus, Merced, Fresno, Madera, Tulare, and Kern		Bakersfield (BFL), Fresno (FAT), Modesto (MOD)
Other Regions				Monterey (MRY), Santa Barbara (SBA), Arcata (ACV)

High Speed Rail Reduces Demand for Air Travel

Our proposed method estimates cost savings from reducing flight delays by shifting passenger traffic from air to rail. Toward this end, we forecasted what the air capacity and demand will be once HSR is in operation, and to what extent it may affect flight operations. Moreover, we derived these forecasts for each quarter-hour using the sophisticated delay model developed by Dai et al. (2021).

Air Capacity Forecast

Two kinds of air passenger capacity estimates are used in this study. The first one is a conservative estimate, which assumes capacity will remain the same as in 2019 for future years. These capacity estimates are obtained directly from the ASPM dataset and serve as a baseline to represent the worst-case scenario, where there are no future airport capacity improvements.

We also consider a future capacity scenario based on the Airport Capacity Profiles published by the FAA. Specifically, we first match the quarter-hour data record from the ASPM dataset with the hourly arrival/departure rate provided in the Capacity Profiles, according to the airport, runway configuration, and weather (ceiling, visibility) information. Then the quarter-hour airport arrival/departure rate (AAR/ADR) is forecasted to be the future hourly rate divided into four quarter-hours. Note that the Capacity Profiles does not specify the year when improvements will be implemented, but it is reasonable to assume that they will be in place by 2029. Also, it is likely that, should demand grow as forecasted, additional improvements would be made after 2029. In this analysis, we assume that the 2029 and 2033 capacities are the same and comply with the capacity improvements estimated in the Capacity Profiles.

Air Demand Forecast Without HSR Impact

In this section, we forecast future flight scheduled demand by quarter-hour by integrating the ASPM dataset and the TAF data. However, there are two difficulties in utilizing the TAF demand forecast. First, the TAF dataset only gives the annual number of operations and does not provide data by quarter-hours as does the ASPM flight schedule. The second problem lies in the discrepancy between the ASPM and TAF datasets due to the metric difference. As shown in Figure 2, the TAF number is generally higher than the sum of ASPM arrival and departure counts (the two of which overlap) because the TAF data counts itineraries, while the ASPM data considers OAG scheduled operations.

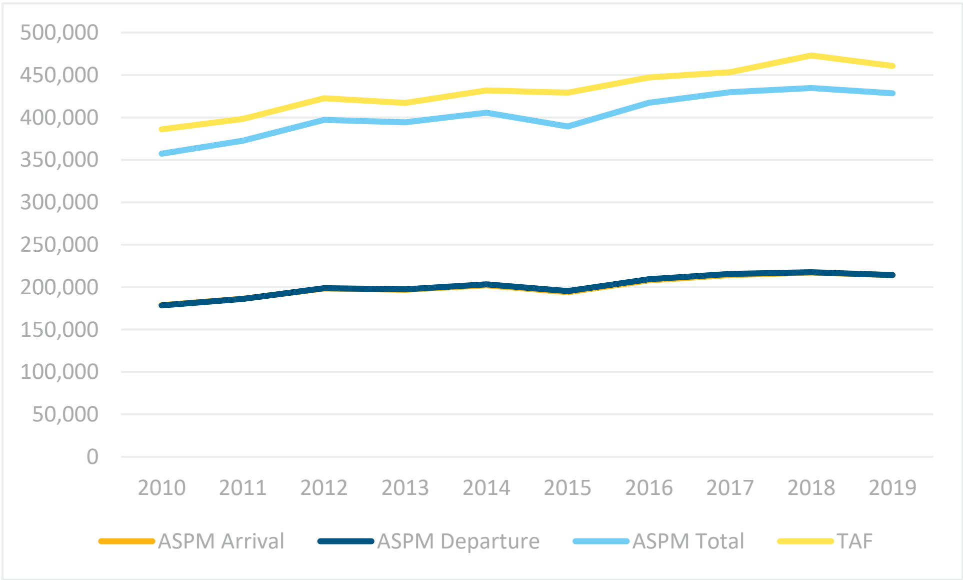

Figure 2. 2010-2019 SFO ASPM and TAF Data Comparison

We first determined the relationship between the annual numbers of the TAF data and ASPM data, then scaled up the ASPM quarter-hour scheduled demand with the annual number ratio to obtain future estimates. For each airport, the historical annual number of OAG scheduled arrivals (Q_{ASPM}^{arr}) and departures (Q_{ASPM}^{dep}) was calculated by aggregating the ASPM quarter-hourly records over the year. Then a linear regression was applied to find the relationship between the annual number of operations from TAF, Q_{TAF}, and the annual OAG scheduled operations from ASPM ($Q_{ASPM}^{arr}, Q_{ASPM}^{dep}$). With all the 77 airports tracked by the ASPM over the ten years from 2010 to 2019, the data yields 770 observations, and the estimation results are as follows:

$$Q_{ASPM}^{arr} = 0.505 \cdot Q_{TAF} - 27649 \qquad (1)$$

$$Q_{ASPM}^{dep} = 0.506 \cdot Q_{TAF} - 27712 \qquad (2)$$

The R^2 values for both regression models are very high – 0.952. With these regression models, we can convert the TAF forecast into equivalent annual values of ASPM arrivals and departures for future years, in this case 2029 and 2033, as shown by the blue histograms in Figure 3 below for the three major airports, LAX, SFO and SAN.

Taking 2019 as the base year, quarter-hour scheduled arrivals and departures can be scaled up with the ratio of ASPM annual operations in a future year to that in 2019. This procedure was repeated for both arrivals and departures, all airports of concern, and all quarter hours for 2029 and 2033, as shown in Table 4. Also, as discussed below, we consider scenarios in which the future demand is “de-peaked” from that obtained using the method above.

