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Political Polarization and Price Dispersion: Recent Evidence from the Airline Industry During COVID-19

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Political polarization and price dispersion: recent evidence from the airline industry during COVID-19

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ABSTRACT
This paper analyzes the relationship between price dispersion and political polarization of the endpoint states on a given route during the COVID-19 pandemic. The sample includes ticket information from the DB1B database between 2020:Q1 and 2021:Q4. The fixed-effect panel instrument variable (IV) estimation finds evidence of increased price dispersion on routes connecting states led by a Republican governor than those linking Democrat-led states. My analysis adds to the literature by exploiting the impact of political factors (i.e. demand shocks triggered by the COVID-19 policy interventions) on price dispersion using the latest data.

KEYWORDS
Price dispersion; political polarization; COVID-19; airline

JEL CLASSIFICATION
L11; L93

I. Introduction

Price dispersion is a ubiquitous and persistent phenomenon. Since the seminal work of Stigler (1961), extensive theoretical literature has concluded that price dispersion is an equilibrium phenomenon, even in the Internet era (Baye and Morgan 2001). While the literature on price dispersion investigates the airline industry extensively, given its ideal oligopoly setting and the abundant data availability (Borenstein and Rose 1994; Gerardi and Shapiro 2009), none has examined the role of political factors in price dispersion. This paper aims to fill the gap.

The recent COVID-19 pandemic has seriously challenged the air travel industry.[1] The political polarization of pandemic responses leads to a wide range of public health policies across states, with more strict mitigation measures such as mask mandates and social distancing requirements in states led by a Democratic governor. For example, in March and April 2020, while all Democratic governors declared state-wide lockdowns, only 19 Republican governors issued a similar order.[2] These statewide policies universally apply to all individuals in the community, including tourists, and affect the spread of COVID-19.[3] This unique feature of the pandemic provides an opportunity to examine the effects of political polarization on price dispersion.

I have assembled a sample from the Airline Origin and Destination Survey (DB1B) from 2020:Q1 to 2021:Q4.[4] The fixed-effect panel IV estimation suggests that as the infection rate rises, routes connecting states with a Republican governor are associated with a higher dispersion than those connecting two Democrat-led states. Thus, I conclude that cross-market price discrimination may play a role in determining price dispersion during the sample period.

A growing literature has documented the effects of COVID-19 on price dispersion, but the results are mixed. Some show an increase in price dispersion during the pandemic (e.g. Dietrich et al. 2022; Ruan, Cai, and Jin 2021), while others find the opposite holds (e.g. Fedoseeva and Irek 2023; Liu, Liu, and Sun 2022). Unlike most industries, the airline industry has been affected by the pandemic through demand shock, as lockdowns and

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[1]For example, airline bookings declined by a 'mid-teen' percentage point in early March 2020 despite 'bargain' fares. (Source: 'Bargain airfares not enough to entice travelers "fearful at any price" amid coronavirus', by Leslie Josephs, *CNBC*, March 9, 2020, https://www.cnbc.com/2020/03/09/coronavirus-leads-to-cheap-airfare-but-not-enough-to-shield-airlines.html).

[2]Source: https://ballotpedia.org/States_that_issued_lockdown_and_stay-at-home_orders_in_response_to_the_coronavirus_(COVID-19)_pandemic,_2020

[3]Luttmann and Gaggero (2023) note that travellers particularly factor in the diffusion of new cases at the destination when making airline reservations.

[4]Source: Origin and Destination Survey Data, Bureau of Transportation Statistics (https://www.bts.dot.gov/topics/airlines-and-airports/origin-and-destination-survey-data).

government-imposed restrictions on travel have led to a temporary but significant decline in demand. In a related study, Luttmann and Gaggero (2023) suggest a decreased price dispersion in the months immediately following the pandemic onset when governments across the globe mandate travel restrictions. However, many such restrictions have since been lifted or relaxed. To that end, my analysis complements theirs by examining the impact of political polarization on the endpoints using the expanded data.

