The Networks Effects of Climate Change: Evidence from Airline Delays*

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Abstract

The literature on the economic impacts of climate change has primarily focused on local effects, but in an increasingly interconnected world it is important to understand the network effects. However, in many cases it has proven difficult to empirically assess the importance of the non-local impact of weather shocks because of general equilibrium effects. In this paper, I present credible evidence of a network effect of climate change in the airline industry by extending the traditional origin-destination pair to include the previous flight from the source airport. I utilize a detailed dataset of daily flights in the U.S. for all major domestic U.S. airports from 2010–2017 to understand how weather shocks at the flight's source, origin, and destination airports affect on-time flight performance. I find that high temperatures at any of these airports increase both the probability and duration of departure delays, and ignoring the network structure leads one to underestimate the local effects at the origin by nearly 50%. Using climate projections from NEX-GDDP, I project total summer departure delays will increase 110,000 hours by mid-century due to rising temperatures, at a minimum cost to airlines and passengers of $1.0–$1.4 billion.

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1 Introduction

The effects of climate change on various sectors of the economy have been well studied, be it in the context of agriculture (Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009; Ortiz-Bobea et al., 2019), human health and mortality (Deschênes and Greenstone, 2011; Barreca et al., 2016), or crime and conflict (Ranson, 2014; Burke, Hsiang and Miguel, 2015), among many others. Previous literature on the economic impacts of climate change has focused on the local effects; for example, how are increasing temperatures and/or the risk of extreme weather events in city X going to effect its residents? But in an interconnected world, the effects in one place may have significant impacts on other locations. As an example, a drought in the Midwest U.S. causing farmers to lose valuable crops is likely to impact the price of these crops on the East coast. Similarly, one can imagine shocks due to climate change on the national level that will have repercussions for international trade. Because these are general equilibrium effects, it has largely proven difficult to empirically assess the importance of the network climate impacts (Missirian and Schlenker, 2017, is one notable exception). In this paper, I estimate the network impact of climate change in an ideal setting with high frequency data and a connected structure – flight delays in the U.S. airline industry.

The cost of flight delays has been estimated to be in excess of $27 billion for 2007 alone (Ball et al., 2010). Further, over 40% of U.S. flight departure delays from 2010–2017 were due to the aircraft arriving late from its previous destination, which I refer to as the source airport.[1] The connected network of airlines presents a unique case where the costs from climate change may be felt due to changes occurring away from your local airport. Airlines connecting disparate locations will face varying local climate shocks in each of these markets, which may in turn lead to substantial impacts on other, connected markets that would otherwise be unaffected. As temperatures rise,

[1] In terms of total delay duration (in minutes); https://www.bts.gov/delay-cause-year-percent-total-delay-minutes.

air density falls and it becomes more difficult for airplanes to generate lift. This can lead aircraft to face weight restrictions, requiring airport workers to offload cargo, fuel, and (in some cases) passengers to offset the lower air density. Indeed, prior literature has shown that high temperatures affect airline operations through weight restrictions (Coffel and Horton, 2015; Coffel, Thompson and Horton, 2017; Zhou et al., 2018), as well as increased heat related illnesses for airport employees and damage to runways and aircraft tires (Baglin, 2012). Given the projected increases in both average temperatures as well as high temperature days in the not so distant future, we can expect an increase in costly airline delays due to climate change.

To estimate this network effect, I utilize a detailed dataset of daily flights in the U.S. from over 300 domestic U.S. airports from Summer 2010–2017. I seek to understand how climate at not just the site of the flight's departure (origin), but also at the airport from which the aircraft servicing the flight came (source) and the flight's destination airport affect flight delays. In particular, I ask: what is the effect of increases in temperature at the source, origin, and destination airports on airline flight delays? And how will climate change be expected to affect flight delays by mid-century?

My data on flights comes from the U.S. Bureau of Transportation Statistics' Reporting Carrier On-Time Performance dataset covering all U.S. certified air carriers servicing at least 1% of domestic scheduled passenger revenues. For each flight on a given day, I observe both the scheduled and actual departure and arrival times, as well as the airline's self-reported cause of delay. I identify the source airport based on the unique tail number of the individual aircraft utilized for each flight. I combine the airline performance data with hourly data from NOAA's Quality Controlled Local Climatological Data (QCLCD) on meteorological conditions including temperature, relative humidity, wind speed, and precipitation from weather monitors located at domestic airports.

Following the literature, I allow for nonlinear effects of temperature on flight delays using 5°C temperature bins, ranging from below 15°C to above 40°C. I estimate regressions for the impact of weather at the source, origin, and destination airports on departure delays at the origin airport, controlling for other contemporaneous meteorological factors and a rich set of fixed effects for each side of the flight route-pair. The effects at each node in my airport network are estimated simultaneously, so the coefficients from my model represent how a change in temperature at one airport node affects flight delays conditional on the meteorological conditions at the other two. As an example, my empirical strategy allows me to measure the estimated effect of ambient temperatures at the source being between 20–25°C on flight delays, conditional on the meteorological conditions at the time of departure or arrival at the origin and destination airports, respectively.

My results provide evidence of a network effect of climate change: high temperatures at the origin, source, or destination airport lead to a significant increase in both the probability and duration of a flight departure delay. Relative to a baseline of 15–20°C, temperatures of 35–40°C at the source, origin, or destination increase the probability of a departure delay at the origin[2] by 4.8%, 10.4%, and 5.5%, respectively and the duration by 3.7, 9.6, and 6.7 minutes per flight. On average in my dataset roughly 20% of flights were delayed by at least 15 minutes, so a 5–10% increase in the probability of a delay is substantial. I find that high temperatures at the source airport primarily affect flight delays through late arriving aircraft, and this effect is larger earlier in the day. Across climate regions, I present evidence of adaptation as regions that are used to elevated temperatures (such as the South and West) see a below average increase in the likelihood of a flight delay as compared to regions where these events are less common (such as the Northeast and Ohio Valley).

My findings illustrate that including the non-local effects are critical in two dimensions. For one, I show that estimates of the local effect without including the non-local effect are biased and lead one to underestimate the local effect by nearly 50%. In addition, ignoring the effects from the connected source and destination would also lead to a significant underestimation of the total effect of a temperature shock at the

[2]Following the definition used by the U.S. Department of Transportation, I consider a flight to be delayed if the delay is at least 15 minutes.

source, origin, and destination airports, as I find that the effect at the origin makes up roughly 50% of this total effect. Using the RCP4.5 and RCP8.5 projections from the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC AR5), I then estimate the increase in flight delays due to the projected changes in daily maximum temperatures at the source, origin, and destination airports. I find that rising temperatures due to climate change will lead to over 110,000 additional hours of departure delays for U.S. domestic flights per summer, at a cost to passengers and airlines of \$1.0–\$1.4 billion.

This paper makes two main contributions to the literature. First, this study provides a reduced form estimation of the network effects of climate change. By explicitly accounting for the connected nature of air travel in the United States, I am able to provide separate estimates of both the local (origin) and non-local (source, destination) effects. I demonstrate the importance of including both the local and non-local effects in the estimation, as ignoring the non-local effects in either the specification or calculation leads to a significant underestimation of the local or total effect, respectively. By including the full network structure, I am able to quantify the costs due to climate change that may occur because of changes away from your local airport. Some areas in the U.S. are projected to be climate "winners" or "losers" depending on both their baseline levels and forecasted relative increases in temperatures. This paper provides one estimate of the additional costs that will be imposed, as even flights from airports receiving more mild temperature effects are likely to be impacted if the aircraft is coming from a climate "loser."

Second, this is the first paper to use a nationwide set of airports for estimating the effects of climate at the source, origin, and destination airports on airline operations. Prior literature can generally be categorized as being a case study of a single airport or airline (Pejovic et al., 2009) or a subset of airports (Forbes and Lederman, 2013; Zhou et al., 2018; Borsky and Unterberger, 2019). Mayer and Sinai (2003) estimate the nationwide impact of hub behavior on airline delays, but notably do not control for measures of climate in their analysis. My sample allows me to estimate both the average impacts of climate on airline operations at a national level, as well as heterogeneous treatment by climate region. My approach provides a significant expansion on the previous literature in terms of both *scope* through the inclusion of the source airport and *scale* with over 300 airports across the U.S. over 8 years.

The paper proceeds as follows. Section 2 provides a background on the relationship between flight delays and climate. Section 3 presents the conceptual framework and empirical strategy for my analysis of the impacts of weather on flight delays. Section 4 describes the data used in the analysis and discusses some descriptive statistics, while section 5 presents the results. Section 6 extends the framework to project the changes in flight delays due to climate change. Lastly, Section 7 concludes.

2 Background on Airlines and Climate

2.1 Effects of Temperature on Airline Operations

The ways in which high temperatures affect airlines can generally be categorized into two main mechanisms: 1) aircraft performance and weight restrictions and 2) damages to airport operations and infrastructure. A weight restriction involves removing passengers or cargo from an aircraft that is too heavy to reach the minimum speed required for the plane to takeoff. This minimum takeoff speed is determined by several factors in addition to the weight of the aircraft, including the length of runway as well as the ambient temperature. Higher temperatures reduce air density which makes it more difficult for an aircraft to generate lift. As temperatures rise airplanes must reach a higher takeoff speed to offset the loss in air density, all else equal (Coffel and Horton, 2015). Alternatively, airports can increase the length of runway to mitigate the effects of high temperatures – however as noted by Coffel, Thompson and Horton (2017), in some congested areas (for example, New York's LaGuardia and Washington's Reagan National airport) extending the length of runway is not feasible. Other limitations on factors such as maximum tire speed or braking ability for a given takeoff weight prevent an airport from continuing to extend runways indefinitely to combat higher temperatures (Coffel, Thompson and Horton, 2017).

The second channel through which temperatures affect airline operations, damage to airport operations and infrastructure, is described in a 2012 report from the Airport Cooperative Research Program (Baglin, 2012). In addition to the aforementioned reductions in airplane performance and increased weight restrictions leading to delays and cancellations, the report explains that high heat days will lead to: limitations on aircraft maintenance and increased risk of heat related illnesses for airport employees; buckling or melting runways and tarmacs; and increased energy demand and/or construction improvements for cooling airport facilities.[3] Due to the known relationship between temperature and ozone formation, the authors note that airports in non-attainment counties can also experience delays in the construction of the very projects intended to mitigate the effects of high temperatures. Aside from heat illnesses, the effects of high heat on airport workers is likely to reduce productivity (Hancock, Ross and Szalma, 2007) as they work to turn the aircraft between flights.

