Telecommuting and the Recovery of Passenger Aviation Post-COVID-19*

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Abstract

Air passenger transport has been dramatically impacted by the COVID-19 pandemic due to lockdown policies and social distancing mandates. However, once restrictions were lifted, air traffic has reverted very slowly to pre-pandemic levels with many markets still recovering from the downturn. We try to understand what causes this sluggish recovery of air passenger transport and ask whether it could be related to structural changes in business and working arrangements post-pandemic. Specifically, we consider if the dramatic shift towards telecommuting and remote work has transformed the nature of business interactions in the marketplace, leading to a negative demand shock for air travel. We use U.S. city-level data on the fraction of jobs that can be performed remotely to proxy for telecommuting, and employ a difference-in-differences estimation method to investigate if air travel demand post-COVID is lower in cities with a larger share of remote work, all else equal. An event study analysis using monthly data evaluates differences in air passenger traffic across cities in the periods leading up to the COVID-19 outbreak and during its aftermath, distinguishing between cities with a higher versus lower share of remote jobs. All the estimation results lend support to the hypothesis that the raise in telecommuting following the COVID-19 pandemic has slowed down the recovery of air travel to pre-pandemic levels.

JEL: R41, R12, J21
Keywords: air travel, air passenger transport, aviation industry, COVID-19, telecommuting, remote work

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1 Introduction

The COVID-19 pandemic has led to extensive unexpected disruptions to economic activity worldwide. The evidence documenting such disruptions has mostly focused on production of goods. The complex network structure of manufacturing sectors – a direct consequence of global supply chains – exacerbated disruptions in those sectors. Services, on the other hand, have been more resilient to global shocks, as during the 2008-09 financial crisis (Borchert and Mattoo, 2010; Ariu, 2016). An inspection of global trade patterns in goods versus services during the COVID-19 pandemic seems to support this claim, but only when excluding transport and travel services. Figure 1 illustrates this by depicting the value of global trade in goods and in non-transport services relative to 2019, i.e., pre-pandemic levels.

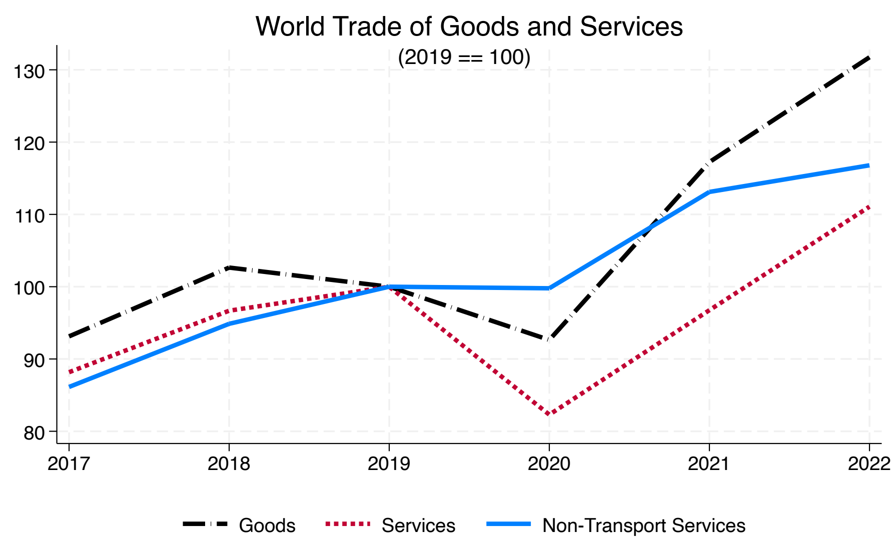

Figure 1: Impact of COVID-19 on Global Trade in Goods and Services

Notes: Sample size N = 15,120. The estimation sample is balanced across 210 consolidated CBSAs. The sample period is monthly and covers the interval 2017-2022. Consolidated CBSAs above sample median are considered large CBSAs.

Surprisingly, trade in travel and transport services departed drastically from the pattern of other services trade. As Figure 1 shows, not only did transportation services experience a dramatic drop at the height of the pandemic, but the recovery to pre-pandemic levels took a much longer time, even more than the recovery of goods trade. What explains this sluggish recovery of transportation services? This paper will focus specifically on air passenger transport services.

The COVID-19 disruptions to the aviation industry are well documented (Sun et al., 2021, 2022). Airports and airplanes became major sources of viral infections and outbreaks. Lockdown policies grounded most flights in an effort to stop the transmission of the COVID-

19 virus. All this resulted in a dramatic drop in air passenger flows during 2020. The recovery of passenger travel, however, has been slower than expected. More than three years since the COVID-19 outbreak, the aviation industry has not returned to passenger levels registered pre-pandemic (IATA, 2022). This raises the question: why has the recovery taken this long? Does the demand for air travel remain low because of lingering health concerns or changes in preferences and expenditure patterns? Is the supply of aviation services restricted from capacity constraints caused by prevailing labor shortages or aircraft depreciation?

This paper investigates the factors influencing the recovery of the aviation industry post-pandemic using rich data on U.S. domestic travel. In our analysis, we focus on one particular factor that could explain the slow uptake in air travel: the increased use of remote work and substitution away from in-person business relations. The COVID-19 pandemic has forced firms to experiment and quickly acclimate to remote work options for their workers and, more broadly, remote coordination with suppliers and business partners. We ask whether the sudden rise in remote work during the COVID-19 pandemic could negatively impact the demand for air travel. Locations with a higher concentration of occupations and business activities that can be performed remotely may see a larger decline in the demand for air travel services. Understanding the extent to which remote work conditions impact the aviation industry is important given that this mode of operation may become a new reality of post-pandemic labor markets. The magnitude of the effect is also crucial for better forecasting the demand for air travel services.

We use monthly data for US domestic air passenger travel over the period 2017-2022. Our sample covers 210 consolidated core-based statistical areas (CBSAs).[1] For each of these origin locations, we construct the total number of passengers flown within the continental US. We then combine the data on passenger aviation with information at the CBSA level on population size and personal income, socio-demographic characteristics, the severity of the COVID-19 pandemic (i.e., number of new infections,) and the fraction of jobs that can be done at home (Dingel and Neiman, 2020). Using a difference-in-differences methodology, we investigate the extent to which CBSAs with a larger share of remote jobs experience a slower recovery in air passenger travel post-pandemic, all else equal. We further employ an event study analysis to understand the dynamics in the recovery of the U.S. aviation industry post-pandemic.

Our findings provide direct evidence that the substitution towards remote work and away from routine face-to-face interactions, which we observe in the labor market via work-from-home schedules, has impacted the recovery of the U.S. aviation sector post-pandemic. Our results indicate that a one standard deviation increase in the fraction of employment

[1] We use the terms "CBSA" and "city" interchangeably throughout the paper.

in remote work within the CBSA results in a 8.8 percent decline in air passenger flows after the onset of the COVID-19 pandemic in March 2020. When looking at the effects by city size or prevalence of remote work specialization, our estimates suggest that the differences in responses between small and large cities is not statistically significant. We also find that the demand for air travel in majority Republican cities recovers faster than in the majority Democratic cities; on average, cities classified as Republican experience a smaller drop in the demand for air travel during the pandemic. We connect this result to the fact that COVID-19 became more than a public health issue and was highly politicized, leading some Republican cities to remove mask mandates, travel restrictions, and other public health safety measures as soon as vaccination became widely available.

Our results are important for several reasons. First, they help identify new factors (that were not considered pre-pandemic) that affect the demand for air travel. Knowledge of their magnitude is important for generating more accurate predictions about the scale and growth of the aviation industry. Second, our results could raise questions about air carrier survival and about competition in aviation markets. A slow recovery of air travel may force airlines out of business or induce consolidations, which in turn would affect airfares and connectivity within the aviation network. While our data does not separate passenger flows by class of service, it is conceivable that business-class travel has been more severely affected by the shift towards telecommuting. Similarly, the substitution away from in-person meetings could impact the recovery of international air travel recovery too given that the COVID-19 pandemic forced firms worldwide to transact remotely and learn the feasibility of telecommuting. As business-class and international routes are the most lucrative services offered by major airlines, their financial recovery could take longer than expected with implications for government stimulus spending.