II. Data

The sample consists of several data sources. The ticket information for one-way or round trips with non-stop flights is obtained from the DB1B database between 2020:Q1 and 2021:Q4. I also use the T-100 domestic segment data to create competition measures, following the standard practices in the literature.

Given the prevailing partisan divide on pandemic responses across states/regions, I collect information on the party affiliation of the governors for all states and territories during the sample period.[5] Next, I collect the COVID-19 information from the Centers for Disease Control and Prevention (CDC).[6] Furthermore, I gather the annual data on county-level economic and labour-market conditions to control for time-varying market characteristics that might affect airline competition and pricing. The final sample has 36,186 observations at the route-quarter-year level.

III. Model

I estimate the following model and use the Gini log-odds ratio to measure price dispersion:

$$\log odds_{jqy} = \beta_0 + \beta_1 * RDroute_j + \beta_2 * DRroute_j + \beta_3 * RRroute_j + \beta_4 * covid_{jqy} + \beta_5 * HHI_{jqy} + \gamma * \Omega_{jqy} + \theta_{qy} + \varepsilon_{jqy} \quad (1)$$

where j indexes the route, q the quarter, and y the year.

The key variables of interest, $RDroute_j$, $DRroute_j$, and $RRroute_j$ are defined as one if the origin state is led by a Republican/Democratic/Republican governor and the destination state is by a Democratic/Republican/Republican governor, respectively, and zero otherwise. The routes with Democratic governors at both the origin and destination states are the reference group. $covid_{jqy}$ measures the state/region-level infection rate. Specifically, I define two measures: $\ln acase_{jqy}$ is the logarithm of the average case number between origin and destination states on route j in quarter q of year y, and $posrate_{jqy}$ is the average ratio of the case number to the total population between origin and destination states on route j in quarter q of year y.

In addition, HHI_{jqy} measures competition in quarter q of year y on route j. Given the time frame of my sample, the unobserved time-varying factors specific to COVID-19 could collectively affect both competition (HHI_{jqy}) and airfares, which might lead to biased estimation results since both are determined as equilibrium outcomes in the market. To address the potential endogeneity problem, I develop three instrument variables for HHI_{jqy} (Luttmann and Gaggero 2023): the lagged competition measure ($HHI_{jq,y-1}$), quarterly jet fuel prices (jet), and the interaction between jet fuel prices and flight distance ($jetdist$).[7]

Ω_{jqy} denotes a vector of time-varying county-level economic and labor-market conditions for route j in quarter q of year y. These include the averages of the population (in logs), per-capita income (in logs), unemployment rate, and annual employment (in logs) in accommodation and food service (A&FS) and arts, entertainment & recreation (AE&R) industries between the endpoint counties. Finally, error terms may be heteroskedastic and possibly correlated within a given route over time. Thus, I report robust standard errors clustered by route.

Table 1 reports the summary statistics by route types. *DDroute* has the lowest means of $\log odds$ (0.27) and *HHI* (0.713), while *RRroute* has the highest with $\log odds$ of 0.266 and *HHI* of 0.833. Interestingly, the average prices are ranked in the

[5]Washington DC is treated as a Democratic state for this analysis. Several new governors took office during 2020–2021, but the party affiliation remained the same as their respective predecessors. Thus, it does not affect the coding of state party affiliation. (Source: https://ballotpedia.org/Documenting_Alabama%27s_path_to_recovery_from_the_coronavirus_(COVID-19)_pandemic,_2020–2021).
[6]Source: https://data.cdc.gov/Case-Surveillance/United-States-COVID-19-Cases-and-Deaths-by-State-o/9mfq-cb36.
[7]Jet fuel prices are obtained from the U.S. Energy Information Administration (https://www.eia.gov/dnav/pet/hist/EER_EPJK_PF4_RGC_DPGD.htm).