My approach in this paper, detailed in Section 3, is agnostic as to the specific mechanism(s) through which high temperatures affect airline operations. Nonetheless, it is straightforward to see how weight restrictions causing planes to offload passengers, cargo, and/or fuel could lead to flight delays. Similarly, tarmac workers tasked with loading luggage and refreshments, re-fueling the aircraft, and performing general maintenance that are slowed down by the effects of high heat may also affect an airline's on-time performance. The other impacts of high temperatures on the aviation industry, such as requiring longer runways or increasing the need for airport infrastructure improvement, operate more on the extensive rather than the intensive margin that is the focus of my analyses in this paper. However, these extensive margin impacts suggest some potential avenues to adaptation for the aviation industry to mitigate the impacts of climate change, which I discuss in more detail in Section 2.3.

[3]The authors also present a case study for Dallas Fort-Worth which highlights additional concerns from water restrictions on hot days that may impact the facility's ability to cool the terminals.

2.2 Background on Flight Delays

More broadly, there is a substantial literature on airline delays. Mayer and Sinai (2003) illustrate the importance of considering the network structure of airlines in understanding delays, attributing most of the delays to the hubbing design of the airline network. Pejovic et al. (2009) examine the impacts of a set of climate variables on departure delays at London's Heathrow airport and project the resulting impacts to 2050.[4] Forbes and Lederman (2013) look at the impacts of major versus regional airline operations on delays for a set of major U.S. airports in 2000, finding a lower average duration of departure delay from major-owned vs. independent regional airlines. Forbes, Lederman and Tombe (2015) analyze the effects of the U.S. Department of Transportation's 15 minute threshold for arrival delays and variations in manual versus automated reporting of arrival times by airlines,[5] finding evidence of threshold effects and misreporting of arrival times with manual reporting.

Several recent studies have looked at the impacts of weather on airline or aircraft performance. Zhou et al. (2018) analyze the impacts of temperature on aircraft takeoff weight restrictions for seven airports in China and project the future impacts in the early 22nd century. Borsky and Unterberger (2019) examine the effects of extreme weather events at 10 major U.S. airports using a linear cross-sectional model of daily data at the origin airport and find significant increases in departure delays due to high levels of rainfall, snow, or wind but no effect of higher temperatures (defined as daily temperature above 35 or 40 degrees Celsius). Finally, Gratton et al. (2020) look at the effects of daily minimum temperature and headwinds on the required distance for take-off and weight restrictions for 10 Greek airports and find increasing minimum temperatures averaging roughly 0.6°C per decade have contributed to an increase in the length of runway required for take-off.

The robust research into flight delays is driven in no small part by the high costs

[4]Notably, they utilize minimum temperature instead of maximum temperature in their study, which is likely driven by the existing climate patterns in London.

[5]The authors note that automatic reporting was fully adopted by all major carriers by 2007.

associated with flight delays and airlines' on-time performance. Recent estimates from the commercial aviation industry suggest that the direct cost of flight delays to airlines alone are around \$74 – \$78 per minute of delay.[6] These costs to airlines come from factors such as increased fuel outlays, compensation for crews, and additional aircraft maintenance; notably they exclude costs for additional airport personnel, goodwill losses, or costs to passengers such as lost wages or productivity. Forbes (2008) estimate that the average price of flights decrease by \$1.42 per minute of flight delays at LaGuardia based on a 2000 policy change.[7] Gayle and Yimga (2018) utilize a discrete choice model of consumers value for on-time performance and find a willingness to pay of \$1.56 per minute of flight delay. Outside of delays, Luttmann (2019) estimates that flights are priced \$42.74 – \$47.60 lower for each additional hour of layover time. The current valuations used by the FAA suggest a value of travel time savings of \$47.10 per hour in 2015\$ with an implicit cost of \$0.79 per minute for passengers (FAA Office of Aviation Policy and Plans, 2016).[8]

To put this into context, in 2017 there were over 741 million passengers on nearly 8.2 million U.S. domestic flights.[9] Therefore, using the lower bound of the FAA's suggested value of passenger time, each departure delay of 15 minutes costs passengers \$1,075 on average. Adding the cost of delays to airlines based on their reported cost of \$74 per minute, each flight departure delay costs over \$2,175. This is likely a lower bound, as it is not inclusive of the many indirect costs of flight delays – Peterson et al. (2013) estimate that a 10% reduction in U.S. flight delays would increase net welfare by \$17.6 billion. Minimizing congestion at airports through mitigating flight delays would also have significant benefits outside of the airline industry through the reduction in exposure to harmful local air pollutants, particularly CO and NO_x (Schlenker and

[6]See www.cnbc.com/2013/11/27/chart-of-the-day-airlines-losing-78minute-today.html and www.airlines.org/dataset/per-minute-cost-of-delays-to-u-s-airlines/.

[7]This estimate is for direct passengers only, as the author finds a lower cost of \$0.77 for connecting passengers. Competitive routes see a higher impact on airfares at \$2.44 per minute.

[8]The FAA suggests a higher value of travel time of up to \$63.20 per hour for business travelers.

[9]Data comes from U.S. Bureau of Transportation Statistics; see: www.bts.dot.gov/newsroom/2018-traffic-data-us-airlines-and-foreign-airlines-us-flights.

Walker, 2016).[10] In the paper, the authors instrument for network delays at a few major hub airports outside of California to analyze the impacts on daily average pollution measured at 12 airports in California. They argue that a weather shock in New York should be orthogonal to other factors influencing daily pollution concentrations in California besides its impact on increasing runway congestion and propagating flight delays. I leverage a similar intuition to explicitly examine the impacts of weather shocks at airports away from the origin on on-time performance at the origin airport.

Additionally, while it is not the focus of this study it should nonetheless be noted that the long-run relationship between airlines and climate is bi-directional due to the high emissions levels of aircraft operations (Lee et al., 2009). This may be an important area for future research as a recent paper suggests that airlines have thus far been more successful at reducing flight delays than CO_2 emissions (Huang et al., 2020).

2.3 Adaptation

How can the aviation industry mitigate the impacts of high heat and climate change on delays? There are four main ways for airlines to adapt to increasing temperature: infrastructure investments at airports, technological improvements, scheduling changes, and management practices. Aside from the benefits to local employment and wage growth (McGraw, 2020), investments in airport infrastructure can combat the negative effects of high temperature. An example of an airport improvement would be extending the runways for airlines: as temperatures rise and air density falls, it takes longer for a plane to reach the point at which it can take-off (Thompson, 2016; Coffel, Thompson and Horton, 2017). Technology improvements to airplane technology over time could improve a plane's ability to operate effectively and/or efficiently at higher temperatures. Changes to scheduling can occur either by adjusting the times at which airlines fly particular routes (for example to avoid peak afternoon heat) or by changing

[10] The authors note that airports are some of the largest emitters of local air pollution, with Los Angeles International (LAX) ranking as the largest source of CO and 2nd largest source of NO_x in the state of California.

the locations of hubs or the shape of their routes. Finally, management practices were noted in a recent paper as improving fuel loading and fuel efficiency (Gosnell, List and Metcalfe, 2020), which could in turn reduce weight restrictions that lead to flight delays.

However, there are limitations on the feasibility of each approach to mitigate the impacts of climate change. Airports choosing to invest in extending runways could help mitigate the effects of high temperature on flight delays and operations; however, not all airports have the space to expand. Notably, this includes some of the busiest airports such as LaGuardia in New York and Reagan National in Washington, D.C., as noted in Coffel and Horton (2015). Additionally these investments are costly; a recent estimate suggests a 1,500 foot runway extension would cost over $6.5 million in construction costs (National Academies of Sciences, Engineering, and Medicine, 2019). Technological improvements that are not currently available are likely to take time to develop, and eventually there will be limits on the improvements it can provide (particularly with unknown costs of development and/or implementation). Schedule changes may simply be infeasible; while it may seem beneficial to avoid peak heat in some of the hottest airports such as Phoenix's Sky Harbor International Airport (PHX), the loss of options to consumers and lost revenue for airlines likely makes this untenable. Management practices are promising, since they provide a low cost way to improve flight efficiency and reduce emissions (Gosnell, List and Metcalfe, 2020). But it seems unlikely that these practices alone will be sufficient to offset the projected increases in temperature due to climate change.

3 Conceptual Framework and Empirical Strategy

3.1 Conceptual Framework

In this section I outline the conceptual framework for my analysis. Recall that the key issue I seek to address in my empirical setting is quantifying and distinguishing between the local and non-local effects of climate change. Understanding the local and the non-local effects is critically important for estimating the impacts of climate change and crafting optimal policy to mitigate future economic damages. From the social planner's perspective, policymakers can then provide incentives to those airports with adaptation potential (outlined in Section 2.3 above) that will be most affected. The previous literature on airline delays, described in Section 2, focuses primarily on the local effect at the origin while controlling for non-local characteristics at the destination. I extend the origin-destination pair to include the source airport, or the airport from which the previous flight departed from, and estimate both the local (origin) and non-local effects (source and destination airports) simultaneously.

Figure 1 illustrates my basic framework. Consider a flight from B to C, where B is the origin airport and C is the destination. A departure delay is measured at the origin airport, B, for a flight arriving at C. There are many potential factors contributing to a departure delay, but one of the primary reasons reported by airlines is a late arriving aircraft to the origin from the previous flight. In the diagram, this would be the prior flight from A to B where A is the source airport for the flight of interest from B to C (the origin-destination pair). In this paper, I measure delay as the delay on the flight from B $\rightarrow$ C, controlling for meteorological conditions affecting both that flight as well as the prior flight from A $\rightarrow$ B. It is worth noting that the source and destination airports could be from similar or vastly different parts of the country; they could even be the same airport. However, irregardless of their locations the *times* at which flights are departing from A and arriving to C will be hours apart.

In this paper, I focus on the impacts of meteorological conditions at the source, origin, and destination airports on flight delays. Prior studies inform my expectations of the effects of meteorological factors such as precipitation and wind (Borsky and Unterberger, 2019; Pejovic et al., 2009) or extreme temperatures (Zhou et al., 2018; Coffel and Horton, 2015; Coffel, Thompson and Horton, 2017) at the origin airport on increasing takeoff time or weight restrictions that may increase departure delays. Coupling these effects with the known detrimental effects of heat on the airport employees' productivity in preparing and maintaining the aircraft (Baglin, 2012; Hancock, Ross and Szalma, 2007), I further expect high temperatures at the *source airport* to increase departure delays at the origin airport, primarily through late arriving aircraft.