Our paper makes several contributions to the economics literature. First, we offer new evidence on the post-pandemic recovery of the airline industry. To the best of our knowledge, this is the first study to employ econometric analysis to investigate the impact of telecommuting and remote work on the aviation industry. Several papers have studied the evolution of passenger aviation in the aftermath of the COVID-19 pandemic. Sun et al. (2021) and Sun et al. (2022) provide insightful surveys of the literature on air transport, discussing the main challenges facing airlines, airports and air passengers in the aftermath of the pandemic. Abate et al. (2020) examines the determinants and consequences of government support measures to the airline industry in the aftermath of the pandemic. Generally, the timeframe of most COVID-19-related studies is the immediate months following the outbreak (e.g., Dube et al., 2021), which limits the perspective on the path to recovery of the airline industry. Nevertheless, there is consistent support for the view that the aviation sector has struggled to return to pre-pandemic levels of air passenger traffic, with international traffic being particularly affected (IATA, 2022; Caputo et al., 2023; Georgiadis, 2024). In fact, Javadinasr et al. (2022) use survey data to document the expectation of business travelers to fly less post-pandemic, in large part because of the effectiveness of conducting business meetings via conference calls/video conferencing.

Second, our paper contributes to the growing literature on telecommuting and the implications of remote work arrangements observed since the COVID-19 pandemic. According to Barrero et al. (2023), 28 percent of paid workdays in June 2023 involve working from home. This represents a four-fold increase relative to 2019 levels.[2] The pandemic catalyzed the shift to remote work by forcing a mass social experiment in working arrangements between employers and employees, business providers and their clients. Barrero et al. (2023) and Hansen et al. (2023) provide insightful discussions into the factors that explain the persistency of remote work arrangements post-pandemic. Our econometric analysis is motivated by the descriptive evidence presented in these studies. Dingel and Neiman (2020) is among the first studies to evaluate the economic impact of "social distancing" measures imposed at the peak of the COVID-19 pandemic. One of their main contributions is to develop a work-from-home measure that captures the possibility of an occupation to be performed remotely. They combine this occupational classification with employment shares observed in an industry, a city or a country to assess the fraction of jobs in a market or economy that can be performed remotely. In our analysis, we use their CBSA-level measure of remote jobs to capture differences in telecommuting across U.S. cities. Most of the papers to date that examine the implications of remote work focus on labor market outcomes (Dingel and Neiman, 2020; Gibbs et al., 2023; Choudhury et al., 2024), urban density and real estate markets (Delventhal et al., 2022; Monte et al., 2023), or economic geography considerations (Althoff et al., 2022; Delventhal and Parkhomenko, 2023). Other than implications for daily commuting patterns, we are not aware of research that connects the insights from the remote work literature to the transportation literature.

Lastly, our paper speaks to the regional economics and international trade literatures. Air travel is an important determinant of regional growth (e.g., Brueckner, 2003; Green, 2007; Bel and Fageda, 2008; Blonigen and Cristea, 2015; Sheard, 2019); it is also a contributor to goods trade and a component of services trade (e.g., Poole, 2010; Cristea, 2011; Mayer et al., 2024). Learning more about the dynamics of the aviation industry in the aftermath of the

[2] Brynjolfsson et al. (2023) design a nationally-representative survey to measure the extent of remote work in the American economy triggered by the COVID-19 pandemic. They find that as of December 2020, about half of the U.S. workforce worked remotely at least one day per week. They provide explanations for why the measurement of remote work constructed from public data sources may underestimate the extent of telecommuting.

COVID-19 pandemic could influence our understanding of trade patterns and production networks (Botero Garcia et al., 2021).

The remainder of our paper is organized as follows. Section 2 describes the econometric model and the identification strategy pursued in this study. Section 3 introduces our data and provides descriptive statistics characterizing the US urban locations (i.e., CBSAs) in our sample. The estimation results are discussed in Section 4, including the robustness exercises and the heterogeneity analyses implemented. Section 5 discusses the main policy implications of our results and concludes.

2 Estimation Methodology

Our goal is to examine the slower than expected recovery of passenger aviation following the COVID-19 pandemic, with a particular focus on the role that telecommuting may have played in reducing the demand for business travel. To that end, we propose the following estimation model for the demand for air travel at the local level:

$$ln\text{Pax}_{imy} = \alpha_i + \alpha_{my} + \beta\big(\text{Remote}_i \times \text{COV19}_{my}\big) + X_{iy}{}'\gamma + \epsilon_{imy} \tag{1}$$

where i indexes a CBSA in our sample, m indexes a month period, and y indexes a year between 2017-2022. The dependent variable $lnPax$ denotes the natural log of the number of air passengers flying domestically out of city i in month m and year y.[3] Ideally, we would distinguish between personal versus business air travel, however we could not get data that clearly separates the number of travelers by ticket class or purpose of travel. α_i and α_{my} denote CBSA fixed effects, respectively month-year fixed effects. The city-specific effects account for differences across CBSAs in terms of location, geography, time-invariant socio-economic characteristics like amenities, industry composition or the fraction of jobs that can be performed remote (i.e., $Remote_i$), among others. The period-specific effects account for time-varying macroeconomic factors that are common to all cities in our sample, such as labor market tightness (which could affect labor shortages in the aviation industry) or aviation industry-specific factors (e.g., aircraft fleet in use and associated capacity restrictions). Important for our analysis, α_{my} controls for the timeline of the COVID-19 pandemic, including surges in new virus variants, as well as federal mandates concerning safety measures such as lockdowns, masking and later on vaccination requirements.

[3] In unreported results, we have experimented with several related dependent variables such as the number of departures offered, the number of seats available (i.e., supply capacity), or the number of destinations reached via direct service. We opted to focus on passenger counts only as measure of air transport services because of the high correlation between this variable and the unreported ones (i.e., seats, departures and destinations). The unreported results are available upon request.

The variable of interest is the interaction term between the prevalence of remote work in city i, as measured by $Remote_i$, and the indicator variable $COV19$ which equals 1 for the period starting in March 2020 and continuing till the end of our sample period in December 2022. The identification of the coefficient of interest β relies on the difference-in-differences estimation methodology, which calculates the average change in monthly air traffic in the periods before versus after the pandemic and compares it between cities with a high share versus a low share of remote work. Our testable hypothesis is that by the nature of the COVID-19 pandemic, firms were forced to experiment and discover *all at the same time* the scope and limitations of telecommuting. In addition to employees working from home, many firms substituted in-person business meeting with teleconferencing following the pandemic. To the extent that this substitution has led to new business models and practices for firms, this could reduce the demand for air travel, slowing down the recovery of air transport services to pre-pandemic levels. Thus, a negative coefficient for β would be indicative of such a business shift.

In order to precisely measure the coefficient of interest β from equation (1), we need to ensure that we control for any time-varying factors that affect the demand for air travel independent of the existence of remote work. Thus, the vector X_{imy} includes observable time-varying factors that determine air travel, such as city-level population and personal income, as well as the number of COVID-19 infections over recent periods such as the past three months.[4]

Equation (1) represents a standard difference-in-differences model, where the coefficient of interest β measures the average treatment effect over the post-pandemic period 2020-2022. However, we expect that the effect of telecommuting on the demand for air travel varies over time. To investigate the dynamic effect of remote work on the demand for air travel during the post-pandemic period, we estimate an event study model of the following form:

$$ln\text{Pax}_{imy} = \alpha_i + \alpha_{my} + \sum_{t \neq 2019} \beta_t \big(\text{Remote}_i \times \mathbb{1}(y = t)_{my}\big) + X_{iy}{}'\gamma + \epsilon_{imy} \tag{2}$$

where $\mathbb{1}(y = t)_{my}$ represents an indicator variable equal to one for all the months m of year y, with $y \in \{2017, 2018, 2020, 2021, 2022\}$. We designate year 2019 as the reference pre-COVID period against which all the other periods will be compared. So the coefficients of interest β_t will measure the effect of remote work on the average monthly demand for air travel in year $t \neq 2019$ relative to the base year 2019. Since the mass transition to remote work has been triggered by the COVID-19 pandemic, we expect β_{2017} and β_{2018} to not be distinguishable

[4] In unreported results, we experimented with the number of reported deaths by CBSA, with similar estimation results. We opted to use the number of COVID-19 infections recorded over a 3-month rolling period because of the lower incidence of zeros.

from zero (a direct test of the parallel trends assumption necessary in difference-in-differences estimations). At the same time we expect β_{2020}, β_{2021} and β_{2022} to be negative and possibly decreasing in absolute value (a sign that eventually air traffic returns to levels observed in 2019).