Impact of Shifting Air Traffic to HSR

In this section, we consider the HSR impact on air transportation by estimating flight reductions for each airport OD pair based on the HSR ridership forecast provided in the 2020 Business Plan.

Annual Diverted Passengers by Market

With the assumption[12] that the number of diverted passengers from each mode to HSR is proportional to their current mode share, the number of diverted passengers from air to HSR, P_m^{yr}, for market m, for the future years ($yr = 2029, 2033$) is calculated:

$$P_m^{yr} = N_m^{yr} \cdot \alpha_m \quad (3)$$

where N_m^{yr} is the total HSR ridership of the market m at the given year yr obtained from the 2020 Business Plan, and α_m is the pre-HSR airline mode share of market m obtained from 2012-2013 CHTS. The result for the SANDAG-MTC market is shown in Table 6.

Table 6. Annual Diverted Passengers from Air to HSR by Airport Pair for SANDAG-MTC Market

Origin	Destination	2019 Passengers	2019 Share	Passenger Reductions Forecast (Thousands)	
				2029	2033
OAK	SAN	435,854	0.11	11.02	38.59
SAN	OAK	438,953	0.11	11.10	38.86
SAN	SFO	859,207	0.22	21.73	76.07
SAN	SJC	659,539	0.17	16.68	58.39
SFO	SAN	833,083	0.22	21.07	73.75
SJC	SAN	647,787	0.17	16.39	57.35
Total			1.00	97.99	343.01

The total number of diverted passengers from air to HSR for all markets is 906K for 2029 and 2,557K for 2033, as shown in Table 6 accounting for 5.6 percent and 7.2 percent of all forecasted HSR ridership in the corresponding year. These shares are much less than the 20 percent assumed in the ECA method (CHSRA, 2019). This significant difference is one source of the difference between the final total benefit estimates that we will discuss later. The HSR ridership range estimates provided in Cambridge Systematics (2016) are also included in this study to reflect the uncertainty in our benefit estimates. Unless otherwise specified, the following steps

[12] This assumption is based on the main mode choice model used by Cambridge Systems, which rejected the nested structure where air, HSR and conventional rail are nested under [the designation] “common carrier” and then compete with car travel. In the final model, car, air and rail are three parallel choices and only HSR and conventional rail are grouped in the category “rail.” Please see California High-Speed Rail Ridership and Revenue Model Chapter 5.1 for more details.

were all performed for the different quantiles of HSR forecasts. However, the tables, if not specifying the quantiles, only show the numbers using base run estimates due to limited space.

Annual Diverted Passengers by Airport Pair

Next, we decomposed the market-based passenger diversion figures for each airport OD pair utilizing the BTS T-100 Domestic Market data and grouped the passenger volume by origin and destination airport pairs for each market m, then calculated the traffic shares of each OD pair, β_{od}^{m}, among airports. We assume that annual number of passengers diverted from air to HSR follow the same traffic distribution probability. Thus, the number of diverted passengers P_{od}^{yr} for each airport pair od in a future year yr is estimated as:

$$P_{od}^{yr} = P_{m}^{yr} \cdot \beta_{od}^{m} \qquad (4)$$

Flight Reductions by Airport Pair

Next, we transformed the diverted passenger estimates to the number of eliminated flights for each airport pair. We used the BTS T-100 Domestic Segment data to compute the average number of passengers per flight, γ_{od}, which was calculated as the ratio of the total number of passengers to the total number of flights for the OD airport pairs. We then estimated the flight reduction F_{od}^{yr} by airport pair od in the future year yr to be:

$$F_{od}^{yr} = P_{od}^{yr} / \gamma_{od} \qquad (5)$$

Table 7 gives example results for airport pairs with SFO as the flight origin.

Table 7. Annual Flight Reductions by Airport Pair with SFO as Flight Origin

Origin	Destination	Pax per Flight (2019)	Passenger Reductions Forecast (Thousands)		Flight Reductions Forecast	
			2029	2033	2029	2033
SFO	BUR	78	15	40	190	509
SFO	LAX	107	97	259	906	2417
SFO	LGB	115	4	12	38	103
SFO	ONT	63	8	22	130	347
SFO	PSP	63	10	28	164	439
SFO	SNA	85	20	55	240	640
SFO	SAN	114	21	74	185	649

Air Demand Forecast with HSR Impact

Given the annual flight reductions between airport pairs resulting from travel diverted to HSR, we translated these annual reductions into changes in air traffic arrivals and departures for each quarter-hour from the baseline air demand forecasts obtained in Section 4.2. We assumed that those quarter-hours with more arrivals (or departures) from a certain origin (or to a certain destination) in 2019 are more likely to experience flight reductions for that origin (or destination) in future years. Accordingly, we randomly chose the quarter-hours with flight reductions for a given directional airport-pair based on the temporal distribution of flights for that pair in 2019. We then summed up the number of flight reductions from all origin (or destination) airports to the specified airport to obtain the quarter-hour arrivals (or departures) for that airport. These are shown as the orange histograms in Figure 3 below for the three major airports. The annotated numbers on the top of the paired columns show the difference between the air demand forecast with and without HSR.

Our demand forecast does not consider capacity constraints and may result in extremely large quarter-hour demand rates. We followed the current practice in the airline industry to "de-peak" the demand within the hour to increase schedule reliability (Zhang et al., 2004). Specifically, the new quarter-hour demand rate is calculated as the mean of the four quarter-hour demand rates of that hour.