Table 1. Summary Statistics.

Variable	Obs	Mean	Std. dev.	Min	Max
DD routes					
Gini log-odd	9,626	0.270	0.060	0.067	0.503
HHI	9,626	0.713	0.265	0.136	1
price	9,626	$ 201.60	$ 147.91	$ 11.00	$ 1,903.00
DR routes					
Gini log-odd	8,875	0.276	0.062	0.083	0.515
HHI	8,875	0.773	0.256	0.179	1
price	8,875	$ 183.56	$ 134.19	$ 10.50	$ 1,461.00
RD routes					
Gini log-odd	8,790	0.281	0.065	0.084	0.526
HHI	8,790	0.774	0.256	0.179	1
price	8,790	$ 184.53	$ 131.66	$ 10.50	$ 1,394.00
RR routes					
Gini log-odd	8,895	0.266	0.061	0.044	0.501
HHI	8,895	0.833	0.223	0.213	1
price	8,895	$ 170.60	$ 113.64	$ 10.50	$ 1,352.00

exact reverse order, from *RRroute* with $170.60, followed by *DRroute* with $183.56 and *RDroute* with $184.53, to *DDroute* with $201.60. The same pattern is also evident in Figure 1.

IV. Discussions

In Table 2, the first two columns use the pooled OLS approach and the last two use a two-stage fixed-effect panel IV approach.[8] The estimates for $RDroute_j$, $DRroute_j$, and $RRroute_j$ are all positive and largely statistically significant (except for $RDroute_j$ and $DRroute_j$ in the last two columns), indicating that the dispersion in airfares is higher than the reference group – the routes connecting two Democrat-led states.[9] Leisure and business travelers alike would avoid traveling to destinations where popular sightseeing spots and businesses, such as restaurants, museums, and offices, are closed under stricter COVID-19 measures. Thus, all could be incentivized to resume travel, especially for discretionary purposes.

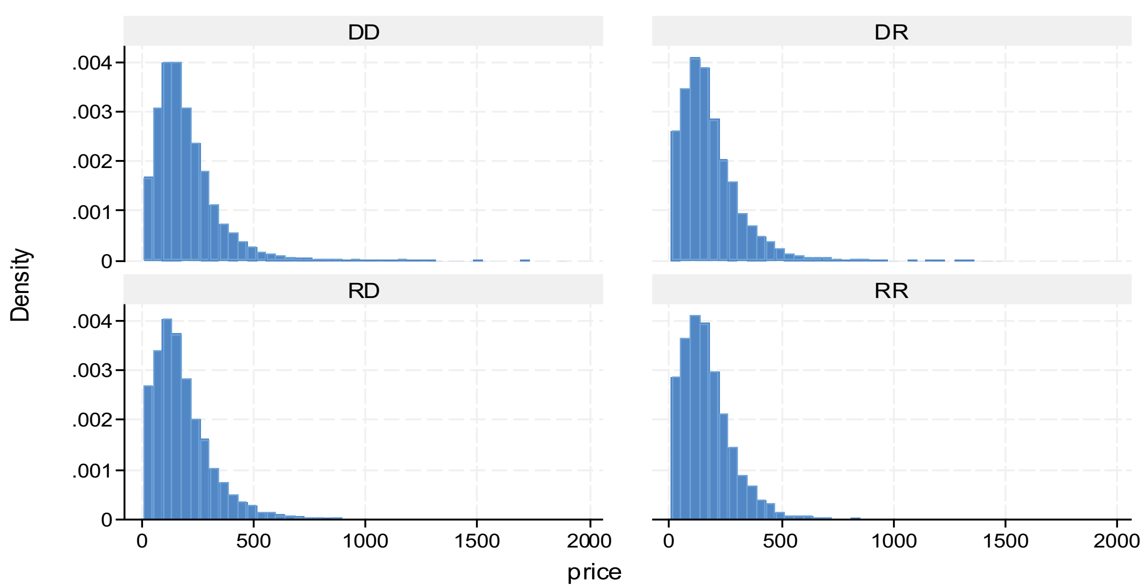

Figure 1. Distributions of fares by route type.