We can further refine the estimation in equation (2) to allow the β coefficients to take values at month-year frequencies. We experiment with 10 month leads defined relative to the start of the COVID-19 pandemic and with 24 month lags. This would cover a year prior and two years post March 2020. Despite the demands in terms of data variation for such an event study estimation, a visual representation of the estimated coefficients of interest could illustrate pre-trends as well as more granular dynamics in the recovery of air passenger travel in the post-pandemic period.

3 Data

To estimate our regression model, we need to combine three main sources of information available at the CBSA level: i) data on air passenger travel, ii) data on prevalence of remote work, and iii) data on socio-economic characteristics. We describe the main data sources below.

Air Passenger Data. Data on U.S. domestic air passengers comes from the T-100 Domestic Market Data series collected by the U.S. Department of Transportation, the Bureau of Transportation Statistics. We focus on monthly travel data for the period 2017-2022, covering three years before and three years after the onset of the COVID-19 pandemic. The T-100 Domestic Market database is compiled from Form 41, a document that all U.S. certified airlines are legally required to fill out and that reports all the domestic flight operations of these carriers between airports located within the boundaries of the United States and its territories. For each origin - destination airport pair, which is defined as a "market", the carriers report number of passengers, seats, and departures scheduled and operated.

Figure 2 plots the total number of air passengers flying on domestic routes between 2017-2022, constructed from the T-100 Domestic Market Data. The trend is de-seasoned by removing the month-specific effects. Confirming the patterns observed at global level, US domestic air traffic has experienced a slower rebound effect post-COVID. By the end of 2022, U.S. passenger counts were not back yet to pre-pandemic levels.

For our econometric analysis, we modify the T-100 Domestic Market data in the following way. Given that our unit of analysis is a CBSA, we aggregate the number of air passengers traveling to all domestic destinations into a total value of air passengers by origin airport. We then assign each airpot to the nearest CBSA to get the total number of out-

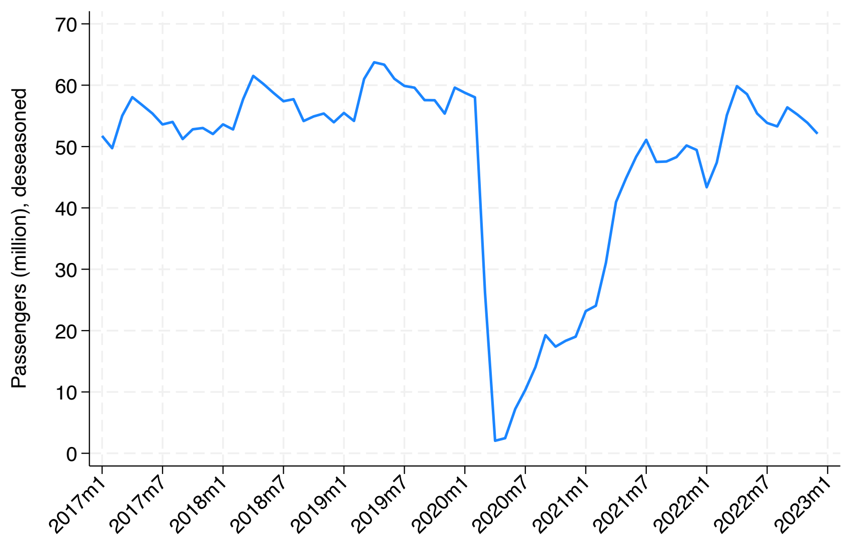

Figure 2: U.S. Domestic Air Passenger Travel

Notes: This figure plots total monthly domestic air passenger flows, adjusted for seasonality. Source: T-100 Domestic Market data.

bound air passengers by CBSA.[5] This aggregation removes the US carrier and the destination dimensions from the data.

Remote Work Data Our intention is to capture the extent to which firms replace in-person business meetings with telework. We hypothesize that the COVID-19 pandemic was the perfect storm to force firms to experiment and learn all together and at the same time the extent to which some business meetings can be switched to a remote format. Some of this transition may have been facilitated by employees opting to telecommute and work from home post-pandemic. Since we lack specific data on telework adoption by firms in a city, we exploit the available data on remote work or work from home. In doing so, our implicit assumption is that cities with a higher share of jobs performed remotely are more likely to substitute some of the more routine in-person business meeting with telecommuting.

Our first proxy for telework is the widely used work-from-home variable constructed by Dingel and Neiman (2020). Using the O*NET database from the U.S. Bureau of Labor Statistics (BLS), Dingel and Neiman (2020) identify occupations that can be performed from home judged based on the nature of the work involved. They then merge this information with BLS data on the number of workers employed in each occupation in 2018 by metropolitan area. The resulting work-from-home variable captures the share of jobs that can be performed remotely at the CBSA level. We refer to this work-from-home measure as our "remote work" variable.

[5]As in Blonigen and Cristea (2015), we consolidate the CBSAs that are served by the same airport(s).

A second measure of telework captures the growth in job vacancies advertising hybrid work during 2019-2022 period. The data comes from Hansen et al. (2023), who exploit the "near-universe" of online job postings and machine learning tools to identify the percent of job vacancies that explicitly advertise the possibility of working remotely one or more days per week. For the U.S., such data is reported monthly by county level. We use a mapping of counties to CBSAs constructed from the U.S. Census Gazetteer files and aggregate the job vacancies data at annual level by CBSA. We then construct the percentage point change in job vacancies that advertise remote work between 2019 (i.e., pre-pandemic year) and 2022 (i.e., last year in our sample). Our intention is to capture differences across US cities in firms' adoption of telework.

Socio-Economic Data. In our estimation analysis, we need to control for economic and demographic factors that affect the demand for air travel. Some of these factors may correlate with city-level industry composition, which influences telework. So, accounting for them is important.

Annual data on population and personal income are available at county level from the Bureau of Economic Analysis (BEA). We use our mapping of counties to CBSAs to construct annual data on population and personal income for all the CBSAs in our sample over the period 2017-2022. In some specifications we also employ multiple (decade-long) lags of population to account in the most flexible way for pre-existing urban growth trends. Decennial population data going back several decades also comes from the BEA.

Following the COVID-19 pandemic, air travel has been impacted by social distancing policies and the risk of virus infection. To capture the severity of COVID-19 infections across CBSAs, we use data on the number of COVID-19 cases collected by the Johns Hopkins University Center for Systems Science and Engineering (JHU CSSE, 2023). The original data reports confirmed cases and deaths at daily frequency by U.S. county. For our analysis, we aggregate the data by CBSA - month level and then calculate the rolling 3-month sum of all confirmed COVID-19 cases per CBSA. We use a rolling sum of cases rather than cases each month to pick up any recent waves in COVID-19 infections and the fact that when planning travel, people would look at the recent trends in infections rather than just considering the number of cases in the month of travel.

We also collect cross-sectional data on local economic and demographic characteristics, which could potentially influence the demand for air travel and the likelihood of telework. We construct socio-economic variables at CBSA level by aggregating county-level information for the pre-sample year 2016 on the share of workforce that is employed in manufacturing, on the fraction of population that is female, and the fraction of population that is non-white. County-level data on population by age, race and gender from 1969 onwards come from the NBER, which collects this information from the Survey of Epidemiology and End Results (SEER). County-level data on manufacturing employment comes from the U.S. Census County Business Patterns. The choice to employ cross-sectional data for 2016 is motivated by the fact that there is little (if any) time variation in socio-demographic characteristics over the sample period 2017-2022. In fact, in our preferred specifications, we will replace the socio-demographic characteristics by CBSA fixed effects.