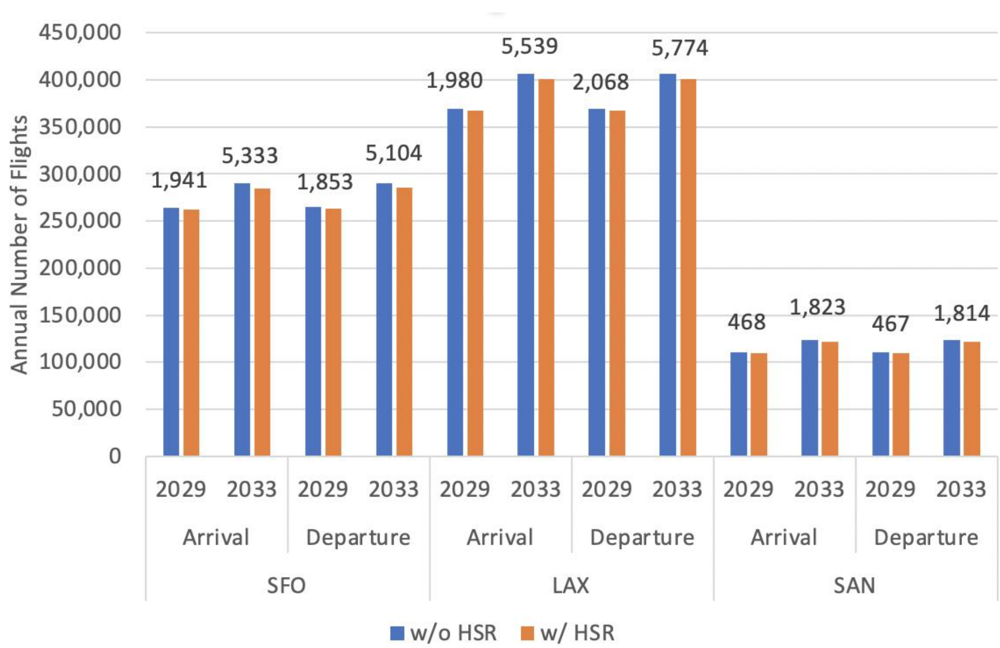

Figure 3. Airport Annual Number of Arrivals and Departures Forecast with and Without HSR Impact

Predicted Flight Delay Savings Depend on Capacity Improvements and Flight Scheduling

Methodology

The analysis described above yielded forecasts of future airport capacity, and flight demand schedules with and without diverting passenger traffic from air to HSR. In this section, we estimate the flight delay cost savings from diverting some trips to HSR for selected California airports, and the NAS. Although the CHSRA cost-justified the HSR project, at least in part, on potential savings from avoiding constructing some airport improvements due to reduced air travel demand, it is possible that some or all of them may be undertaken anyway in which case there may be additional delay savings through increased airport capacity. In addition, further savings may be achieved by reducing delays though de-peaking. Obviously, consumers would benefit from the overall increase in airport capacity and the reductions in flight delays, however as we show below, it would decrease the effectiveness of the investment in HSR in terms of shifting from air to rail travel and the accompanying benefits to the environment. To account for these possibilities we construct four scenarios from the air travel forecast results:

1) ***Baseline*** scenario with baseline air traffic demand (without de-peaking) but no capacity improvement (retaining the 2019 capacity levels)
2) ***Capacity Improvements*** scenario with baseline air traffic demand and capacity improvements
3) ***De-peaking Only*** scenario with de-peaking air traffic demand but no capacity improvements, and
4) capacity and de-peaking (***Cap & De-peak***) scenario with both capacity improvements and de-peaking air traffic demand.

The following analysis was performed on all four scenarios. We first employed a simple queuing model to estimate the arrival and departure queuing delays at each airport based on the air capacity and demand forecasts. Then we adapted the predictive delay model proposed by Dai et al. (2021) to study the impact of queuing delays on flight operation performance at SFO, LAX, and San Diego Airport (SAN), as well as the NAS. Furthermore, we used the results to evaluate the impact of flight reductions resulting from HSR traffic diversion on flight delays.

Queueing Delay

A basic building block of the delay models used in this research is the deterministic queuing diagram. In this study, we employ the cumulative input-output (I/O) queueing diagram to compute the queueing delays based on the forecasted quarter-hour flight schedules and airport capacity values for both arrivals and departures.

We refer to the quarter-hour arrival and departure capacities as the AAR (Airport Arrival Rate) and ADR (Airport Departure Rate) respectively. Assume that for a given day, we have the scheduled demand (say for arrivals, i.e., scheduled arrival demand, SAD_t) and associated capacity (AAR in this example) for each quarter hour. Then the total queuing delay for the day is obtained using:

$$\boldsymbol{CSD_t = \sum_{i=1}^{t} SAD_t} \quad (0\text{-}1)$$

$$\boldsymbol{CARR_1 = \min(CSD_1, AAR_1)} \quad (0\text{-}2)$$

$$\boldsymbol{CARR_t = \min(CARD_t, CAAR_{t-1} + AAR_t)} \quad (0\text{-}3)$$

$$\boldsymbol{ARDEL = 15 \sum_{t} CSD_t - CARR_t} \quad (0\text{-}4)$$

Equation (5-1) yields the cumulative scheduled demand over the day for each time period (CSD_t). Equation (5-2) provides the actual arrivals in the first period, which is the minimum of the scheduled demand and the capacity. Equation (5-3) provides the cumulative actual arrivals for each subsequent period ($CARR_t$), which cannot exceed either the cumulative demand or the sum of the cumulative arrivals in the previous period $t-1$ and the capacity in period t. Finally, equation (5-4) provides the total delay, in minutes, assuming that 15-minute time periods are used.