[8]First-stage estimates are reported in Table A1.
[9]The effects become more pronounced in Table 3 after Q12020 is excluded from the sample.

Table 2. Estimation results (Dep: log-odds ratio).

	(1) OLS	(2) OLS	(3) FE-2SLS	(4) FE-2SLS
DRroute	0.067***	0.052***	0.052	0.046
	(0.009)	(0.009)	(0.035)	(0.035)
RDroute	0.094***	0.079***	0.029	0.022
	(0.009)	(0.009)	(0.032)	(0.032)
RRroute	0.075***	0.046***	0.089**	0.077**
	(0.010)	(0.011)	(0.037)	(0.037)
posrate	0.066		0.087	
	(0.054)		(0.053)	
lnacase		0.042***		0.019***
		(0.004)		(0.004)
lnrecreation	0.151***	0.144***	−0.060	−0.008
	(0.014)	(0.014)	(0.145)	(0.145)
lnaccomm	0.057***	0.089***	0.524***	0.498***
	(0.019)	(0.019)	(0.175)	(0.174)
urate	0.039***	0.032***	−0.035***	−0.035***
	(0.003)	(0.003)	(0.003)	(0.003)
lnincome	−0.056***	−0.052***	0.794***	0.748***
	(0.018)	(0.018)	(0.223)	(0.224)
lnpop	−0.207***	−0.238***	0.469	0.320
	(0.015)	(0.015)	(0.364)	(0.371)
HHI	−0.333***	−0.340***		
	(0.012)	(0.012)		
$\widehat{HHI}$			−0.275**	−0.287**
			(0.117)	(0.116)
Constant	0.231	0.118	−21.064***	−18.819***
	(0.222)	(0.216)	(6.179)	(6.229)
Observations	34,798	34,798	28,960	28,960
R-squared	0.187	0.196		
K-P LM statistic			92.31***	93.88***
K-P Wald F statistic			47.93***	48.83***

All model specifications include quarter-year fixed effects but are not reported for brevity. Standard errors are in parentheses and are clustered by route. The null hypothesis of the K-P LM statistic is that the equation is underidentified. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 3. Panel estimation results without Q12020 (Dep: log-odds ratio).

	(1) FE-2SLS	(2) FE-2SLS
DRroute	0.077*	0.074*
	(0.040)	(0.040)
RDroute	0.048	0.044
	(0.037)	(0.037)
RRroute	0.132***	0.125***
	(0.043)	(0.043)
posrate	0.077	
	(0.054)	
lnacase		0.010**
		(0.004)
$\widehat{HHI}$	−0.247***	−0.247***
	(0.080)	(0.080)
Constant	−23.210***	−23.306***
	(7.208)	(7.201)
Observations	24,673	24,673
K-P LM statistic	186.42***	186.35***
K-P Wald F statistic	104.85***	104.74***

All model specifications include quarter-year fixed effects, as well as county-level controls, but are not reported for brevity. Standard errors are in parentheses and are clustered by route. The null hypothesis of the K-P LM statistic is that the equation is underidentified. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

This observation becomes more evident in Table 4, where the first two columns include an indicator of whether the origin state has a Republican governor (*Rorigin*), and the last two columns include an indicator of whether the destination state is led by a Republican governor (*Rdestination*). The respective reference groups are the origin/destination state led by a Democratic governor. While there is no statistically significant difference between whether an origin state is led by a Republican or a Democratic governor, the party affiliation of the destination state matters. This is consistent with anecdotal evidence that considerable political polarization exists on the COVID-19 pandemic response at the state level, with Democratic governors taking more aggressive measures than their Republican counterparts (Grossman et al. 2020).