Given how polarizing the COVID-19 epidemic was politically, it is important to control for political allegiances. To do so, we use the County Presidential Election Returns 2000-2020 dataset collected by MIT Election Data and Science Lab and obtained through Harvard Dataverse (Data and Lab (2018)). We calculate the share of population that voted for a Republican or Democratic president in the 2020 US Presidential election to assign political majority to a CBSA. We use the distinction between Republican and Democratic CBSA in our heterogeneity analysis.

Table 1: Summary Statistics

	Mean	**St. Dev.**	**Min**	**Max**
Population (millions)	1.104	2.109	0.061	20.049
Personal Income (‘000)	51.124	11.849	25.794	138.973
Manufacturing employment share, 2016	0.161	0.049	0.051	0.323
Fraction female, 2016	0.500	0.013	0.435	0.527
Fraction non-white popoulation, 2016	0.175	0.111	0.022	0.579
Share Republican vote, 2020 Presid Election	0.508	0.126	0.166	0.775
COVID Cases (‘000), 3-month rolling sum	13.453	59.754	0.001	2,309.221
Growth in hybrid job ads, 2019-2022	0.052	0.031	-0.036	0.248
Fraction employment in remote work	0.336	0.050	0.233	0.511
Frac remote work in above median CBSAs (by pop)	0.356	0.047	0.259	0.511
Frac remote work in below median CBSAs (by pop)	0.316	0.044	0.233	0.494
Frac remote work in above median CBSAs (by remote work)	0.371	0.037	0.319	0.511
Frac remote work in below median CBSAs (by remote work)	0.293	0.020	0.233	0.318
Frac remote work in majority Democrat CBSAs	0.360	0.055	0.233	0.511
Frac remote work in majority Republican CBSAs	0.322	0.040	0.238	0.429

Notes: This table presents summary statistics for the independent and control variables outlined in this section. Below and above median indicators for fraction of remote work are calculated based on the population size of the CBSA (by pop), and based on the prevalence of remote work in each CBSA (by remote work).

After combining all of the data sources, we restrict our dataset to a balanced sample of 210 consolidated CBSAs, each observed for 72 periods (monthly, from January, 2017 to December, 2022) for a total of 15,120 observations. Table 1 reports the summary statistics for the estimation sample. There is quite a bit of variation among CBSAs in size, socio-demographic composition (e.g., non-white population share, political leaning), in industrial structure (e.g., share of manufacturing) or potential for remote work. For some CBSAs, as much as half of the jobs could be performed remotely. This is true for both “small” CBSAs – defined as below median in population size, or “large” CBSAs.

Table 2: Effect of Remote Work on the Demand for Air Passenger Travel

	Dependent variable: log number of air passengers				
	Controls	**Benchmark**	**Pop lags**	**COVID x Ctrls**	**Omit LgCity**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Remote work × COVID-19	-1.784***	-1.755***	-1.777***	-1.750***	-1.775***
	(0.444)	(0.434)	(0.396)	(0.499)	(0.435)
Log Population	1.643***	0.938	-0.578	0.069	0.958
	(0.073)	(0.673)	(0.752)	(0.641)	(0.694)
Log COVID-19 Cases (3mo)	-0.005	-0.001	-0.007	-0.012	-0.000
	(0.014)	(0.010)	(0.009)	(0.009)	(0.011)
Log Personal Income	1.539***	0.796***	0.402*	0.975***	0.802***
	(0.512)	(0.237)	(0.208)	(0.231)	(0.235)
Manufacturing employment share, 2016	-6.268***				
	(1.603)				
Fraction female, 2016	-3.030				
	(5.479)				
Fraction non-white popoulation, 2016	-1.612				
	(0.990)				
Share Republican vote, 2020 Presid Election	0.869				
	(0.552)				
Fraction employment in remote work	3.438**				
	(1.599)				
Log Population Lag, t-10			2.524***		
			(0.833)		
Log Population Lag, t-20			1.120**		
			(0.482)		
Log Population × COVID-19				0.055***	
				(0.015)	
Log Personal Income × COVID-19				-0.057	
				(0.085)	
Manufacturing share × COVID-19				-1.613***	
				(0.505)	
Frac female × COVID-19				-2.025*	
				(1.063)	
Frac non-white × COVID-19				-0.160	
				(0.183)	
Share Republican × COVID-19				0.720***	
				(0.167)	
State fixed effects	yes				
CBSA fixed effects		yes	yes	yes	yes
Month-year fixed effects	yes	yes	yes	yes	yes
Obs.	15,120	15,120	15,120	15,120	14,760
R^2	0.886	0.988	0.988	0.988	0.987

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered at the state level. Each column shows results of various approaches to estimation of equation (1). Column (2) presents the benchmark results; column (1) includes CBSA-level controls in place of CBSA fixed effects; columns (3) and (4) introduce additional CBSA-period controls; sample used for estimation in column (5) omits 5 outlier CBSAs by population (New York City, Atlanta, Chicago, Los Angeles, Fort Worth).

4 Estimation Results

This section presents the findings from four sets of empirical exercises. First, we discuss the results from our baseline regression in equation (1). We perform several robustness exercises to ensure that the model is well specified. Second, we explore the heterogeneity in our benchmark result by examining the variation in the coefficient of interest across CBSAs with different socio-demographic characteristics. Third, we examine dynamic effects by presenting event study analyses based on the estimation model in equation (2). Lastly, we extend our regression analysis to a data sample of bilateral origin-destination air passenger flows to verify the consistency of our findings regarding the influence of remote work on air travel.

4.1 Benchmark Specification and Robustness Exercises

We begin our analysis by estimating equation (1), which defines our benchmark specification. The results are presented in column (2) of Table 2. Focusing on our variable of interest, we find evidence of a statistically significant reduction in the number of passengers traveling from CBSAs with a higher prevalence of remote work. The estimate suggests that a one standard deviation increase in the fraction of remote jobs in a CBSA results in a 8.8 percent average decline in the monthly volume of air passengers after the onset of the COVID-19 pandemic, relative to pre-pandemic levels.[6] This finding supports our hypothesis that following the pandemic firms may indeed substitute in-person business meeting with teleconferencing, which reduces their demand for air travel.

Next, we provide several robustness measures to ensure our specification holds. In column (1) of Table 2, we replace the CBSA level fixed effects with state level fixed effects and add a variety of CBSA controls, such as logged personal income, the manufacturing employment share in 2016, the fraction of females in the labor force and the fraction non-white workers in total employment in 2016, the share of voters voting for a Republican president in the 2020 Presidential elections, and the fraction of employment in jobs that can be performed remotely. The coefficient of interest on the interaction term between the share of remote work and post-COVID-19 indicator variable, is statistically significant at 1%, and of similar magnitude as the benchmark coefficient value in column (2).

In the second robustness check, in addition to controlling for the CBSA population, we include population lags of 10 and 20 years (column (3)), following Duranton and Turner (2012) and Duranton and Turner (2011). In their 2012 study they estimate the impacts

[6] A standard deviation in the fraction of employment in remote work per CBSA is equal to 0.05 or 5 percentage points. When multiplied by -1.755, which is the coefficient estimate of interest from column 2 of Table 2, we get an average decrease in monthly air traffic of 0.088 log points or 8.8 percent.

of interstate highways on urban growth in the US, and use logs of population levels in decennial years as controls, because past populations are likely correlated with unobservable CBSA characteristics that determine transportation demand (2011 study). The statistical significance of the coefficient of interest and its magnitude remain similar to our benchmark estimate in column (2).

The third robustness check includes interaction terms between the post-COVID-19 indicator variable and the CBSA-specific controls from the first robustness check. Given that these CBSA controls are time-invariant, they get dropped when we control for location fixed effects. In order to ensure we are not introducing omitted variable bias by excluding them, we create these interactions to allow temporal variation in these controls. The statistical significance and the magnitude of our coefficient of interest remains similar to the benchmark estimate, as notice from the results reported in column (4) of Table 2.