I also expect meteorological conditions at the destination airport to impact departure delays. If bad weather is expected at the destination airport then the flight may delay departure until it clears. Similarly, if high temperatures are expected they may in turn be affecting flight departures at the destination airport, causing congestion on the runway and/or at the gates. Rather than burn additional fuel while circling and waiting to land, the carrier may instead choose to simply delay departure.

The aviation industry is well aware of the impacts of high temperatures on flight operations, as described in Baglin (2012). A survey of senior leadership at a handful of major U.S. airports rated heat waves as the factor that they believe will increase disruptions of flight operations the most by 2030 as compared to 2010 (Baglin, 2012). The respondents further acknowledged concerns about the risks associated with heat at both their airport and at other airports in terms of schedule disruptions.

3.2 Empirical Strategy

As outlined above, the airplane's current trip is defined as going from the origin airport to the destination airport. I refer to the airport from which the plane arrived to the origin airport some hour(s) earlier as the source airport. In the regressions that follow, the outcome variables of interest refer to delays in departure of at least 15 minutes for the flight departing the origin airport for the destination airport.[11]

The regressions are of the general form:

[11] I use 15 minutes here since this is the threshold defined in the dataset; this is the minimum threshold at which a flight delay is typically counted by the U.S. BTS.

$$
\begin{aligned}
y_{jt} = \beta_0 + \sum_{s=i,j,k} \{ & \beta_{s1}\mathbb{1}(Temp^C_{st} < 15) + \beta_{s2}\mathbb{1}(20 \leq Temp^C_{st} < 25) \\
& + \beta_{s3}\mathbb{1}(25 \leq Temp^C_{st} < 30) + \beta_{s4}\mathbb{1}(30 \leq Temp^C_{st} < 35) \\
& + \beta_{s5}\mathbb{1}(35 \leq Temp^C_{st} < 40) + \beta_{s6}\mathbb{1}(Temp^C_{st} \geq 40)\} + \sum_{b=1}^{4} \lambda_j * 4hour_b \\
& + X'_{it}\rho_1 + X'_{jt}\rho_2 + X'_{kt}\rho_3 + \delta_{dmy} + \gamma_i + \omega_j + \phi_k + \alpha_c + \epsilon_{jt}
\end{aligned} \tag{1}
$$

where $Temp^C_{st}$ represents indicators for 5 degree Celsius bins of hourly temperature from below 15 to above 40 degrees C at the source, origin, and destination airports; the omitted category at each airport is 15–20°C. The hourly temperature measured at the source and origin is at the time of the flight's scheduled departure from that airport; the temperature at the destination is based on the flight's scheduled time of arrival. Following Deschênes and Greenstone (2011) and Heutel, Miller and Molitor (2020), I model daily temperature semi-parametrically without relying on strong assumptions about functional forms; the lone restriction is I am assuming that the effects of hourly temperature on flight delays are constant within each 5°C bin. The flexible choice of seven temperature bins reflects an effort to allow the data to determine the relationship between temperature and flight delays, rather than strict parametric assumptions. X is a vector of other contemporaneous meteorological variables measured at each airport: relative humidity, dew point, wind speed, and precipitation. I separate out flights within a day by including controls for 4-hour departure windows throughout the majority of the travel day (7:00AM—11:00PM) in $\lambda_j * 4hour_b$. Standard errors are clustered at the origin airport level.

I include fixed effects for the origin, source, and destination airports (γ_i, ω_j, ϕ_k), as well as the airline carrier (α_c) and day-by-month-by-year (δ_{dmy}). Day-by-month-by-year fixed effects flexibly control for common unobserved time-varying shocks, such as those induced by national policy changes or holidays causing higher congestion across all airports on a particular day(s). Origin, source, and destination-specific airport fixed effects control for any time-invariant characteristics of an airport in any part of the chain, like runway length, number of runways and gates, and baseline levels of congestion. Carrier fixed effects control for unobserved differences across my sample among carriers, such as persistent differences in scheduling practices and fleet technologies or load factors.[12]

Flights are scheduled months in advance, so the realization of a weather shock in a given hour should be plausibly exogenous. Thus, my identification comes from variations in exogenous temperature shocks at each node in my airport network to a previously determined flight schedule.

4 Data

Flight data comes from the U.S. Bureau of Transportation Statistics' (BTS) Reporting Carrier On-Time Performance dataset, which covers all U.S. certified air carriers servicing at least 1% of domestic scheduled passenger revenues. For each flight on a given day, I observe both the scheduled and actual departure and arrival times, as well as information on when the plane landed and the time spent taxiing at the origin and destination airports. In addition, for each flight delayed at least 15 minutes, airlines report the cause of the delay – carrier, weather, national air system, security, or a late aircraft.[13] Finally, I observe the unique tail number of the individual aircraft utilized for each flight. I identify the source airport by matching the unique tail number and air carrier of the origin-destination flight to that of the most recent preceding flight arriving at the origin airport on the same day.

My dataset covers all reported flights in the lower 48 states during the summer months from 2010–2017. Figure 2 shows the locations of the airports in my sample,

[12]One potential issue would be if there are route-specific factors affecting flight delays that are not captured in the fixed effects for the source, origin, and destination in my main specification and are confounding my estimates of the effect of temperature. For example, if there were time-varying shifts in route-specific schedules due to unobserved factors, this might cause additional or fewer flight delays through widening/tightening the schedule buffers between flights. Using source-by-origin-by-destination-by-month fixed effects, I estimate an alternative specification for my main results in Tables A.9 and A.10 in the Appendix and the results are qualitatively similar.

[13]This information is self-reported beginning in June 2003.

highlighting those airports that are in the top quartile of departure flights over the summer period. Figure 3 plots the average number of flights per day with summary statistics on daily flight delays for each summer over the sample period (2010–2017). Overall, the number of flights decreased over the period from nearly 18,000 in 2010 to just under 16,000 by 2017. The proportions of flight delays did not decrease at the same rate, however, increasing from 19.7% to 21.7% on average over the time frame. Flight delays were at their highest in the summer of 2013, with an average of over 4,100 flight delays per day and a peak of nearly 6,800 flight delays (36.2%) on June 28th, 2013. The airports that are most frequently delayed in my dataset are shown in Table 1; unsurprisingly, leading the list are some of the busiest airports in the U.S.[14]

Hourly data on meteorological conditions, including temperature, relative humidity, wind speed, and precipitation, are provided by NOAA's Quality Controlled Local Climatological Data (QCLCD) dataset. The weather monitors in this dataset are located at domestic airports across the U.S., so my measure of hourly weather reflects the local conditions experienced at the level of observation in my flight data. Suggestive evidence of the relationship between temperature and flight delays at the source and origin airport is shown in Figure 4. The two sets of vertical bars in Panel A (Panel B) represent the average temperature at the source (origin) airport for a) all flights and b) flights delayed at least 15 minutes. Across all months and years in my sample, the average monthly temperature at either the source or the origin airport is higher for delayed flights.

[14] A list of the airports with the largest number of departure delays can be found in Table A.8 in the Appendix.

5 Results

5.1 Main Results of Temperature on Airline Delays

My main results for the sample period (Summer, 2010 – 2017) can be found in Figures 5 and 6.[15] Figure 5 presents the results from the estimation of my preferred specification in Equation (1) where the outcome variable is an indicator for a departure delay of at least 15 minutes.[16,17] Looking first at the coefficients on *Temp* at the origin airport in Figure 5, if a flight is scheduled to depart when the ambient temperature at the origin is 20–25°C, the probability of a departure delay increases by about 5.5% relative to a baseline temperature of 15–20°C, *ceteris paribus*. Similarly, if the temperature at the source airport at the time of the prior flight's departure was 20–25°C or the temperature at the flight's destination is 20–25°C at the scheduled time of arrival, the probability of a delay increases by 1.7% and 2.9%, respectively, relative to temperatures of 15–20°C at each airport.[18]

At each of the origin, source, and destination airports, moving to higher temperature bins towards the right side of the Figure leads to larger effects on the probability of a departure delay. Relative to the baseline, temperatures of 35–40°C at the source, origin, or destination increase the probability of a flight delay by 4.8%, 10.4%, and 5.5%, respectively. These results highlight the importance of the network structure in the analysis. Consider a temperature shock that occurs at each of the source, origin, and destination airports. In the results shown in Figure 5, the effect at the origin makes up roughly 50% of the total effect of the temperature shock. Ignoring the effects from the connected source and the destination airports would lead one to significantly underestimate the total impact of temperature on airline flight delays.

[15] The regression results with coefficient estimates and standard errors for these and all of the other Figures in the paper can be found in Section A.2 of the Appendix.

[16] In the Appendix, I estimate Equation (1) where the outcome variable is arrival delays in Tables A.21 and A.22; the results are qualitatively similar.

[17] In Table A.1 I show several alternative specifications with a less comprehensive set of fixed effects; the estimates in the Figure correspond to the preferred specification in Column (3).

[18] These temperatures correspond to going from about 59–68°F to 69–77°F.

The network is also critically important in the specification, as estimating the local effect at the origin without the source in the model leads to omitted variable bias. I estimate a version of Equation (1) excluding any controls for the source airport and present the results in Table A.23 in the Appendix. When I omit the source airport from the estimation, temperatures of 25–30°C at the origin would suggest only a 4.3% increase in the probability of a flight delay, as compared to 6.3% in the fully specified model. Even if one is only interested in the local effect at the origin, ignoring the network of airline operations in the specification causes estimates of the impacts of temperature on flight delays at the origin to be biased. Comparing the results in Table A.23 with the main results in Table A.1, I show that one would underestimate the local effect of high temperatures on airline on-time performance at the origin airport by nearly 50%.[19] Using the lowest cost estimates of passengers' cost of travel time from the FAA and the estimated direct cost to the airlines, this translates to missing an additional \$100–\$150 million per year in delay costs at 25-30°C.