Figure 4 illustrates a queuing diagram of flight arrivals at an airport on a given day, with the orange curve depicting $CARR_t$ and the blue curve showing CSD_t. The area between the two curves is the total deterministic queuing delay for all flights arriving at this given airport on the given day.

Next, we calculated five features based on this queueing diagram. First, we segmented the queuing delay by four daily time periods: 0:00-6:00, 6:00-12:00, 12:00-18:00, and 18:00-24:00. Specifically, we used the scheduled arrival curve (CSD_t) for the segmentation so that the total queueing delays for the time periods (TD_{1-4}) are the sum of the queueing delays experienced by all flights that are scheduled to arrive or depart in this time period. The reason for using CSD_t rather than $CARR_t$ for segmentation is to prevent extremely large delays from propagating to the next day. In practice, flights will be cancelled to prevent these delay "left-overs," so it is reasonable to restrict the delay impact within the same day. Then we derived four "flight-average" queueing delay features by dividing the total queueing delays for the time periods (TD_{1-4}) by the total number of scheduled arrivals for that day (N). Note that these features are not really "flight-average" since the numerator is the total number of scheduled arrivals of that day instead of that time period. We choose the former to ensure the flight delays for different time periods on the same day share the same weight. Another action to prevent the queueing delay from propagating to the next day was to cutoff the queueing delay at 24:00 every day and start a new queueing diagram for the next day. By doing this, we avoided having the previous day's scheduled flights occupy the next day's capacity. We then introduced another feature of unserved demand, which is the difference between total scheduled demand and total served demand, to capture the impact of these unserved demands. In sum, we derived five features, including four 6-hour time period delay features and the daily unserved demand feature, for each airport, and both arrivals and departures.

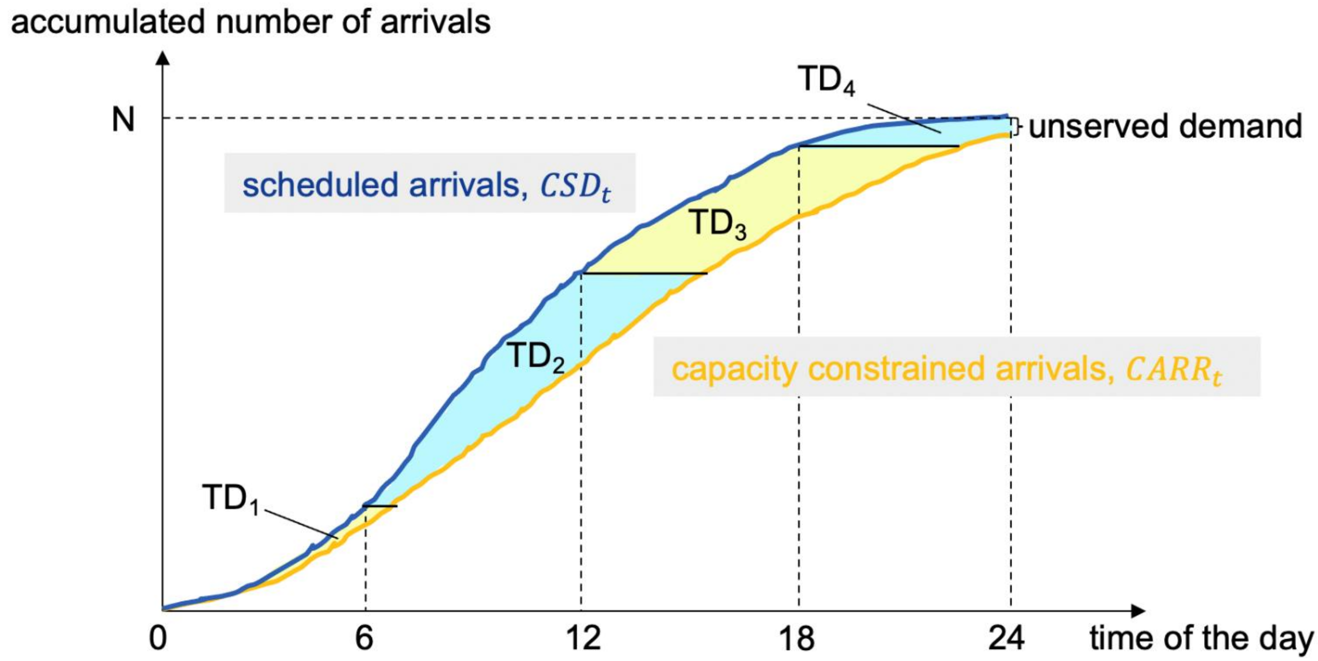

Figure 4. Queueing Diagram

Predictive Modeling

Next, we utilized the comprehensive predictive models proposed by Dai et al. (2021) to model the flight delay at the three major California airports (SFO, LAX, and SAN) and the NAS. Dai et al. applied various machine learning algorithms to model the NAS delay for the period from 2010 to 2019 using a broad scope of spatial-temporal features, including queuing delays, terminal conditions, en route weather, wind, traffic volume, and special events. We adapted this feature matrix for our study by updating the queueing delay features, scheduled arrival features, and including the new unserved demand features. We also further expanded the response variables to be airport specific. The response variable in their model is the daily average arrival delay (in minutes per flight), which is computed based on average positive delay against schedule for all scheduled arrivals into the Core 29 U.S. airports, adjusted to include flight cancellations. In addition to this nationwide delay metric, we also included the daily average flight arrival delay for SFO, LAX, and SAN. We ran the models independently for these four response variables to capture the effects at different scales. Table 8 gives a description and the summary statistics of these four different response variables. SFO appears to have the highest delay and variability, while LAX and SAN have a more moderate level of delay close to the national average.