The fourth robustness check deals with the fact that very large CBSAs could be skewing our results. For example, large metropolitan areas such as New York City, Los Angeles, Chicago, Dallas, or Atlanta have a larger prevalence of remote work, as well as initiate significantly more air travel.[7] We exclude the top 5 CBSAs by passenger volume from our sample and re-estimate equation (1). The results reported in column (5) of Table 2 indicate a similar magnitude and statistical significance to our benchmark estimate in column (2).

Finally, in our last robustness exercise, we experiment with an alternative measure of telework, which captures the growth in job vacancies that advertise hybrid work during the 2019-2022 period. Our new variable of interest becomes the interaction term between the growth in job ads at CBSA level and the post COVID-19 indicator variable. We include it in equation (1) to replace the original interaction term of interest. The results are reported in Table 3, which replicates the same set of regression specifications as in Table 2. We find a negative and statistically significant impact on post pandemic air travel for states that have a higher growth in job posts advertising hybrid work across all columns in Table 3. For example, the results for our benchmark specification on column (2) are interpreted as follows: a one standard deviation increase in growth of remote work ads within the CBSA results in 8.1 percent decline in passenger flows after the onset of the COVID-19 pandemic in March 2020. Thus, we provide evidence that the predisposition of firms to offer telework created differences to how post-pandemic travel was approached across the US cities.

After completing these four robustness checks, we are confident with proceeding with our benchmark specification in column (2) for the purposes of further analysis.

[7] We present the list of 20 largest CBSAs by population, share or prevalence of remote work, and the growth in hybrid ads jobs in Table A1 of the Appendix.

Table 3: Alternative Measure of Remote Work: Growth in Hybrid Job Ads (2019-22)

	Dependent variable: log number of air passengers				
	Controls	Benchmark	Pop lags	COVID×Ctrls	Omit LgCity
	(1)	(2)	(3)	(4)	(5)
Hybrid jobs × COVID-19	-2.750***	-2.690***	-2.856***	-2.501***	-2.702***
	(0.630)	(0.630)	(0.528)	(0.606)	(0.636)
Log Population	1.665***	1.418**	-0.691	0.660	1.450**
	(0.072)	(0.627)	(0.732)	(0.618)	(0.646)
Log COVID-19 Cases (3mo)	-0.008	-0.003	-0.010	-0.013	-0.002
	(0.013)	(0.009)	(0.007)	(0.009)	(0.009)
Log Personal Income	1.981***	0.855**	0.310	0.979**	0.859***
	(0.536)	(0.320)	(0.237)	(0.412)	(0.314)
Manufacturing employment share, 2016	-7.416***				
	(1.514)				
Fraction female, 2016	-3.356				
	(7.147)				
Fraction non-white population, 2016	-2.097**				
	(0.870)				
Share Republican vote, 2020 Election	1.023**				
	(0.464)				
Growth in hybrid job ads, 2019-2022	2.372				
	(3.379)				
State fixed effects	yes				
CBSA fixed effects		yes	yes	yes	yes
Month-year fixed effects	yes	yes	yes	yes	yes
Obs.	14,040	14,040	14,040	14,040	13,680
R^2	0.888	0.989	0.989	0.989	0.987

Notes:*p<0.1; **p<0.05; ***p<0.01. Standard errors clustered at the state level. This table replicates results in Table 2, but an alternative measure of remote work is used, i.e., the growth in job vacancies advertising hybrid work in each CBSA in 2019-2022.

4.2 Heterogeneity Analysis

We proceed by analyzing the heterogeneity in the response of air travel during the post COVID-19 period to CBSA characteristics such as population size, prevalence of remote work, or political leaning. These results are presented in Table 4, in which column (1) reproduces the benchmark coefficients for ease of comparison.

The first heterogeneity analysis focuses on the difference in the response of air travel post COVID-19 pandemic between large and small CBSAs. If the availability and undertaking of remote work differs across cities based on their size, with larger CBSAs being more likely to offer opportunities for remote work, then we could expect a larger impact of the pandemic on the demand for air travel in those CBSAs. To test this hypothesis, we create an indicator variable, that captures whether a CBSA's population size is below the median population across all CBSAs present in our panel. This indicator variable is then interacted with our variable of interest and included in the benchmark equation (1). The estimation re-

Table 4: Heterogeneity in the Effect of Remote Work on Air Travel Demand

	Dependent variable: log number of air passengers			
	Benchmark	CBSA Size	Less Remote	Political
	(1)	(2)	(3)	(4)
Remote work × COVID-19	-1.755***	-1.761***	-2.375***	-1.600***
	(0.434)	(0.432)	(0.718)	(0.456)
Log Population	0.938	0.853	0.806	0.700
	(0.673)	(0.676)	(0.675)	(0.633)
Log COVID-19 Cases (3mo)	-0.001	-0.009	-0.002	0.003
	(0.010)	(0.009)	(0.010)	(0.011)
Log Personal Income	0.796***	0.772***	0.863***	0.964***
	(0.237)	(0.245)	(0.248)	(0.243)
Remote wk × COV19 × Below med CBSA by pop		-0.132		
		(0.108)		
Remote wk × COV19 × Below med CBSA by remote			-0.284	
			(0.232)	
Remote wk × COVID-19 × Majority Republican				0.282***
				(0.085)
CBSA fixed effects	yes	yes	yes	yes
Month-year fixed effects	yes	yes	yes	yes
Obs.	15,120	15,120	15,120	15,120
R^2	0.988	0.988	0.988	0.988

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered at the state level. This table shows results of the heterogeneity analysis of the responses of travel post COVID-19 based on such CBSA's characteristics as its population size, prevalence of remote work, and political leaning. Column (1) presents baseline results for comparison. In column (2) we distinguish the response of demand for air travel for "small" versus "large" CBSAs based on the population size. CBSA is considered "small" if its population in year 2019 is below the median population of the sample. The interaction term between the variable of interest and the dummy variables for the "small" CBSA is included in equation (1) and the equation is re-estimated. Column (2) presents heterogeneity in the responses of air travel in CBSAs with prevalence of remote work below the sample median, compared to the ones with share or remote workers above the sample median. Column (4) distinguishes the heterogeneity of responses between the majority Republican and majority Democratic CBSAs, as determined by the voting shares in the 2020 Presidential elections. Significance of interaction terms determines whether the difference in the responses of the two categories is statistically significant.

sults are reported in column (2) of Table 4. We do not find statistically significant difference between post COVID-19 travel disruption between "large" and "small" CBSAs.

Similarly, we check whether the difference in prevalence of remote work itself could drive the difference between travel responses within CBSAs. Our approach is similar to the one described above. Instead of the indicator variable that captures the population size of CBSAs, we construct a dummy variable that takes the value of one if the share of teleworking employees in a given CBSA is below the median value across all CBSAs present in our sample. As evident from column (3) of Table 4, CBSAs with shares of remote employees above, respectively below the median value, experience statistically significant negative impact of COVID-19 on air travel, and this difference is not statistically significant.

Lastly, we check whether the political leaning of a CBSA could drive any difference in responses. While Republican states tended to be more lenient about the pandemic, Democratic states adopted stricter mask and vaccine mandates, and restrictions. Our hypothesis is that Republican states had fewer restrictions on air travel, which would somewhat reduce the negative impacts of the pandemic shock. To test this hypothesis, we proceed as follows. We interact our main variable of interest with the Republican majority dummy, described in Section 3, and include it in equation (1). We present these results in column (4) of Table 4. Indeed, we find that Republican leaning CBSAs experienced a smaller decline in air travel post COVID-19 pandemic. While a one standard deviation increase in remote work leads to a 8 percent decrease in passenger flows in Democratic CBSAs, in Republicans CBSAs this effect represents a decline of 6.6 percent. This difference is statistically significant, which confirms our hypothesis that a more lenient approach to COVID-19 pandemic in the Republican CBSAs had a mitigation effect on the severity of the air travel impacts of the pandemic.