Shifting to delay duration, I find that late aircraft delays are affected by temperatures at the source (and origin) as expected and consistent with the results in Figure 5. Figure A.2 presents the results where my dependent variable is now late aircraft delays. On average, ambient temperatures at the source airport of 20–25°C increase a flight delay by 4 and a half minutes; extreme temperatures of 35–40°C and above 40°C increase the duration of a late aircraft delay by 6.5 and nearly 9 minutes, respectively. To put these into context, based on the FAA estimate of the value of travel a 4.5 minute delay would cost each passenger roughly \$3.56; based on estimates from Forbes (2008) and Gayle and Yimga (2018) airlines would need to compensate passengers with fares \$6.39 – \$7.02 lower. On a per flight basis, this translates to \$322 per flight and a total reduction in fares of \$580 – \$637. In the airline industry's own estimation of direct costs to crew and aircraft fuel and maintenance, this additional delay would cost them

[19] Although the 95% confidence intervals of the estimates overlap, a test of the difference between the models with and without controls for the source for the coefficient on 25–30°C at the origin results in a z-score of approximately 2.14, indicating the difference is statistically significant at the 5% level.

over \$333 per flight. In summation, temperatures of 20–25°C at the source airport thus cost passengers and airlines at least \$655 – \$970 per late aircraft delay.

When examining all departure delays, I find significant increases in delay duration at all airports with a relatively smaller effect at the source that suggests high temperatures at the source primarily affect origin delays through late arriving aircraft. Results examining all departure delays are shown in Figure 6. I still find significant increases in delay duration caused by high temperatures at each of the source, origin, or destination airports. However, the relative ranking among each of these airports in terms of their respective contribution to the length of departure delays has shifted as compared to Figure A.2. The largest increases in delay duration from high local temperatures occur at the source and origin airports for late aircraft delays; when considering all departure delays, these are the origin and destination airports. This suggests two things: first, that the labeling of late aircraft delays in the dataset appear to be fairly accurate; and second, that temperature changes at the source airport primarily affect flight delays at the origin airport through the delay they cause by having the flight arrive to the origin airport late. This makes sense since departure delays include many issues attributable to the origin airport that should not be expected to be affected by the source airport, such as security or airplane malfunctions at the origin. However, while the coefficients on temperatures at the source airport are relatively lower for all departure delays as compared to late aircraft delays, they represent a statistically and economically significant increase in delays of 2 – 4 minutes. Further, as noted above omitting these controls for the source leads to biased estimates that greatly underestimate the probability and duration of the delay.

In both Figures 5 and 6, we see a negative and statistically significant coefficient on temperatures below 15°C. Recall that my period of analysis is the summer, so cooler temperatures are more moderate in my sample and factors such as freezing or snow/ice that one might be concerned about are not present here. Rather, this presents further evidence of the effects of increasing temperatures on flight delays. Increasing temperatures from below 15°C to the baseline of 15–20°C leads to both a higher probability and duration of a flight delay, all else equal.

5.2 Heterogeneous Treatment Effects

In this section, I explore several potential sources of heterogeneous responses from aircraft operations to high temperatures in time and space. First, I look at whether earlier or later flights experience larger effects from temperature changes at the source, origin, and destination airports in Section 5.2.1. I show that higher temperatures at the source (destination) have a larger effect on later (earlier) flights. I argue that this is likely driven by the connected structure of flights, with the source (destination) experiencing the hottest temperatures of the day more for later (earlier) flights. Next, I analyze how the effects vary over space in two ways: when the origin airport is or is not a hub in Section 5.2.2, and by climate region in Section 5.2.3. The overall effects of temperature on flight delays are larger when the origin is a hub, consistent with prior research by Mayer and Sinai (2003). However, the effects at the source and destination are larger when the origin is not a hub. When examining the results by climate region, I find the largest effects of high temperatures at the origin on delays in the regions least accustomed to them as compared to regions where they occur more frequently, suggestive of adaptation. But even in those regions with below average impacts of high temperatures, temperatures at the source airport still have a significant effect, highlighting how local airports will feel the impacts from non-local temperature shocks.

5.2.1 Local and Non-Local Effects By Time of Day

Are flights earlier or later in the day more susceptible to temperature changes at the source airport? In Figures 7 - 8, I decompose the temperature effects by the time of day by interacting each term in Equation (1) with whether flights were scheduled for departure before or after 2PM.[20] Panel A presents the estimates for flights before 2PM, and Panel B does the same for flights after 2PM.

[20] 2PM is used as the cutoff since it splits the daily flights roughly in half.

Focusing first on the probability of a delay, we see in Figure 7 that holding all else constant, higher temperatures at the source airport increase the probability of a delay more later in the day. The same holds true for temperatures at the origin airport, but not for the destination airport. For late aircraft delays, flights earlier in the day are primarily affected by high temperatures at the source and destination airports and later in the day by the source and origin airports (see Figure A.3). Examining all departure delays in Figure 8, while the coefficients for temperatures of at least 35°C are larger earlier in the day, they are not statistically different from later flights for either the origin or source airports. The notable exception is for temperatures at the destination airport, where higher temperatures earlier in the day lead to 10 – 12 minute increases in departure delays compared to 3 – 4 minutes later in the day.

One possible explanation for these phenomena could be in the connected structure of flights. On average, we would expect hourly temperatures to increases as we move from early to late morning, peak in the early to mid-afternoon, and decline into the evening. From late morning to early afternoon, the source flight is likely to fall in mid- to late morning, while flights from mid-late afternoon are likely to have source flights in early to mid-afternoon when temperatures are on average higher. The same logic applies in the opposite direction for destinations, which would be expected to experience higher temperatures on average for flights arriving early to mid-afternoon versus those arriving in the evening.

5.2.2 Larger Local (Non-Local) Effects at Hub (Non-Hub) Airports

Mayer and Sinai (2003) illustrate different patterns of scheduling behaviors at hub airports that drive an increase in airline delays relative to non-hub airports. Therefore, I estimate a modified version of Equation (1) where the nonlinear temperature bins are interacted with indicator variables for whether or not the origin airport is a hub.

I first check for heterogeneous effects by defining a hub as being in the top quartile in terms of the total number of summer flights in both 2010 and 2017. Figures 9 and 10 present the results using this hub definition. We see in Figure 9 that high temperatures increase the likelihood of a departure delay more at hub versus non-hub airports. In contrast, weather at the source or destination airports has a larger effect on the probability of a departure delay when the flight is departing from a non-hub airport. Additionally, comparing the results in Panel A of Figure 9 to Figure 5, we can see that the results from my main estimation appears to be driven by flights from hub airports. This is consistent with Mayer and Sinai (2003) noting the trend of airlines to concentrate flight operations at hub airports at the expense of flight delays.

I also perform the same estimation for a list of airports classified as hubs from the major domestic carriers.[21] Results from this alternative estimation are shown in Figures A.5 - A.7 in the Appendix and are qualitatively similar.

5.2.3 Heterogeneity By Climate Region and Adaptation

In addition to heterogeneous responses to weather shocks by time of day as in Section 5.2.1, one would expect variation in the response to weather by geographic region. I estimate an alternate version of Equation (1) where I interact each term with an indicator for the origin airport being in one of the nine NOAA climate regions, and report the results in Figure 11. This is similar to the approach used to estimate the temperature-mortality relationship in Deschênes and Greenstone (2011) and Heutel, Miller and Molitor (2020). As discussed in Heutel, Miller and Molitor (2020), if one assumes there are no underlying differences in baseline characteristics across climate regions (after controlling for airport specific characteristics through the fixed effects), then this cross region heterogeneity in the nonlinear effects of temperature on flight delays is indicative of adaptation.

The results in Figure 11 provide evidence of regional adaptation to temperature. Focusing first on the origin, we see the largest effects of high temperatures on the probability of a departure delay in regions least accustomed to them (such as the

[21] The list, including both hubs and focus cities, comes from this 2017 article: https://www.nasdaq.com/articles/airline-hubs-which-carrier-dominates-your-airport-2017-07-19.

Rockies, Ohio Valley, and the Northeast) as compared to regions where these likely occur more frequently (for example, the West, South, and Southwest).[22] Airports in areas that typically experience high heat have strong incentives to invest in the necessary infrastructure to allow for safe takeoff or sufficient cooling for employees and passengers. My results suggest that airports in the warmest regions have indeed undertaken these or other investments, in contrast to traditionally cooler places that may need to allocate their resources to combat extreme cold temperatures and ice in the winter.

However, the connected nature of the airline network means that regions that have mitigated the local effects of temperature still feel the effects from non-local sources that have not adapted to the same degree. Even in regions with minimal or below average impacts of high temperatures on the probability of departure delays, temperatures at their source airports still have a significant effect. For example, while a temperature of 35–40 or above 40 degrees Celsius for an origin airport in the West results in a below average effect, similar temperatures at their source airport have an above average impact on the probability of a departure delay. This highlights the importance of considering the network structure of airlines in understanding the effects of weather on flight delays, as weather shocks away from the origin airport (or the origin-destination route pair) have a significant impact on the likelihood of a departure delay. Even for airports in regions that may be well adapted to the effects of climate, weather shocks in other parts of the airline network may have resulting impacts on their on-time performance.

Alternatively, I can estimate the model where I define the climate region separately for each of the source, origin, and destination airports. The results utilizing the climate region of the origin airport in Figure 11 show the impacts of temperature on flight delays under the existing network structure; this alternative definition is useful in projecting

[22]The Southeast also shows above average effects of high temperatures on delays as compared to the national average in Figure 5, but this may be driven in large part by having the airport with the most delayed flights in my sample (Hartsfield-Jackson International Airport in Atlanta, GA, see Table A.8).

the effects of temperature on flight delays into the future, as it allows me to examine the regions that may be relatively more or less harmed by temperature increases due to climate change. Results for this alternative estimation are presented in Figures 13 and 14. The relative ordering of the effects of temperature at each of the source, origin, and destination airports on the probability of a flight delay are largely the same across climate regions as compared to Figure 11. However, there appears to be some variation in the effects at the source airport for eastern versus western regions. The effect of rising temperatures when the source is in regions such as the Northeast, Ohio Valley, and Upper Midwest are close to zero, while when the source is in the Northwest, Southwest, or West the effect on flight delays is as large or larger than when these regions serve as the origin or destination.

6 Projected Delays by Mid-Century

I quantified the relationship between temperature and flight delays in Section 5. In this section, I project how flight delays can be expected to increase in the future due to rising temperatures from climate change. The regional heterogeneity examined in Section 5.2.3 can be used to project the effects of high temperatures due to climate change on flight delays inclusive of adaptation.