Table 8. Description of the Response Variables

	Airports Considered	Mean (min)	Standard deviation (min)	Minimum (min)	Maximum (min)
National	Core 29 U.S. airports	14.08	7.19	2.62	55.51
SFO	\	20.76	18.86	1.22	132.90
LAX	\	13.28	7.22	2.33	79.42
SAN	\	11.44	6.41	0.59	67.34

Among the seven machine learning models they experimented with, Dai et al. chose Lasso as the final model considering interpretability, computational efficiency, and model performance. Therefore, we opted for the Lasso model as well. We removed the same outlier observations – 42 days that have detected outlier features and 20 days with daylight savings time transition – as in Dai et al.'s work. The evaluation results of these models with the optimal hyperparameters on the exact same testing set in terms of mean absolute error (MAE), R squared, and root mean squared error (RMSE) are summarized in Table 9. These results show how accurately the models, when trained on a historical data set of days between 2010 and 2019, predict delays on a testing set of other days in the same time period, which were not used in training. The results show that the performance of the Lasso model varies for different response variables. SFO has both a higher MAE and R squared error than LAX and SAN. The model performance is close for the training and testing set, which means these models are not overfitting. We thus can generalize them to a new dataset where the queuing delay features are manipulated to reflect the HSR impact.

Table 9. Evaluation results of the Models

	Training			Testing		
	MAE	R squared	RMSE	MAE	R squared	RMSE
National	2.16	0.84	2.87	2.67	0.75	3.60
SFO	4.52	0.87	6.82	4.82	0.85	7.19
LAX	2.91	0.65	4.34	3.23	0.53	4.56
SAN	2.57	0.68	3.58	3.02	0.54	4.57

Scenario Analysis

We used the above models to predict how average arrival delay, for either the major California airports or the NAS, will change after the introduction of HSR, keeping all other factors (e.g., capacities) equal. Specifically, we first updated *four* sets of features in the feature matrix to reflect the future year condition impacted by HSR: airport-specific time-of-day average arrival queuing delay; airport-specific time-of-day average departure queuing delay; airport-specific time-of-day scheduled arrival counts; and airport-specific daily unserved demands. In total, values for 377 variables (3 feature sets * 29 airports * 4 time periods of the day + 1 feature set * 29 airports) were updated to construct the *four* different scenarios defined in Section 5.1. Next, we applied the trained model to the new feature matrix and obtained future delay predictions. Finally, for each response variable, each future year, each scenario, and each HSR ridership quantile, we calculated the difference between delay prediction with and without HSR impact. The difference represents the delay savings induced by the factor of change — HSR operations — on day t. We calculate δ_t using:

$$\boldsymbol{\delta_t} = \hat{\boldsymbol{f}}(\boldsymbol{X_t}) - \hat{\boldsymbol{f}}(\boldsymbol{x_{tc}}, \boldsymbol{X_{t\backslash c}}) \text{ (0-5)}$$

where $\hat{f}(\boldsymbol{X_t})$ is the predicted average arrival delay on day t provided by the selected model based on the feature matrix without HSR impact; $\boldsymbol{x_{tc}}$ are the amended flight queueing and traffic features after taking HSR traffic diversions into account; and $\boldsymbol{X_{t\backslash c}}$ are the remaining unchanged features. Thus δ_t represents the difference in predicted delay at a particular California airport, or the NAS as a whole, for a day whose weather and wind features match those for the corresponding day in 2019. The queueing and traffic features of this future day are based on 2019 demand scaled to predicted traffic growth, which in some scenarios is de-peaked, and 2019 capacity, which in some scenarios is adjusted based on anticipated capacity enhancements.

We repeated this procedure for the four delay variables (for SFO, LAX, SAN, and the NAS), two future years (2029 and 2033), the four scenarios defined in Section 5.1, and with or without HSR impact, under different HSR ridership estimates for various quantiles. Our focus was on delay savings resulting from HSR operation. Thus, for each airport and the NAS, each capacity/demand scenario, each HSR ridership estimate quantile, and two future years, the difference in predicted delay (i.e., delay savings) with and without HSR impact was calculated. Figure 5 compares the mean value of predicted daily average delay savings induced by HSR operation using the different HSR ridership quantiles and under different scenarios. The vertical axis represents the delay savings computed by subtracting the with-HSR delay predictions from the without-HSR delay predictions. Each subplot shows the results for the NAS, SFO, SAN, and LAX (clockwise), with lines indicating the baseline, capacity improvement, and de-peaking scenarios in 2029 and 2033. Note that although each plot has eight lines, only four are visible; this is because scenarios with and without de-peaking have almost identical delay savings. In addition, we plot the 25% and 75% percentile of the predicted daily average delay savings for the 2033 Cap & De-peak scenario to show the variability in delay savings.

The results are summarized as follows:

1) The delay savings of all scenarios, including the cases investigated in Figure 5, are positive. This indicates that the introduction of HSR will improve aviation system performance. HSR, as a new mode choice, will lead some air passengers to divert to HSR, reduce the number of flight operations, and thus ease airspace congestion.

2) SFO has both the highest delay saving and the largest variability in delay savings, LAX the second, SAN the third, and the NAS the least. The delay savings for the California airports are larger than those for the NAS as a whole because they are the locus of the reductions in flight traffic resulting from HSR. Among the California airports, delay savings differences reflect baseline levels of congestion and delay (shown in Table 7); the more congested airports may gain more delay savings from the introduction of HSR.