4.3 Dynamic Effects

As we mentioned in Section 1, during the COVID-19 pandemic, trade in travel and transport services departed drastically from the pattern of other services trade, and their recovery to pre-pandemic levels took a much longer time. Thus, we also investigate the dynamic effects of the COVID-19 pandemic on the demand for air travel. Our objective is to trace how fast travel recovers as pandemic restrictions ease up. Towards that goal, we conduct two analyses: (1) we calculate average annual effects of remote work on air travel demand between 2017-2022 using the two independent variables previously used, i.e., the prevalence of remote work and growth in hybrid job ads; and (2) we conduct an event study that exploits the monthly frequency of our estimation sample. These exercises serve as additional checks of the parallel trends assumption required by our difference-in-differences (DiD) methodology. That is, they ensure that our DiD coefficient of interest captures the effect of telecommuting adoption post-pandemic, rather than be an artifact of pre-existing omitted factors. The exercises can also test whether, prior to the pandemic, there exists no statistically significant difference in the trends between the control and treatment CBSAs.

To calculate the average annual effects, we create indicator variables for each year between 2017 and 2022. We then interact these indicator variable with the two measures of remote work, and include the newly defined interaction terms in our regression model for air travel demand. Year 2019 serves as the pre-pandemic reference point and our comparison group, and thus we omit it from the estimations. Equation (2) formalizes the regression model that we estimate using both measures of remote work. We present the estimation results in Table 5. Confirming the parallel trends assumption, we find no statistically significant effects prior to 2020. However, we do find evidence of a statistically significant decrease in

Table 5: Dynamic Effects of Remote Work on Air Travel Demand

	Dep var: log number of air passengers	
	Telework measure used:	
	Remote Work	Hybrid Jobs
	(1)	(2)
Telework × 2017	0.486	0.753
	(0.343)	(0.478)
Telework × 2018	0.396	0.600
	(0.280)	(0.361)
Telework × 2020	-2.208***.	-2.984***
	(0.371)	(0.712)
Telework × 2021	-1.741***	-2.281***
	(0.388)	(0.678)
Telework × 2022	-0.064	-1.040
	(0.418)	(0.622)
CBSA fixed effects	yes	yes
Month-year fixed effects	yes	yes
Obs.	15,120	14,040
R^2	0.988	0.989

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered at the state level. This table presents average annual effects of remote work for the two dependent variables (prevalence of remote work in column (1) and growth in hybrid job ads in column (2)) on logged passenger flows between 2017 and 2022.

air travel for the years 2020 and 2021. We find that by 2022, the average annual effect of teleworking on the demand for air travel loses statistical significance, suggesting a recovery of air passenger volumes to pre-pandemic levels. These results are true for both remote work measures.

As a last step of the dynamic analysis, we conduct an event study of the effect of remote work on air travel demand. Our goal with this analysis is to chart the recovery of air travel demand post-pandemic, and to provide evidence of a slower rate of recovery in cities with a larger prevalence of remote work. For the event study we create indicator variables for 10 month-year periods prior to the onset of the COVID-19 pandemic in March 2020, and for 24 periods after the pandemic (including March 2020). We interact these lead and lag dummies with our main remote work variable and include them in the benchmark specification, replacing the original interaction term of interest. We plot the coefficients and the 95% confidence levels in Figure 3. The figure confirms once again the slow recovery of the demand for air travel in cities with larger share of remote work, which returns to pre-pandemic level in the end of 2021 - 2022. Slow recovery begins in summer of 2021, which corresponds to the roll-out of first wave of COVID-19 vaccines, followed by a lift of mask mandates and other pandemic restrictions in many counties.[8]

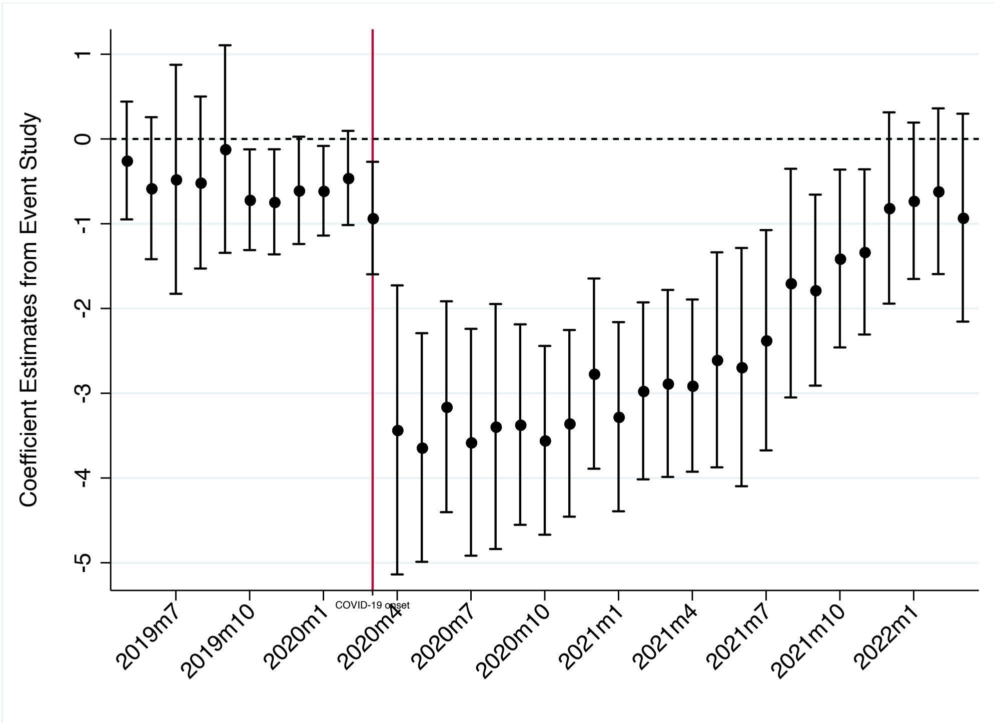

Figure 3: Event Study for the Effect of Remote Work on Air Travel Demand

Notes: This figure depicts 10 leads and 24 lags of the estimated effects of prevalence of remote work on the slower recovery in demand for air travel post-pandemic. The 95% confidence intervals are represented by the cap bars around the coefficients

4.4 Bilateral Travel

For our last set of exercises, we utilize origin-destination air passenger data to test our main hypothesis that the prevalence of remote work may be a factor explaining the slower-than-expected recovery of the aviation industry following the COVID-19 pandemic. Our motivation for this is twofold. First, we want to ensure that the results found so far at CBSA level are consistent and reflect travel patterns observed across most origin-destination aviation routes in our U.S. domestic data. Second, the use of bilateral data allows us to employ a more restricting set of regression fixed effects, which helps mitigate any remaining

[8]There is a lot of heterogeneity in the timing of lifting of the restrictions. For example, Texas governor Abbot lifted the state mask mandate in March, 2021, prior to the mass vaccination roll-out, while in Oregon mask mandate remained in place until March, 2022. We conduct another event study, separating the effects by the political affiliation of the CBSAs. These results are presented in Figure A1 of the Appendix. We find that the demand for air travel recovers faster in Republican CBSAs.

concerns about omitted variable bias. In what follows, we will first describe construction of the bilateral data, after which we will describe the empirical strategy and results.

As with the previous analysis, we continue to utilize the T-100 Domestic Market data, but we modify it in the following way. We assign each origin and destination airport to a particular CBSA, following the same methodology as described in Section 3. For each possible CBSA pair, we aggregate the number of air passengers traveling from the origin CBSA to the destination CBSA to get the total number of air passengers traveling between the CBSAs every month. In the new dataset, each observation captures the number of air passengers traveling from $CBSA_i$ to $CBSA_j$ every month-year time period my.

The data on demographic controls, new COVID-19 cases over a three-month rolling period, as well as data on telecommuting (using the two separate measures), are then merged with the new bilateral dataset. Both origin and destination CBSAs receive their own set of demographic controls.