Daily climate projections come from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP).[23] The dataset provides daily maximum temperatures at the 0.25°by 0.25°resolution level globally for 21 model runs and 2 scenarios (RCP4.5 and RCP8.5). I map these projection points to each of the nine NOAA climate regions and calculate the projected average daily temperature for each region across the 21 model runs for each scenario. The averages are compared to a baseline, the projected temperature by bin averaged across the 21 model runs for each scenario for 2015–2018. I calculate the change in the forecasted values from this historical period and apply

[23]From the Coupled Model Intercomparison Project Phase 5 (CMIP5) for the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC AR5) for 2030-2100.

this rate of change to the average from my historical data for 2010–2017 to predict the future number of days by temperature bin (Auffhammer et al., 2013). I then calculate the difference between the projections by mid- and late-century (2030–2059 and 2070–2099, respectively) and the number of days by temperature bin in my sample for Summer 2010–2017.

Using the results for all departure delays in Figure 14, I then calculate the projected change in delay minutes per flight over the summer for each of the source, origin, and destination by climate region.[24] For the source (destination), I use the historical shares of source (destination) flights by region for each origin climate region, i.e., what percentage of flights whose origin is in the Northeast are sourced from (destined for) the Upper Midwest? I calculate the projected change in delays at the source (destination) by weighting these historical shares for each origin climate region. For example, suppose for flights originating in the Northeast, 30% are sourced from the Upper Midwest, 20% from the Ohio Valley, and the remaining 50% from the Northeast. The projected effects of the source on departure delays for the Northeast would then be calculated by summing 30% of the estimated source effect for the Upper Midwest with 20% of the estimated source effect for the Ohio Valley and 50% of the same for the Northeast.

Panel A of Figure 15 presents the *additional* departure delay minutes (in thousands) we can expect due to rising temperatures by mid-century. Across all climate regions, we see an economically significant increase in the duration of departure delays both overall and due to non-local temperature increases at the source and destination. The figure shows that by mid-century, increases in temperature will lead to over 110,000 additional hours (6.6 million minutes) of departure delays for U.S. domestic flights per summer, a 33% increase in the total duration of departure delays as compared to summer 2010–2017. The majority of this increase will be due to non-local temperature

[24] Since a delay is only counted if it exceeds 15 minutes, I apply the projected change in delay minutes per flight to the average number of delayed flights per summer from 2010–2017. I have previously shown that temperature also increases the probability of a delay, and implicitly my approach ignores those flights that were previously delayed by less than 15 minutes which would be delayed by greater than 15 minutes after the projected increase in delay duration. Thus, my estimated increase is conservative.

shocks, as higher temperatures at the source and destination airports will contribute to over 71,000 additional hours of departure delays or nearly 65% of the total. Panel B of Figure 15 displays this share of additional delays from each of the source, origin, and destination by climate region. There is substantial heterogeneity across regions – regions such as the Southeast and South see 40–50% of the additional delays due to temperature shocks at the origin, while the Northwest and the West are projected to see 84–94% of additional delays due to non-local shocks at the source and destination.

I translate these increases in departure delays to dollar terms at the national level in Table 2. Using the FAA's suggested value of travel time of $0.79/min., by mid-century additional delays due to climate change will cost passengers nearly $500 million per summer. If instead I use the estimates from the recent literature (Forbes, 2008; Gayle and Yimga, 2018), these costs to passengers rise to roughly $850 – $940 million per summer. Adding the direct cost to airlines of roughly $500 million per summer, additional departure delays due to rising temperatures will lead to a $1.0 – $1.4 billion increase in costs to passengers and airlines per summer.

7 Conclusion

In this paper, I estimate the effects of temperature shocks at each of the source, origin, and destination airports in the U.S. domestic airline network on flight delays and provide credible evidence of a network effect of climate change. I find that relative to a baseline of 15–20°C, temperatures of 20–25°C at the source, origin, or destination lead to a 1.7%, 5.5%, and 2.9% increase in the probability of a flight delay, respectively. At the temperature extremes, these increase to 4.8%, 10.4%, and 5.5%. Considering that around 20% of flights are delayed and each flight delay costs airlines and passengers over $2,175, these estimated effects are significant. I also show that high temperatures at the source airport primarily affect departure delays through late arriving aircraft and have a larger effect on flights later in the day, while temperatures at the destination airport are more important for flights in the morning and early afternoon hours. There is considerable heterogeneity in the effect across the U.S., as I find evidence of regional adaptation to high temperatures at airports in warmer versus cooler climates.

I also show that accounting for the network structure is critical in two ways. First, non-local effects from the connected source and destination airports make up roughly 50% of the total effect of temperature shocks on airline on-time performance. Second, even if one is only interested in the local effect at the origin, excluding the source airport in the estimation leads to significant omitted variable bias; one would underestimate the true effect by nearly 50%. Using the full network specification, I show that rising temperatures due to climate change will lead to over 110,000 additional hours of departure delays for U.S. domestic flights per summer, at a cost to passengers and airlines of \$1.0 – \$1.4 billion.

Airports are part of the public good, and the infrastructure investments to maintain them can be thought of as being determined at least in part by the social planner. While airlines and passengers will adapt on their own, through management practices or changes to scheduling, it is the social planner's investments into the airport that controls the infrastructure. Most prior cases of adaptation to climate change are at the individual or firm levels; in this case adaptation occurs in the form of public good provision. Adaptation in this setting is thus a combination of both private and public entities, where the private entities are adapting conditional on the existing infrastructure.

My results suggest policymakers should strongly consider incentivizing efforts to combat the impacts of climate change on the airline industry. To mitigate the effects of temperature on airline on-time performance, airports can increase runway length, carriers can adjust flight schedules to avoid times of the day and/or locations projected to see high temperatures, and airplane manufacturers can improve existing aircraft technology. My findings indicate there may be significant potential benefits from infrastructure investments in airport improvements, such as extending runways where possible and improving cooling for both passengers and airport employees.

This study also highlights the importance of considering non-local effects that affect local conditions in the context of climate change. Moving beyond the aviation industry, existing regulation of emissions of CO_2 in the U.S. is at either the state or regional level. The significance of the local and non-local effects in this study indicate an additional benefit of national (if not global) policy aimed at reducing emissions of pollutants such as CO_2 and mitigating climate change. In order to reduce aviation's carbon footprint, additional incentives promoting energy efficiency in airport re-modeling may be particularly beneficial. Besides lowering CO_2 emissions to reduce future flight delays, there may be co-benefits from reducing emissions of harmful local air pollution due to relative reductions in taxi time and less fuel-intensive takeoffs (Schlenker and Walker, 2016).

My analysis looks at the summer period to focus on the responsiveness of airline operations to high temperatures, but future work could examine the changes in the network response to low temperatures and freezing. Further, climate change is expected to lead to more than just changes in the distribution of temperatures, with an increase in both the probability and severity of storms whose effects on daily flight operations and airport infrastructure will be important to understand. More granular analyses examining the particular characteristics of U.S. airports could help determine where policymakers should target expansion or infrastructure improvements and simultaneously optimize routing behaviors away from those airports that may face the harshest conditions with the least potential for adaptation.

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Tables and Figures

Table 1: Most Frequently Delayed Airports (Summer, 2010–2017)

Rank	Airport Name	% of Total Flights	# of Flights Delayed/Year
1	Chicago, IL: Chicago Midway International	30.3%	7,180
2	Houston, TX: William P Hobby	28.8%	4,153
3	Baltimore, MD: Baltimore/Washington International Thurgood Marshall	27.4%	7,327
4	Newark, NJ: Newark Liberty International	26.9%	8,073
5	Dallas, TX: Dallas Love Field	26.6%	3,707
6	Chicago, IL: Chicago O'Hare International	26.6%	21,092
7	Miami, FL: Miami International	25.5%	4,772
8	San Francisco, CA: San Francisco International	25.2%	10,999
9	Dallas/Fort Worth, TX: Dallas/Fort Worth International	24.7%	16,016
10	New York, NY: John F. Kennedy International	24.5%	6,582
11	Denver, CO: Denver International	24.1%	14,851
12	Las Vegas, NV: McCarran International	24.0%	8,997
13	Orlando, FL: Orlando International	23.8%	7,413
14	St. Louis, MO: St Louis Lambert International	23.3%	3,409
15	Fort Lauderdale, FL: Fort Lauderdale-Hollywood International	23.2%	4,077
16	Atlanta, GA: Hartsfield-Jackson Atlanta International	22.8%	23,195
17	Washington, DC: Washington Dulles International	22.7%	3,575
18	Houston, TX: George Bush Intercontinental/Houston	22.7%	9,913
19	Nashville, TN: Nashville International	22.1%	3,182
20	Los Angeles, CA: Los Angeles International	21.7%	12,612
21	West Palm Beach/Palm Beach, FL: Palm Beach International	21.5%	1,069
22	White Plains, NY: Westchester County	21.5%	462
23	Burlington, VT: Burlington International	21.4%	271
24	Savannah, GA: Savannah/Hilton Head International	21.4%	521
25	Charlotte, NC: Charlotte Douglas International	21.2%	6,639

Notes: Based on U.S. BTS On-Time Performance Dataset for Summer 2010–2017. Restricted to airports with a minimum of 1,000 flights per year.

Table 2: Projected Additional Delay Cost ($ millions, Summer 2030–2059)

	Source	**Origin**	**Dest**	**Total**
Costs to Passengers				
FAA	152.8	167.8	155.3	476.0
Forbes ('08)	274.7	301.6	279.2	855.6
Gayles and Yimga ('18)	301.8	331.4	306.7	939.9
Costs to Airlines	157.8	173.3	160.4	491.6
Total Cost	**311 - 460**	**341 - 505**	**316 - 467**	**968 - 1,431**

Notes: Projected temperatures from NEX-GDDP for RCP8.5 from 2030-2059, relative to baseline sample for 2010–2017. Passenger costs estimates per minute of $0.79, $1.42, and $1.56 respectively from FAA Office of Aviation Policy and Plans (2016); Forbes (2008); Gayle and Yimga (2018). Details on the methodology used to project additional delays can be found in Section 6.