3) There is wide variability in delay savings from day to day. In the most extreme cases at SFO, delay savings from HSR exceed 28 minutes per flight. These reflect days with very low capacity, which when combined with expected unattenuated traffic growth result in extremely high baseline delays that can be substantially reduced by eliminating a relatively small number of flights. Also, delays on such days typically result in higher numbers of flight cancellations (recall that our delay metric includes such cancellations).

4) Airport capacity improvements would decrease flight delays, but also diminish the delay reduction benefit of HSR. While demand de-peaking would also decrease flight delays, it does not have an obvious impact on the delay savings of introducing HSR (lines of de-peaking and non-de-peaking scenarios mostly overlap in Figure 5).

5) Delay savings are sensitive to uncertainty in HSR ridership. For example, comparing the 10% and 90% ridership quantiles, the predicted delay savings roughly tripled.

6) Delay savings should increase from 2029 to 2033, as travel demand increases, California airports become more congested, and more passengers are diverted to HSR.

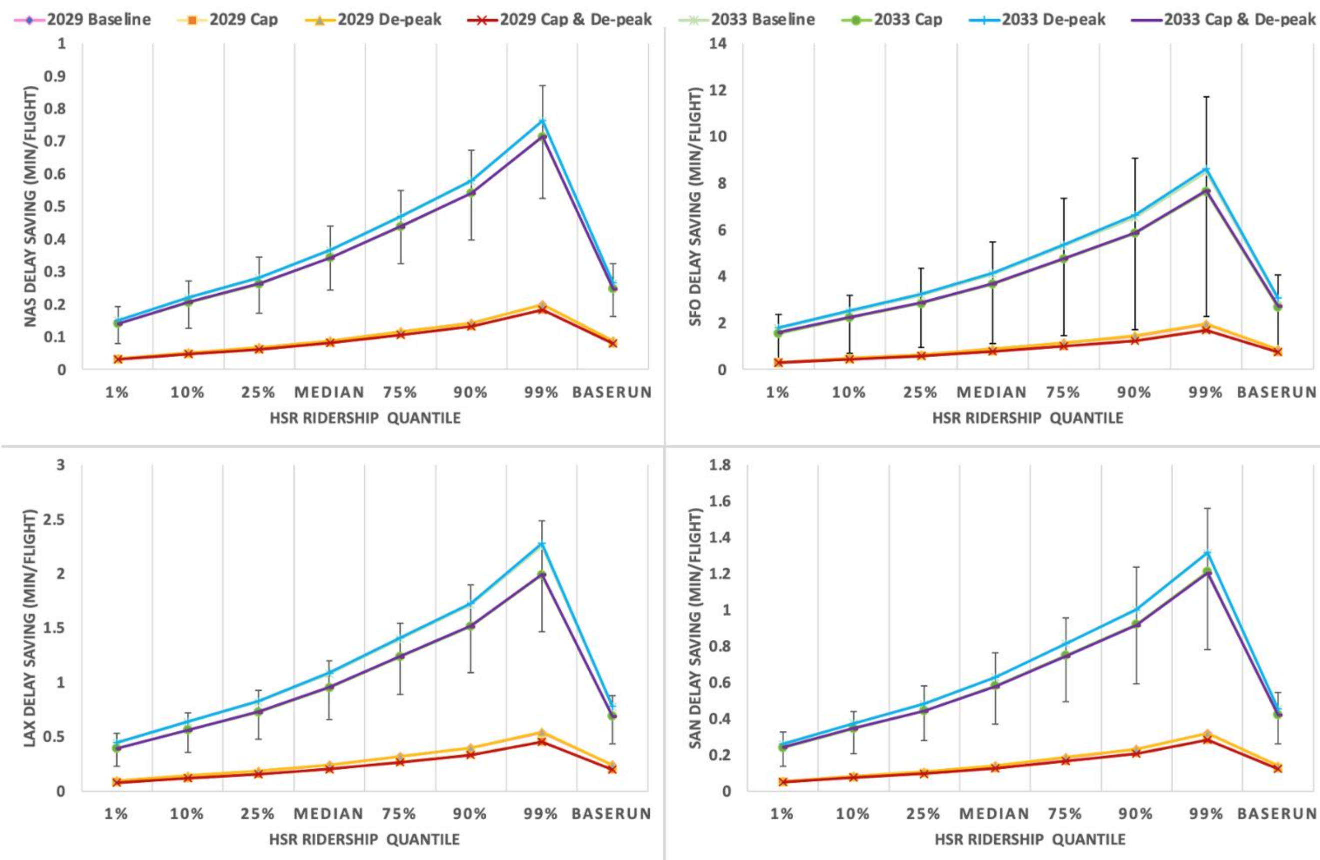

Figure 5. Comparison of Mean of Predicted Daily Average Delay Saving Given by Four Models

Estimating Savings from Delay Reduction

Lastly, we monetized the delay reduction so that the benefits of delay savings can be compared with infrastructure investment costs, as calculated in the ECA method. We performed our benefit cost savings analysis for the NAS, LAX, SAN, and SFO models, which we identify with the subscript *model*. We define the total benefit B_{model}^{yr} as the sum of the airline operation cost savings AS_{model}^{yr} and monetarized passenger time savings PS_{model}^{yr}, and calculate them with the following formulas.

$$\boldsymbol{AS_{model}^{year} = \delta_{model}^{year} \times F_{model}^{year} \times OC/60} \text{ (0-1)}$$

$$\boldsymbol{PS_{model}^{year} = \delta_{model}^{year} \times E_{model}^{year} \times VOT/60} \text{ (0-2)}$$

$$\boldsymbol{B_{model}^{year} = PS_{model}^{year} + AS_{model}^{year}} \text{ (0-3)}$$

where δ_{model}^{year} is the delay saving predicted in the last section, in minutes per flight; F_{model}^{year} and E_{model}^{year} are the total number of flights and the total number of enplanements respectively, given by the TAF dataset; OC and VOT are the aircraft operating cost per hour and the value of passenger time per hour, respectively, given by the FAA (FAA Office of Aviation Policy and Plans, 2021). The figures are adjusted by the inflation rate according to the national Consumer Price Index published by U.S. Bureau of Labor Statistics express in 2018 dollars, same as the results using ECA methods.