We pursue two related estimation strategies that only differ by the set of fixed effects being considered. Our first approach is to we estimate separate effects by origin and destination CBSA on how remote work may impact the bilateral demand for air travel during the post-pandemic period. The model specification would take the following form:

$$\begin{aligned} ln\text{Pax}_{ijmy} = \alpha_{iy} + \alpha_{jy} + \alpha_{ij} + \alpha_{my} + \beta_1\big(\text{Remote}_i \times \text{COV19}_{my}\big) \\ +\beta_2\big(\text{Remote}_j \times \text{COV19}_{my}\big) + X_{imy}{}'\gamma_1 + X_{jmy}{}'\gamma_2 + \epsilon_{ijmy} \end{aligned} \quad (3)$$

where i indexes the origin CBSA in our sample, j is the destination CBSA, m indexes a month, and y indexes a year between 2017-2022. The dependent variable $lnPax$ denotes the natural log of the number of air passengers flying domestically out of city i into city j in month m and year y. α_{iy}, α_{jy}, α_{ij}, and α_{my} represent origin×year, destination×year, origin×destination and month×year fixed effects, respectively.[9] We also control for the number of new COVID-19 cases reported over the past three months at both origin and destination CBSAs. The two X vectors of location-specific control variables account for that.

Our two variables of interest are the interaction terms between the prevalence of telework in the origin city i ($Remote_i$), respectively the destination city j ($Remote_j$), and the indicator variable $COV19$ which is as defined previously. The identification of the β coef-

[9]We utilize the set of fixed effects commonly used in the gravity equation literature when modeling international trade flows between two locations. This comprehensive set of fixed effects controls for all factors that could impact international trade, most notably the multilateral resistance term, i.e., the difference in price indexes between two countries (see Anderson and van Wincoop (2003)). We believe that a similar approach could be applied to the analysis of passenger travel, because CBSAs differ in their characteristics and price indexes.

ficients relies on the same difference-in-differences estimation methodology, which compares the change in monthly air traffic in the months before versus after the pandemic differentiating between origin and destinations with a high share of remote work versus a low share. The advantage of the model specification in equation (3) over the benchmark equation (1) is the use of a more extensive set of fixed effects, which allows for a better control of underlying location-specific characteristics that could jointly determine telecommuting and air travel patterns. Notice that by using origin-year, respectively destination-year fixed effects, we implicitly rely on monthly variation during 2020 to identify the coefficients of interest.

We expect negative coefficients for β_1 and β_2 in equation (3), which would suggest that as firms shift their efforts towards telecommuting during and after the pandemic, they reduce their demand for air travel at origin and at destination CBSAs. By allowing the origin and destination effects to be identified separately, we implicitly assume that firms across the U.S. make independent travel decisions which are not influenced by the mode of doing business in destination cities.

To push our analysis one step further, we also consider the possibility that air travel decisions at route level are influenced by the prevalence of remote work at both origin and destination CBSAs. Perhaps the substitution away from in-person meetings is more likely when both buyers and sellers, or clients and providers, are making the transition towards telecommuting. To test this hypothesis, while controlling in a more rigorous way for time-varying factors at origin and destination CBSAs, we estimate the following triple-differences model:

$$ln\text{Pax}_{ijmy} = \alpha_{imy} + \alpha_{jmy} + \alpha_{ij} + \beta\big(\text{Remote}_i \times \text{Remote}_j \times \text{COV19}_{my}\big) + \epsilon_{ijmy} \tag{4}$$

where the subscripts are as defined previously. α_{imy}, α_{jmy}, and α_{ij} denote respectively origin×month×year, destination×month×year, respectively origin×destination fixed effects. The additional dimension of the data allows us to use more detailed fixed effects and capture any underlying origin-specific and destination-specific time trends, including any location-based measures and responses to the COVID-19 pandemic. Like before, the origin - destination fixed effects capture time-invariant characteristics within the CBSA pairs.

In this specification, our variable of interest is an interaction between the prevalence of telework in the origin city i, the prevalence of telework in the destination city j, and the indicator variable $COV19$, defined in Section 3. The coefficient β captures the effects of remote work prevalence in the origin and destination city on the air travel recovery within the CBSA pair. Our hypothesis is that two cities with relatively larger shares of remote employment would experience a slower recovery in the demand for air travel after the COVID-19 pandemic, as firms in both cities choose to continue telecommuting.

Table 6: Bilateral Air Travel Analysis

	Telework measure used:			
	Remote Work		Hybrid Jobs	
	Separate	Triple diff.	Separate	Triple diff.
	(1)	(2)	(3)	(4)
Origin: Telework × COVID-19	-1.845***		-2.674***	
	(0.314)		(0.486)	
Dest: Telework × COVID-19	-2.039***		-2.812***	
	(0.316)		(0.493)	
$\text{Telework}_{origin} \times \text{Telework}_{dest} \times$ COVID-19		-7.318**		2.951
		(3.333)		(11.53)
Origin - year fixed effects	yes	no	yes	no
Destination - year fixed effects	yes	no	yes	no
Origin - period fixed effects	no	yes	no	yes
Destination - period fixed effects	no	yes	no	yes
Origin - destination fixed effects	yes	yes	yes	yes
Period (month-year) fixed effects	yes	no	yes	no
Obs.	403,092	398,268	403,092	398,268
R^2	0.923	0.934	0.923	0.934

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered at the origin CBSA - destination CBSA level. This table shows results of the bilateral analysis. In the bilateral dataset, each observation captures number of air passengers traveling from $CBSA_i$ to $CBSA_j$ every month-year time period my. In columns (1) and (3), we estimate the first bilateral specification, which includes destination and origin CBSAs effects separately. In columns (2) and (4), remote work effects on post-COVID-19 travel recovery are estimated for bilateral CBSA pairs. Each specification is run for each of the two dependent variable: the prevalence of remote work (columns (1) and (2), and the growth in hybrid work ads (columns (3) and (4)).

We take equations (3) and (4) to the data. We run each regression once for each remote work measure we use (the prevalence of remote work, and the growth in the hybrid job ads). These results are presented in Table 6. The results of our first specification, which estimates the effects of remote work prevalence on the post COVID-19 recovery of air travel separately for the origin and destination cities, show that the β_1 and β_2 coefficients are statistically significant at 1% level, and are of similar magnitude as the benchmanrk results for both of the remote work measures (see column 2 of Table 2, respectively column 2 of Table 3). This confirms our hypothesis that origin cities with higher shares of remote employees experience a larger decline in air travel demand, and that the destination cities with higher remote work share receive fewer air travel passengers.

When analyzing the results of the second bilateral travel specification fromequation (4), we find a negative impact when we measure remote work using our original remote work prevalence variable. The estimated coefficient is statistically significant at 1% level and negative, which again confirms our hypothesis. When we use the growth in job postings advertising hybrid, we find a positive but statistically insignificant coefficient. Nevertheless, taken all together, the estimates obtained from using bilateral travel data confirm our hypothesis that remote work has statistically significant causal impacts on the post-pandemic recovery of air travel.

5 Discussion and Conclusions

This study investigates the factors influencing the recovery of the demand for air travel post-pandemic. In particular, we focus on one such factor, the increased use of remote work during and after the COVID-19 pandemic. We ask if this has triggered a substitution away from in-person business relations towards using teleconferencing more often. Our hypothesis is that locations with a higher concentration of occupations and business activities that can be performed remotely may see a larger decline in the demand for air travel services, thus explaining the slower-than-expected recovery of the aviation sector post-pandemic.

We utilize rich U.S. domestic data on air passenger transport, a difference-in-differences methodology, and two proxy measures for the prevalence of remote work, to establish if the sudden rise in remote work during the COVID-19 pandemic negatively impacts the recovery of demand for air travel post-pandemic. Our results indicate that, indeed, a one standard deviation increase in the prevalence of remote work within a CBSA leads to a statistically significant 8.8 percent average decline in air passenger flows post-pandemic. This result remains consistent across various robustness checks. Moreover, we find that cities we classify as majority Republican, based on the share of votes given to a Republican candidate during the 2020 US Presidential election, experience a smaller drop in the demand for air travel during the pandemic compared to Democratic cities. The air travel demand in those cities also recovers to pre-pandemic level faster than in Democratic cities.