Figure 1: Illustrative Example

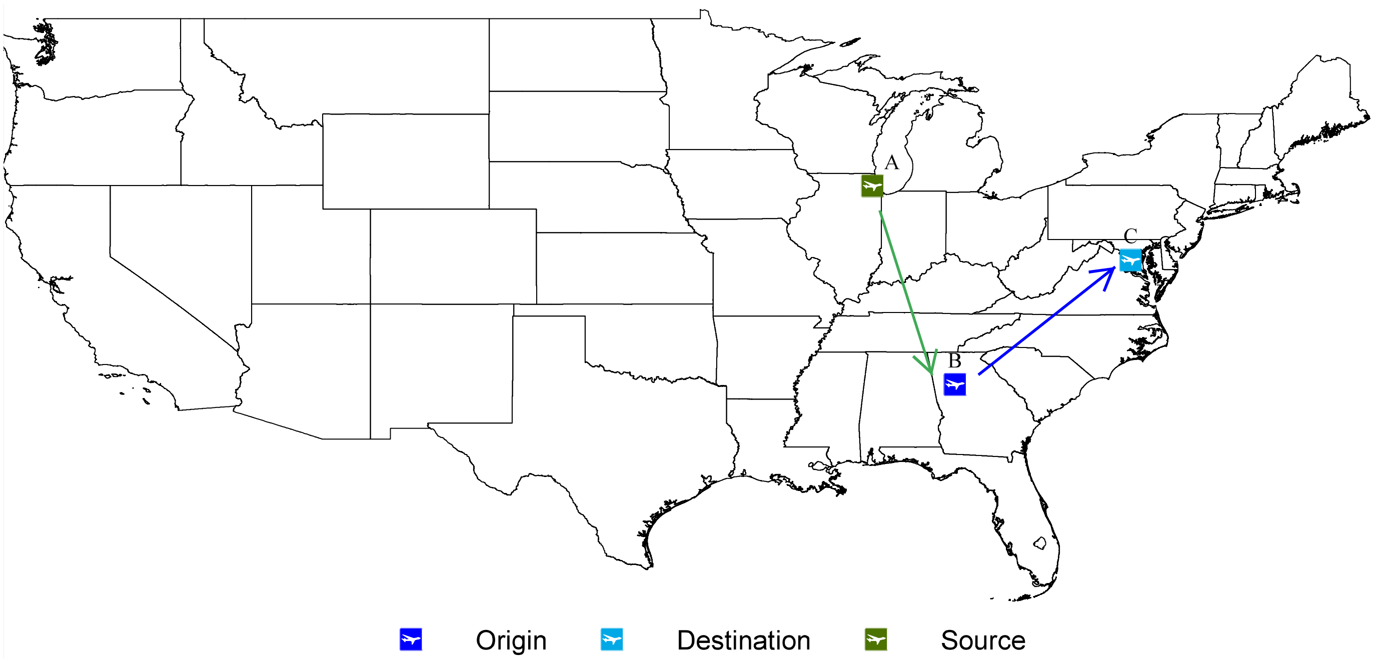
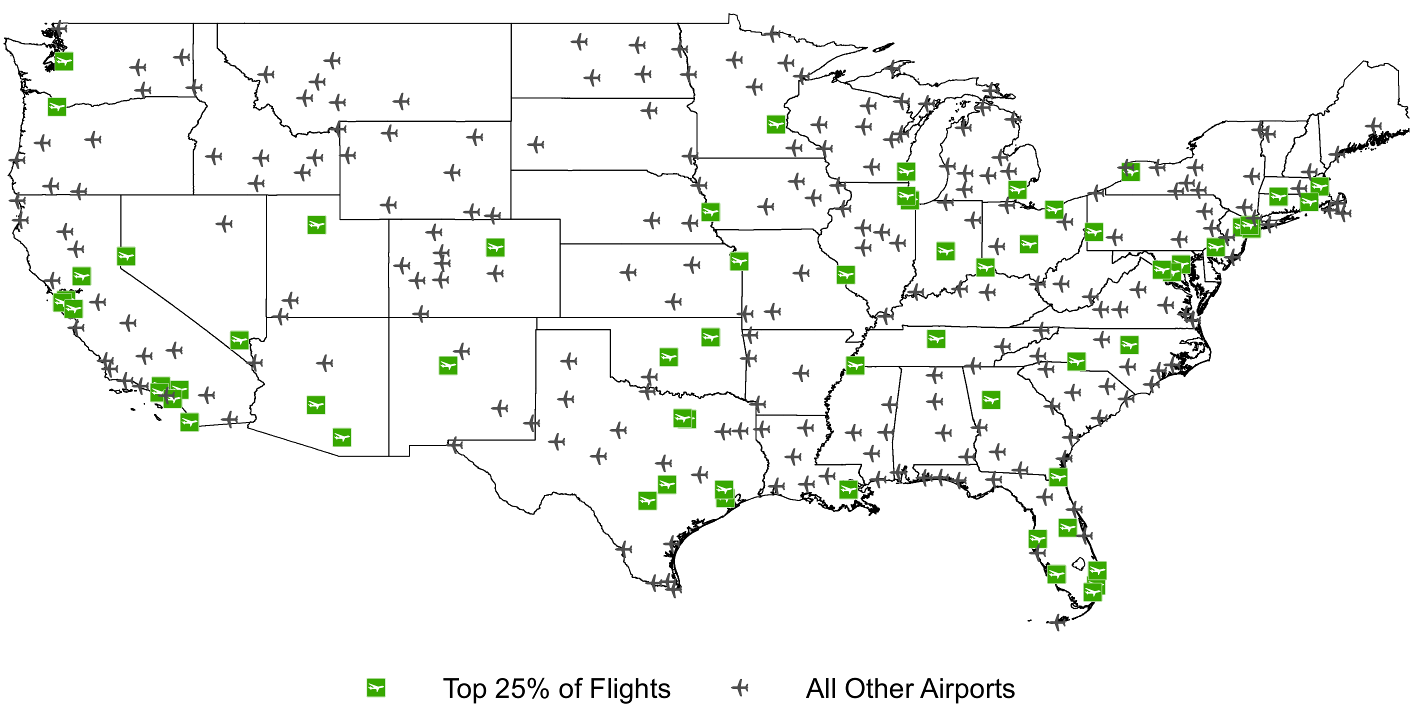
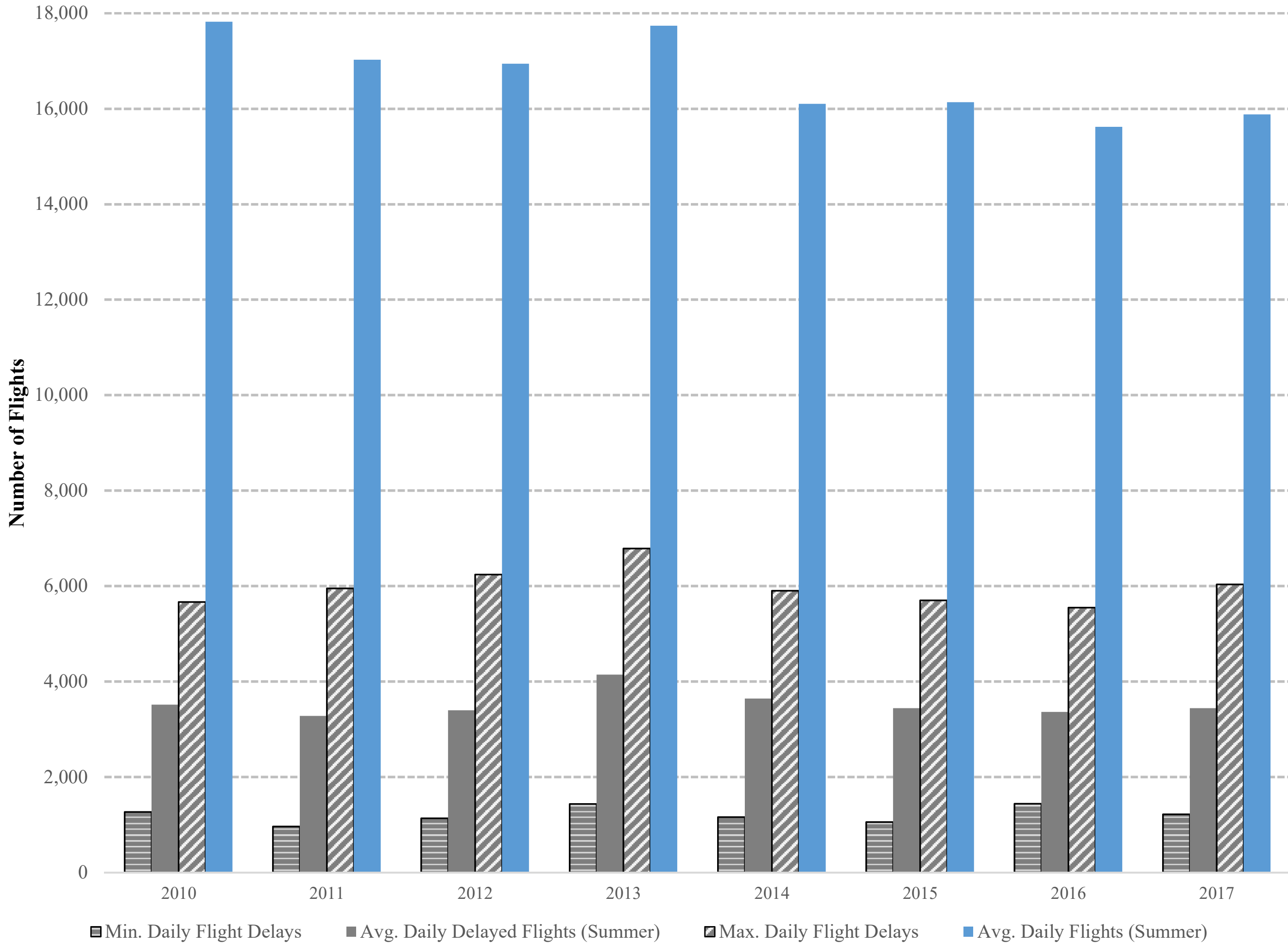


Figure 2: Airports in Sample



Notes: This figure displays the airports in my sample from the U.S. BTS On-Time Performance Dataset matched with NOAA's QCLCD database. Top 25% based on being in the top quartile in number of departure flights for the summer period over 2010–2017.