Table 10. Constants Specifications for Delay Saving Monetization

	Description	Value				
			NAS	SFO	LAX	SAN
F_{model}^{year}	Total number of flights for *model* NAS, LAX, SAN, or SFO in *year* 2029 or 2033	2029	7,210,125	289,151	392,674	136,465
		2033	7,794,705	314,658	429,566	149,601
E_{model}^{year}	Total number of enplanements for *model* NAS, LAX, SAN, or SFO in *year* 2029 or 2033	2029	375,869,300	18,040,749	23,577,747	7,516,378
		2033	410,969,850	19,831,110	26,015,326	8,313,961
OC	Aircraft operating cost per hour in 2018 dollars	$4,250				
VOT	Value of passenger time per hour in 2018 dollars	$\$47.10 \text{ in 2015 dollars} \times \frac{251.1 \text{(2018 CPI)}}{237.0 \text{ (2015 CPI)}} = \$49.90 \text{ in 2018 dollars}$				

Though the introduction of HSR in California has less impact on the national average arrival delay than the three major California airports as shown in Figure 5, as many more flights overall are affected nationally. As a result, the overall cost savings for the three individual airports is roughly the same magnitude as the (national) cost savings of the Core 29 airports. For the Capacity Improvement and De-Peaking Only scenario in 2029, the delay cost saving for the national Core 29 airports is $66 million, and that for the three major California airports is $38 million. Comparison of the two estimates indicates that the spillover effects reducing arrival delays at California airports on the rest of the NAS are substantial, although most of the benefits accrue within the state.

Table 11. Estimated Delay Cost Savings from HSR for a Range of Ridership Forecast Quantiles (Million 2018 Dollars)

		2029				2033			
		Baseline	CAP	De-peak	CAP & De-peak	Baseline	CAP	De-peak	CAP & De-peak
National	1%	28	26	28	26	134	126	135	126
	10%	42	39	42	39	196	184	197	185
	25%	55	51	55	51	250	234	251	235
	median	73	68	73	67	327	306	328	306
	75%	95	89	95	88	419	392	420	392
	90%	118	109	118	108	516	483	518	483
	99%	163	151	164	151	680	638	682	639
	baserun	72	66	72	66	236	221	237	222
Sum of SFO, LAX, SAN	1%	16	15	16	15	96	85	97	87
	10%	25	23	25	22	136	121	138	123
	25%	33	29	33	29	174	155	177	157
	median	45	39	45	39	226	202	229	203
	75%	58	51	59	50	293	261	295	262
	90%	73	65	74	63	360	322	365	323
	99%	100	86	101	85	469	421	476	423
	baserun	44	38	44	38	164	146	167	148

As shown in Table 11, we also estimated and compared the delay cost savings under different ridership forecast scenarios. The median scenario gives an almost identical estimate as the one given by the base run scenario. The cost savings under the 1% (least ridership), 10%, 25%, 75%, 90%, 99% quantile of HSR ridership forecasts are about 40, 60, 75, 130, 160, and 200 percent as much as those under the median ridership scenario. Thus, the difference in ridership between the 1% and 99% quantile is associated with roughly a five-fold difference in delay savings benefit.

The models developed for different delay measures (considering national Core 29 airports, or only the three major California airports), different scenarios (considering capacity improvement and demand de-peaking or not), and different ridership forecasts, led to a range of cost-saving estimates. Although demand de-peaking can reduce delay, it does not greatly impact the difference in delay cost savings with the operation of HSR. For example, the cost savings under the Baseline and De-peaking Only scenarios for 2029 (using the base run HSR ridership forecasts) are both $72 million. In contrast, though capacity improvements do not improve delay as much as demand de-peaking, it has a more substantial impact on delay cost savings attributable to HSR. For example, the $66 million in savings for the NAS under the Capacity Improvement scenario for 2029 (using base run HSR ridership forecasts) is less than the $72 million under the Baseline scenario (no capacity improvements) and the Capacity Improvement scenario, a difference of $6 million (see Table 11). Of course, some environmental benefits would be lost since fewer flights would be diverted, even more so if the improvements lead to higher overall demand and even more air traffic.

To summarize our benefit estimates, we focus on the NAS model since it includes delay savings from throughout the nation. We assume the capacity upgrades are undertaken since these are likely to have occurred by 2029. We also assume demand de-peaking is employed, though as mentioned above this makes little difference in delay reduction. Finally, we consider the range of savings generated using the HSR ridership forecasts between the 25% and 75% quartiles. Based on these assumptions, we estimate delay cost savings of $51-88 million in 2029 and $235-392 million in 2033. This represents a conservative estimate since it assumes that some airport capacity improvements will be made. If those improvements do not occur (Baseline and De-peaking Only scenarios), a higher proportion of air travelers will likely switch to HSR which would result in greater airport delay savings being attributable to HSR.

To compare our 2033 results (full Phase 1) to those from the 2020 Business Report using the ECA method, several adjustments to original ECA figures are required due to the discrepancy between the ridership, passenger diversion and methodology used by our analysis and the ECA method. These calculations are summarized in Table 12 and discussed below.