For robustness reasons, Table 5 uses a subsample of 'purple' counties where both origin and destination airports are located and where less than 60% of residents voted for either presidential candidate in the 2020 election (Furrer et al. 2023). As expected, none of the key variables are statistically significant, indicating that partisan division indeed plays a role in yielding the observed result in Table 2.

Communities in a Republican-led state are often more willing to travel during the pandemic (Barbalat

Table 4. Panel estimation results (Dep: log-odds ratio).

	(1) FE-2SLS	(2) FE-2SLS	(3) FE-2SLS	(4) FE-2SLS
Rorigin	0.031	0.025		
	(0.028)	(0.028)		
Rdestination			0.055**	0.049*
			(0.027)	(0.028)
posrate	0.085		0.086	
	(0.053)		(0.053)	
lnacase		0.020***		0.019***
		(0.004)		(0.004)
$\widehat{HHI}$	−0.273**	−0.286**	−0.273**	−0.286**
	(0.116)	(0.116)	(0.116)	(0.116)
Constant	−21.207***	−18.932***	−21.165***	−18.903***
	(6.157)	(6.206)	(6.154)	(6.204)
Observations	28,960	28,960	28,960	28,960
K-P LM statistic	92.29***	93.86***	92.30***	93.89***
K-P Wald F statistic	47.92***	48.83***	47.92***	48.84***

All model specifications include quarter-year fixed effects, as well as county-level controls, but are not reported for brevity. Standard errors are in parentheses and are clustered by route. The null hypothesis of the K-P LM statistic is that the equation is underidentified. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 5. Panel estimation results with 'purple' counties (Dep: log-odds ratio).

	(1) FE-2SLS	(2) FE-2SLS
DRroute	0.036	0.026
	(0.084)	(0.083)
RDroute	−0.050	−0.060
	(0.060)	(0.060)
RRroute	0.019	0.004
	(0.073)	(0.073)
posrate	0.078	
	(0.101)	
lnacase		0.025***
		(0.008)
$\widehat{HHI}$	−0.581**	−0.607**
	(0.235)	(0.239)
Constant	−54.661***	−52.167***
	(13.938)	(14.019)
Observations	8,237	8,237
K-P LM statistic	23.63***	23.54***
K-P Wald F statistic	12.45	12.40

A subsample is used where all origin and destination counties do not have more than 60% of the residents who voted for either presidential nominee in the 2020 election. All model specifications include quarter-year fixed effects, as well as county-level controls, but are not reported for brevity. Standard errors are in parentheses and are clustered by route. The null hypothesis of the K-P LM statistic is that the equation is underidentified. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

and Franck 2022; Gollwitzer et al. 2020; Prasad and Hswen 2020).[10] In addition, smaller airports serving outdoor leisure destinations are usually located in Republican-led rural states, making them popular pandemic getaway destinations. The extra incentive generated from discount fares would further boost the demand. In contrast, Democrat-led states have stricter pandemic restrictions, such as social distancing and mask mandates, and travel attractions are more likely to remain closed as more contagious variants continue to emerge in those states. Furthermore, despite bargain fares, disproportionally more residents in the Democrat-led states are reluctant to take the health risk of flying when facing a choice. A recent Pew COVID-19 survey concludes a persistent partisan divide as the pandemic wears on that Republicans become more comfortable with a range of daily activities while Democrats remain hesitant.[11] Given the financial constraints, airlines are expected to offer deep discounts in communities and destinations where travel demand is robust and COVID-19 restrictions are less stringent.

V. Conclusion

Using the DB1B data between 2020 and 2021, this paper analyzes the impacts of political polarization in response to COVID-19 on price dispersion in the airline industry. The estimation results suggest a higher dispersion on routes connecting a Republican-led state and that such an effect is more pronounced at destinations with a Republican governor. My analysis adds to the literature by presenting evidence of the role of political factors in determining the price dispersion level.