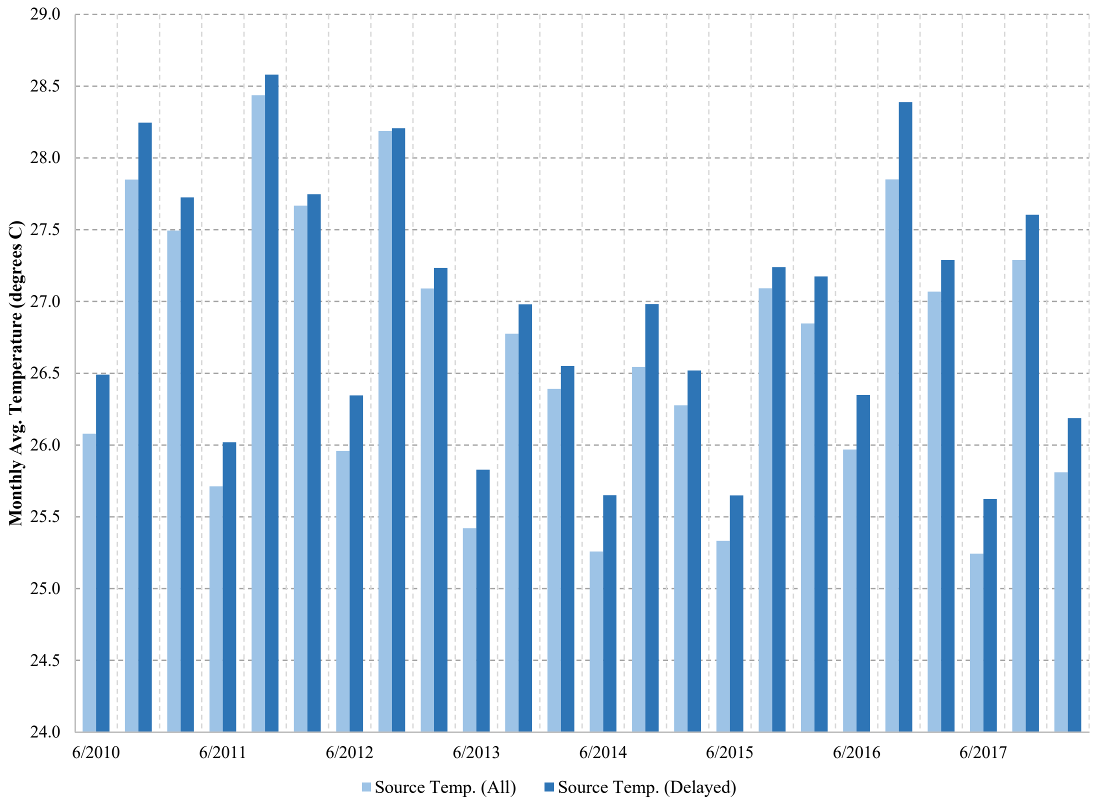
Figure 3: Daily Avg. Flights with Departure Delays (Summer 2010–2017)



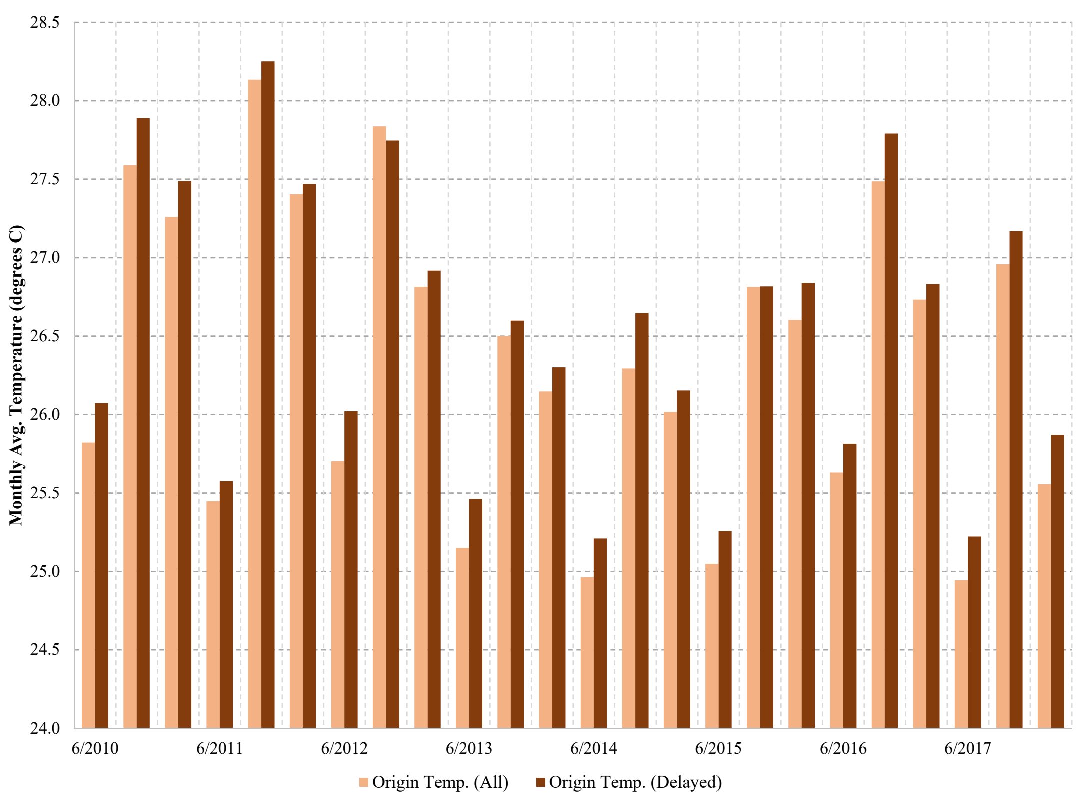
Notes: This figure displays the daily average flights over the summer period for 2010–2017, with the minimum, average, and maximum number of flights per day with departure delays of at least 15 minutes.

Figure 4: Monthly Avg. Temperatures at the Source and Origin (Summer 2010–2017)