Our findings provide direct evidence that the substitution from routine face-to-face interactions to remote work, has impacted the recovery of the U.S. aviation sector post-pandemic. Despite the pushback from some employers, remote work is here to stay, and understanding its impacts on transportation patterns is crucial to our ability to better forecast and analyze the aviation industry in the post-pandemic era.

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APPENDIX

Table A1: Top 20 CBSAs by population and two work from home measures

Rank	Population	Prevalence of remote work	Growth of remote job ads
1	New York-Northern New Jersey-Long Island, NY-NJ-PA	San Jose-Sunnyvale-Santa Clara, CA	Lansing-East Lansing, MI
2	Los Angeles-Long Beach-Santa Ana, CA	Trenton-Ewing, NJ	Little Rock-North Little Rock-Conway, AR
3	Chicago-Naperville-Joliet, IL-IN-WI	Austin-Round Rock-Granbury, TX	San Francisco-Oakland-Fremont, CA
4	Dallas-Fort Worth-Arlington, TX	San Francisco-Oakland-Fremont, CA	San Jose-Sunnyvale-Santa Clara, CA
5	Houston-Sugar Land-Baytown, TX	Boston-Cambridge-Quincy, MA-NH	Boise City-Nampa, ID
6	Naples-Marco Island & Miami-Fort Lauderdale-Pompano Beach, FL	Durham - Raleigh-Cary, NC	Austin-Round Rock-Granbury, TX
7	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	Tallahassee, FL	Madison, WI
8	Atlanta-Sandy Springs-Marietta, GA	Salt Lake City, UT	Burlington-South Burlington, VT
9	Phoenix-Mesa-Scottsdale, AZ	Springfield, IL	Seattle-Tacoma-Bellevue, WA
10	Boston-Cambridge-Quincy, MA-NH	Des Moines-West Des Moines, IA	Cortland-Ithaca, NY
11	San Francisco-Oakland-Fremont, CA	Madison, WI	Boston-Cambridge-Quincy, MA-NH
12	Riverside-San Bernardino-Ontario, CA	Albany-Schenectady-Troy, NY	Morgantown, WV
13	Detroit-Warren-Livonia, MI	Seattle-Tacoma-Bellevue, WA	Salt Lake City, UT
14	Seattle-Tacoma-Bellevue, WA	College Station-Bryan, TX	Trenton-Ewing, NJ
15	Minneapolis-St. Paul-Bloomington, MN-WI	New York-Northern New Jersey-Long Island, NY-NJ-PA	Du Bois - State College, PA
16	San Diego-Carlsbad-San Marcos, CA	Cortland-Ithaca, NY	Fayetteville-Springdale-Rogers, AR-MO
17	Denver-Aurora-Greenley, CO	Baltimore-Towson, MD	New York-Northern New Jersey-Long Island, NY-NJ-PA
18	Orlando-Kissimmee & Palm Bay-Melbourne-Titusville, FL	Minneapolis-St. Paul-Bloomington, MN-WI	Denver-Aurora-Greenley, CO
19	Tampa-St. Petersburg-Clearwater, FL	Lansing-East Lansing, MI	Durham - Raleigh-Cary, NC
20	St. Louis, MO-IL	Atlanta-Sandy Springs-Marietta, GA	Texarkana, TX-Texarkana, AR

Notes: *Population:* we rank the CBSAs from largest to smallest based on total population in 2019. Total population is calculated by the authors from the data from Bureau of Economic Analysis (BEA). *Prevalence of remote work:* source of the data is work-from-home variable constructed by Dingel and Neiman (2020). We rank each CBSA by the remote work prevalence in 2019 and list 20 largest CBSAs. *Growth of remote job ads:* the data is sources from Hansen et al. (2023), who calculate growth in job vacancies advertising hybrid work during 2019-2022 period.

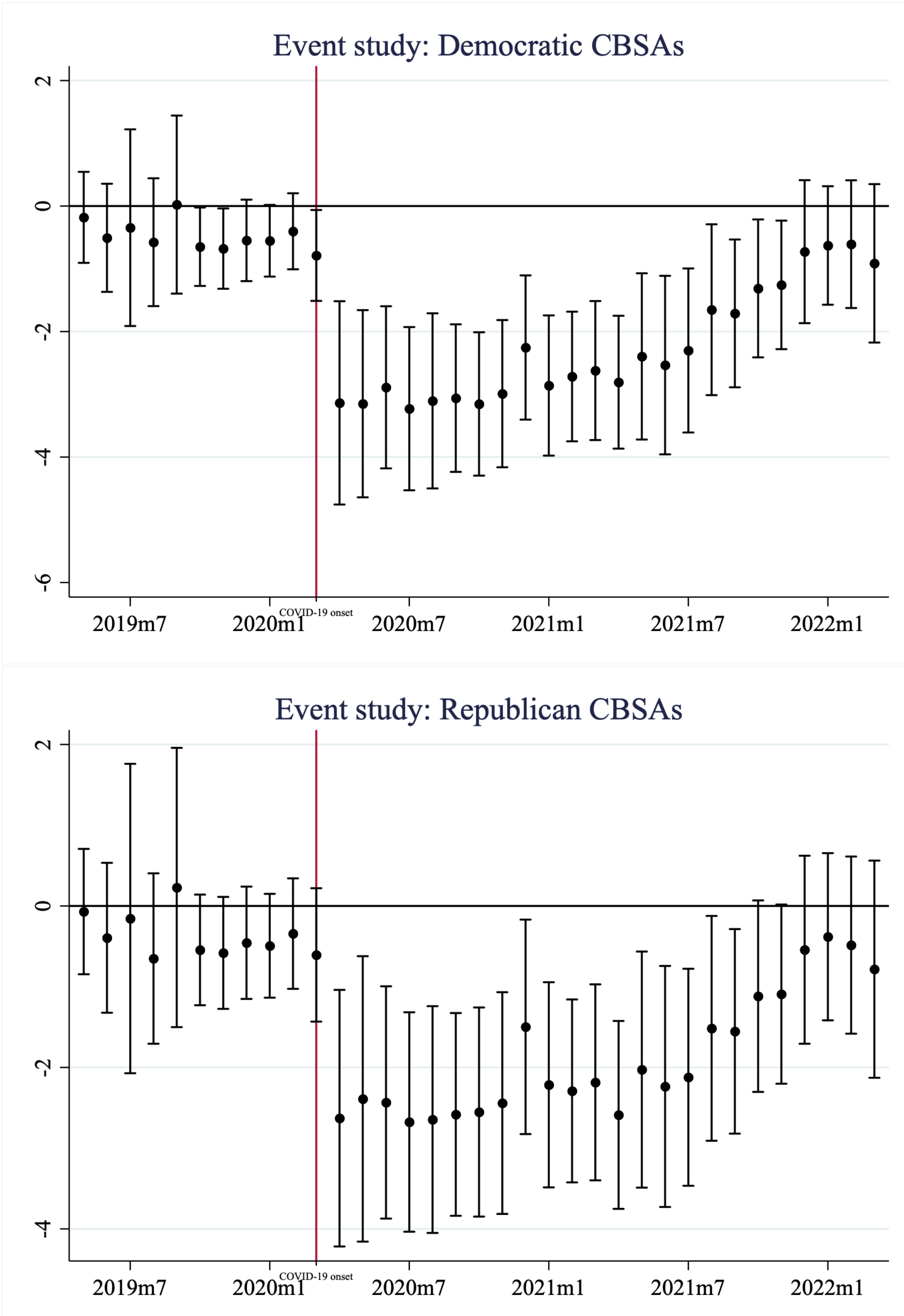

Figure A1: Event Study by Party Affiliation

Notes: This figure depicts 10 leads and 24 lags of the estimated effects of prevalence of remote work on the slower recovery in demand for air travel post-pandemic for Republican and Democratic CBSAs. The party affiliation is determined by the share of votes given to Republican and Democratic candidates during the 2020 US Presidential elections within each CBSA. The 95% confidence intervals are represented by the cap bars around the coefficients