> Step 1: While our study forecasts HSR annual ridership (demand) of 35.6 million passengers in 2033 from Table 3, the ECA ridership estimate is based on *planned* HSR hourly capacity. Specifically, the CHSRA calculates ridership as the product of 12 trains per hour per direction, 900 seats per train, a 70 percent load factor, and two directions, which gives 15,120 passengers per hour in 2033. Based on the 2020 Business Plan Ridership and Revenue Forecasting Technical Report (2020), which specifies the HSR operation pattern as 12 trains per hour in the 6 peak hours and 6 trains per hour in the 12 non-peak hours this translates to about 66.2 million passengers annually (15,120 passengers/hour * (6 peak hours + 12 non-peak hours * 6 trains/12 trains) * 365 days per year). This ridership adjustment reduces the savings estimate by almost half to about $13 billion in avoided infrastructure costs.
>
> Step 2: the ECA method assumes that 20 percent of HSR ridership will come from air passenger diversion; while in our study, only 5.6 percent (in 2029) and 7.2 percent (in 2033) of HSR ridership are assumed to be from air passenger diversion (see Section 4.3.1 above). Since the cost estimate using the ECA method is approximately proportional to ridership (i.e., airport expansion cost is proportional to the needed number of gates, runways, and parking lots at each airport, which is further proportional to the number of diverted air passengers), we scaled down the ECA estimate (for 2033) by a factor of 20% / 7.2% = 2.8 to make the two estimates more comparable. As a result of these first two adjustments to ridership and passenger diversion figures the modified ECA estimate is $4.6 billion (2018 dollars).

Step 3: the ECA method estimates the cost of avoidable airport infrastructure improvements based on year 2018 while our method evaluates the benefits from reducing delay realized in future years. Therefore, we calculated the future value of the ECA estimate by assuming the airport capacity expansion would otherwise have begun in a specific middle year (2027) between 2019, when the study was carried, and 2033, when Phase 1 should be completed, resulting in six years of savings. Applying a rate of 7 percent results in a future value of about $7 billion.

Step 4: the ECA estimate represents lump sum savings in construction costs across multiple years, while our estimate reflects delay cost savings per year. To annualize the revised ECA estimate, we assume a 50-year lifespan for all improvements and a discount rate of 7 percent and obtain a figure of $504 million in airport construction cost savings (2018 dollars). This is somewhat larger, but similar to our estimated range of delay savings for 2033 from HSR (with airport expansion and de-peaking) of between $235 and $392 million. Again, as noted above, the savings attributable to HSR would be even greater if no additional airport improvements are undertaken.

Table 12. Comparison of the National Results of ECA Report Construction Cost Savings and Airport Delay Savings (in million 2018 dollars)

Estimated airport construction cost savings using from ECA report	$23,924
Step 1: ridership correction	$23,924*35.6/66.2=$12,865
Step 2: passenger diversion correction	$12,865*7.2%/20%=$4,632
Step 3: future value	$\$4,632*(1+7\%)^{(2033-2027)}=\$6,951$
Step 4: annualization	$504
Estimated delay savings	$235-392

Conclusions and Recommendations for Future Research

This study proposes a method that estimates flight delay cost savings resulting from some passengers shifting their travel from Los Angeles to the Bay Area from air to HSR. We first forecasted future air passenger capacity and travel demand for three major California airports, with and without HSR, based on a variety of data sources. Then we applied queuing diagrams to translate these capacity and demand forecasts into queuing delays, which we used to predict the extent of airport flight delays for these California airports as well as all major airports in the NAS. The difference between the predicted delays with and without HSR introduction was calculated. Finally, we monetized the delay savings with HSR to compare it with the results of the ECA method used by the California High Speed Rail Authority in their 2020 Business Plan. We estimated the airport delay cost savings to be in the range of \$51-88 million (2018 dollars) in 2029 and \$235-392 million (2018 dollars) in 2033. After considering the differences between our method and the ECA method, the two estimates are of a similar order of magnitude. This finding indicates that the cost of potentially avoidable airport upgrades (\$504 million per year) based on the ECA report is approximately the same as the cost of additional delays without the upgrades (\$250-419 million under the Baseline scenario), which could help to justify the need for airport infrastructure investment. Obviously if airport capacity improvements are undertaken in addition to building HSR consumers may benefit but overall costs would be higher, and some environmental benefits would be lost.

In addition, the rough consistency between the mid-range of the delay cost saving estimates given by the NAS model and the those for SFO, LAX and SAN combined supports the finding from some previous studies (Hao et al., 2014) that the impact of congestion at large airports on flight delays elsewhere in the NAS, though it exists, is rather limited.

A unique feature of our analysis is that it captures day-to-day variability in flight delays and flight delay savings from diverting some air passengers to HSR. We find that the flight reductions from HSR have a disproportionate impact on a small number of delays when airport operating conditions are very unfavorable. In our analysis, these days, while featuring high delays with or without HSR, will be substantially improved under the latter scenario. This effect is particularly pronounced at SFO. It should be noted that HSR will provide a travel option that will be particularly attractive when airport delays are high. There is a need for further research on how to best realize the potential of HSR on days when airports have low capacity and high delay.

This study has several other limitations, which can be addressed in future research. First, the CHSRA Business Plan, FAA traffic forecasts, and flight operational data all come from the pre-pandemic era, and all need to be revisited in light of that calamity. Second, due to the lack of detailed capacity improvement information, we assume the same capacity for 2029 and 2033 as specified in the Airport Improvement Plan, which is likely to overestimate the delay level in 2033. Third, the Lasso model is trained using 2010-2019 data and may not be very well generalized to future scenarios if the conditions are significantly changed. Finally, there are still many benefits resulting from the passenger shift from air to rail that are not captured by this study, for example, improved schedule reliability, and pollution, and emission reductions, which can be further investigated in future research.

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