[10]Using the mobility statistics data provided by the BTS, Figure 2 compares the average percent of residents who did not stay home (2019–2023) by state type, defined based on the 2020 presidential election outcome (https://www.270towin.com/).
[11]Source: 'A Year of U.S. Public Opinion on the Coronavirus Pandemic', by Claudia Deane, Kim Parker and John Gramlich, March 5, 2021, *Pew Research Center* (https://www.pewresearch.org/2021/03/05/a-year-of-u-s-public-opinion-on-the-coronavirus-pandemic/).

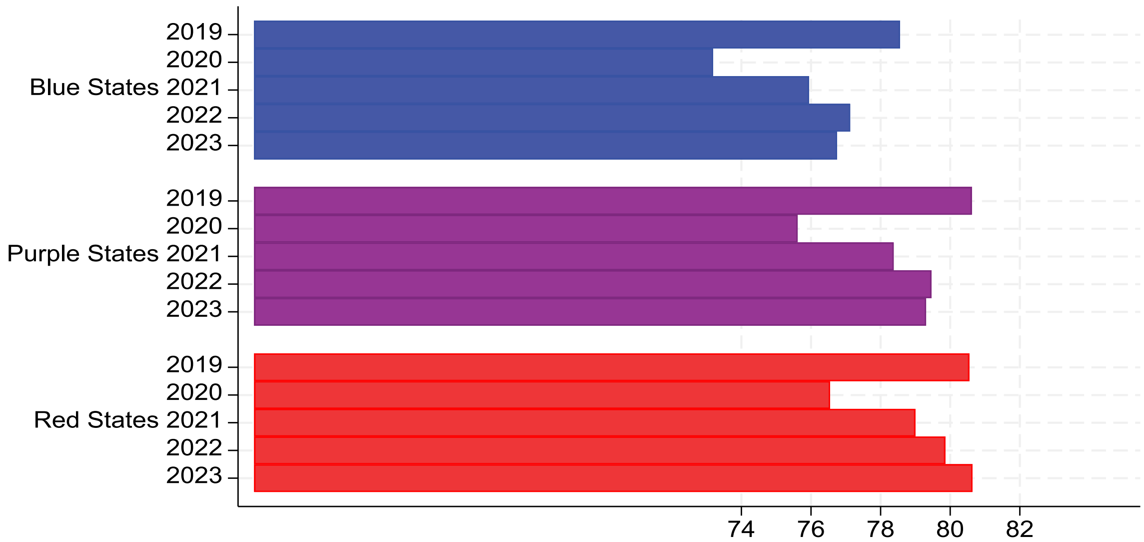

Figure 2. Percent of residents not staying home by state type. Source: the BTS, the mobility statistics data (https://data.bts.gov/Research-and-Statistics/Trips-by-Distance-Annual/famd-xfhk) The state types are defined based on the 2020 presidential election outcome (https://www.270towin.com/)

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References

Barbalat, G., and N. Franck. 2022. "Association of Republican Partisanship with US citizens' Mobility During the First Period of the COVID Crisis." *Scientific Reports* 12 (1): 8994. https://doi.org/10.1038/s41598-022-12790-5.

Baye, M. R., and J. Morgan. 2001. "Information Gatekeepers on the Internet and the Competitiveness of Homogeneous Product Markets." *American Economic Review* 91 (3): 454–474. https://doi.org/10.1257/aer.91.3.454.

Borenstein, S., and N. Rose. 1994. "Competition and Price Dispersion in the U.S. Airline Industry." *Journal of Political Economy* 102 (4): 653–683. https://doi.org/10.1086/261950.

Dietrich, S., V. Giuffrida, B. Martorano, and G. Schmerzeck. 2022. "COVID-19 Policy Responses, Mobility, and Food Prices." *American Journal of Agricultural Economics* 104 (2): 569–588. https://doi.org/10.1111/ajae.12278.

Fedoseeva, S., and J. Irek. 2023. "Within-retailer price dispersion in e-commerce: Prevalence, magnitude, and determinants." *Q Open* 3 (3): qoac021. https://doi.org/10.1093/qopen/qoac021.

Furrer, R. A., K. Schloss, G. Lupyan, P. M. Niedenthal, and A. Wood. 2023. "Red and Blue States: Dichotomized Maps Mislead and Reduce Perceived Voting Influence." *Cognitive Research: Principles and Implications* 8 (1): 11. https://doi.org/10.1186/s41235-023-00465-2.

Gerardi, K. S., and A. H. Shapiro. 2009. "Does Competition Reduce Price Dispersion? New Evidence from the Airline Industry." *Journal of Political Economy* 117 (1): 1–37. https://doi.org/10.1086/597328.

Gollwitzer, A., C. Martel, W. J. Brady, P. Pärnamets, I. G. Freedman, E. D. Knowles, and J. J. Van Bavel. 2020. "Partisan Differences in Physical Distancing are Linked to Health Outcomes During the COVID-19 Pandemic." *Nature Human Behavior* 4 (11): 1186–1197. https://doi.org/10.1038/s41562-020-00977-7.

Grossman, G., S. Kim, J. M. Rexer, and H. Thirumurthy. 2020. "Political Partisanship Influences Behavioral Responses to Governors' Recommendations for COVID-19 Prevention in the United States." *Proceedings of the National Academy of Sciences of the United States of America* 117 (39): 24144–24153. https://doi.org/10.1073/pnas.2007835117.

Liu, T., J. Liu, and Z. Sun. (2022). Online Market as a Buffer to Economic Shocks – Evidence Based on Price Dispersion During the Outbreak of COVID-19 in China. *Working Paper*.

Luttmann, A. and A. A. Gaggero. 2023. How Does COVID-19 Affect Intertemporal Price Dispersion? Evidence from the Airline Industry. *Working Paper*.

Prasad, S., and Y. Hswen. 2020. "Political Affiliation and Human Mobility Under Stay-At-Home Orders: A Difference-In-Difference Analysis with County and Time Fixed Effects." *Harvard Public Health Review: A Peer-Reviewed Journal*. (26). https://harvardpublichealthreview.org/stay-at-home-orders/.

Ruan, J., Q. Cai, and S. Jin. 2021. "Impact of COVID-19 and Nationwide Lockdowns on Vegetable Prices: Evidence from Wholesale Markets in China." *American Journal of Agricultural Economics* 103 (5): 1574–1594. https://doi.org/10.1111/ajae.12211.

Stigler, G. J. 1961. "The Economics of Information." *Journal of Political Economy* 69 (3): 213–225. https://doi.org/10.1086/258464.

Appendix

Table A1. First-stage estimates for table 1 (Dep var: HHI).

	(1)	(2)
DRroute	0.005	0.009
	(0.019)	(0.019)
RDroute	−0.001	0.003
	(0.021)	(0.021)
RRroute	0.023	0.032
	(0.025)	(0.025)
posrate	−0.088**	
	(0.042)	
lnacase		−0.013***
		(0.002)
HHI	−0.107***	−0.108***
	(0.011)	(0.011)
jet fuel price * ln(distance)	−0.002	−0.002
	(0.003)	(0.003)
lnrecreation	0.034	−0.000
	(0.085)	(0.085)
lnaccomm	−0.673***	−0.663***
	(0.094)	(0.093)
urate	−0.001	−0.000
	(0.002)	(0.002)
lnincome	0.029	0.065
	(0.142)	(0.141)
lnpop	0.791***	0.901***
	(0.213)	(0.215)
Observations	28,960	28,960
R-squared	0.098	0.100

All model specifications include quarter-year fixed effects but are not reported for brevity Robust standard errors in parentheses, clustered by route; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.