(A) Source Airports

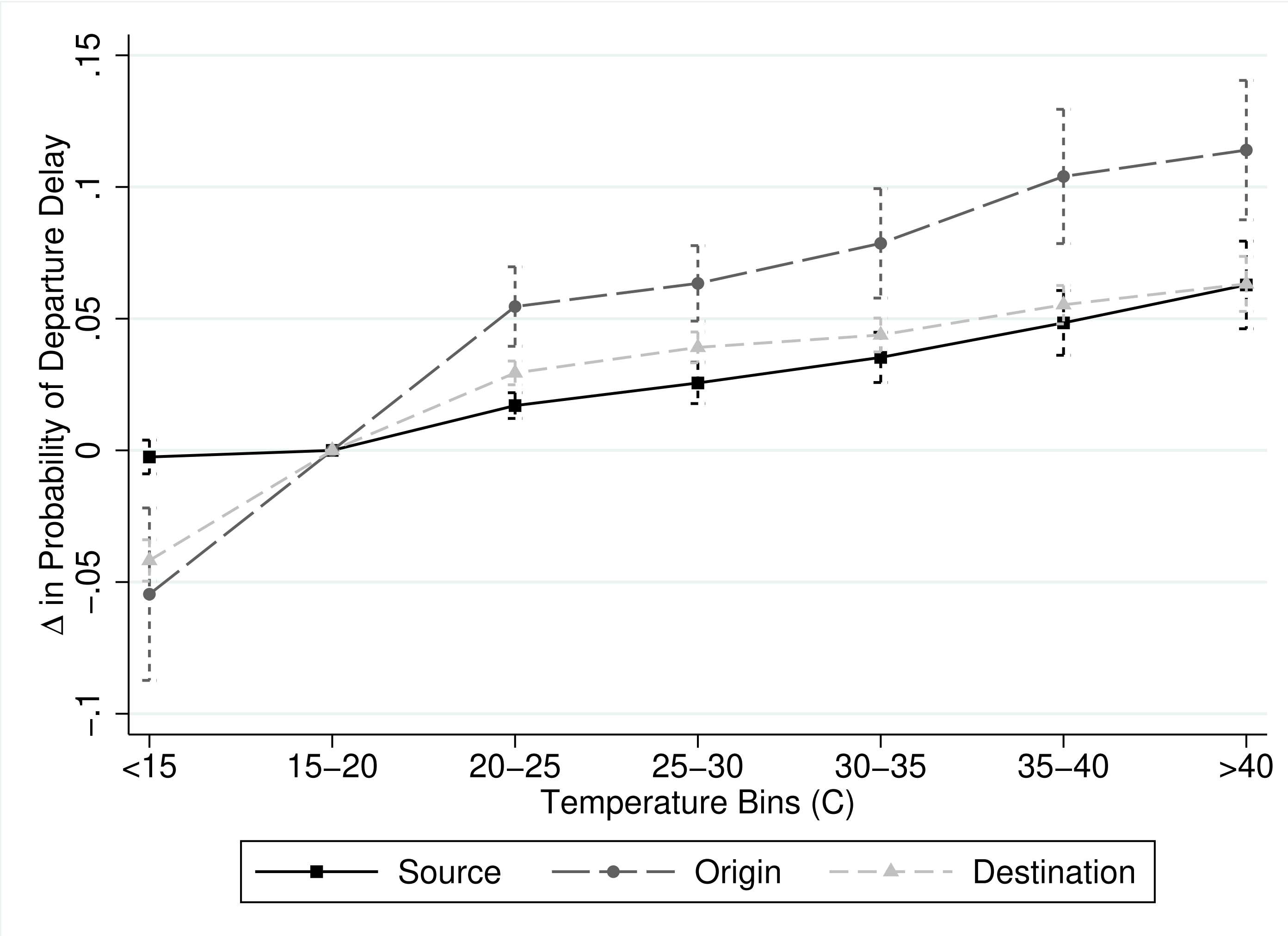


(B) Origin Airports



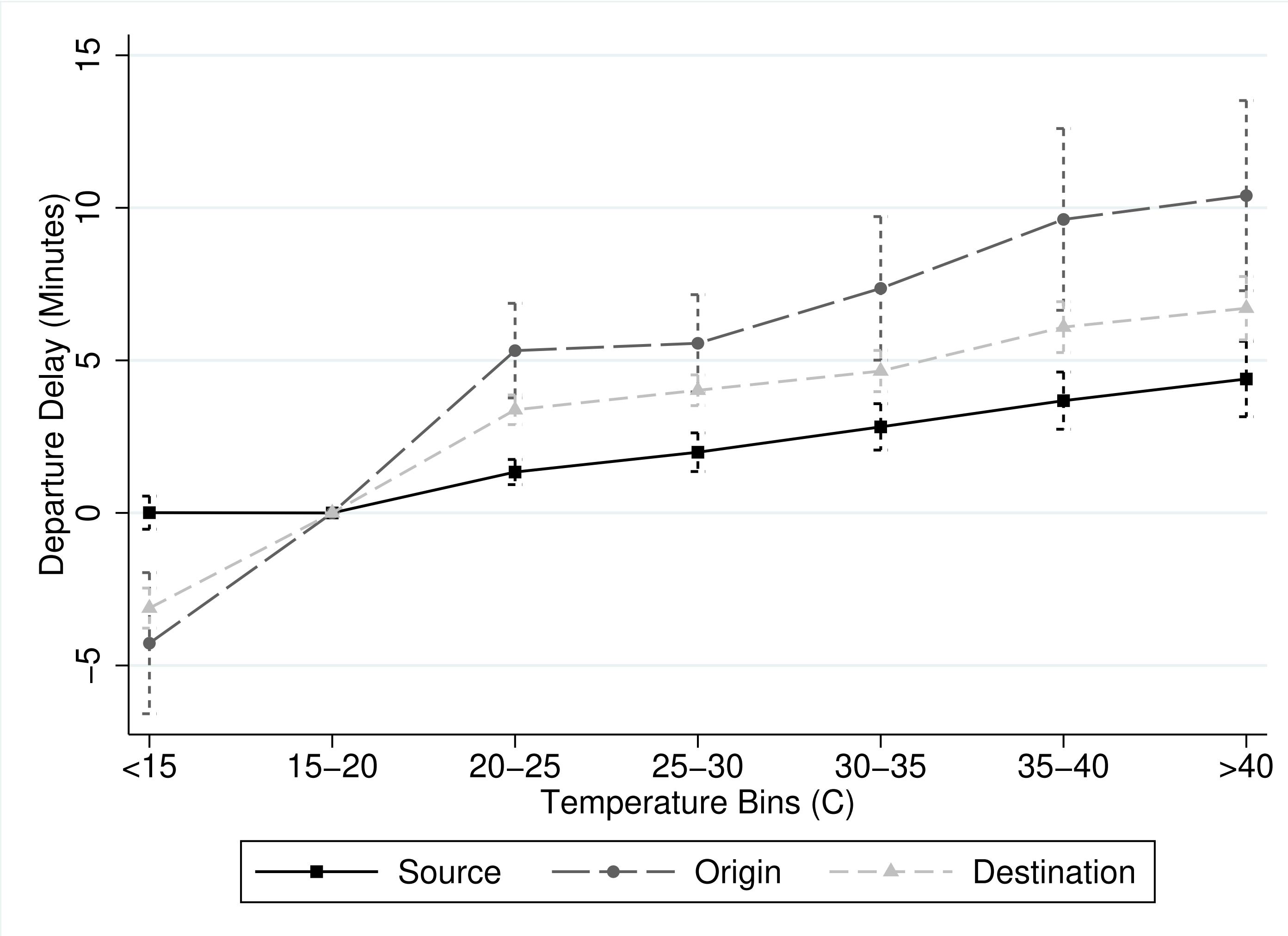
Notes: This figure displays the monthly average temperature at the source and origin airports from Summer 2010–2017 in my main sample, separately for both all flights and flights delayed at least 15 minutes.

Figure 5: Linear Probability Model on Indicator for Departure Delays >15 Mins.



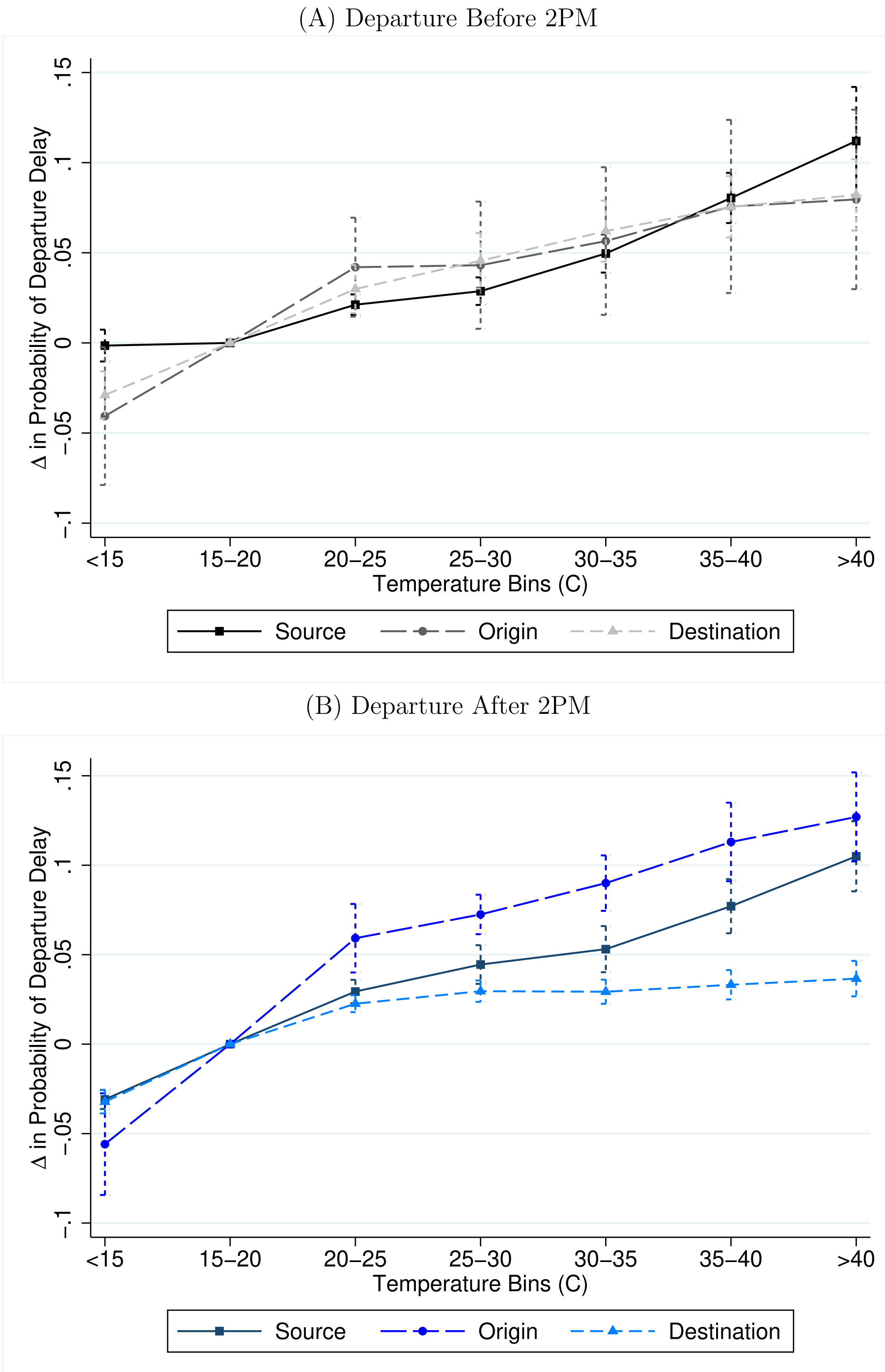
Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Estimation of Equation (1) where the outcome is an indicator for departure delays $>$ 15 minutes. Standard errors clustered at the origin airport level.

Figure 6: All Departure Delays (Minutes)



Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Estimation of Equation (1) where the outcome is departure delays in minutes. Standard errors clustered at the origin airport level.

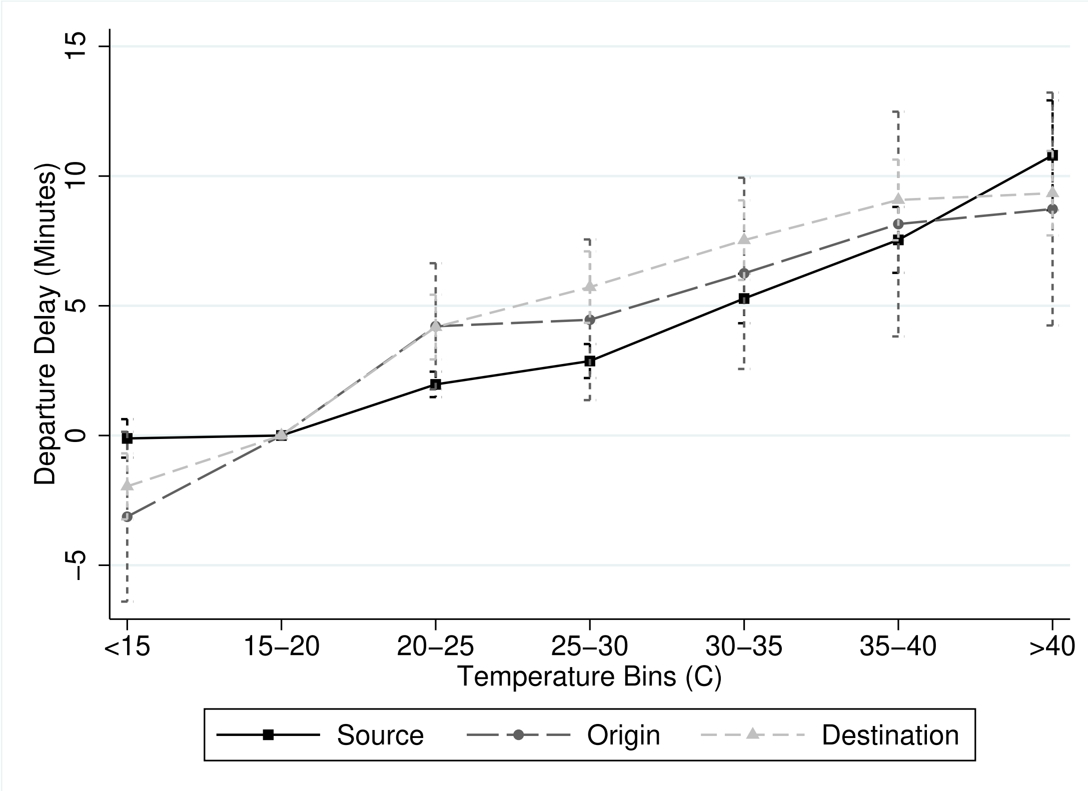
Figure 7: Before vs. After 2PM: Indicator for Departure Delays > 15 Mins.



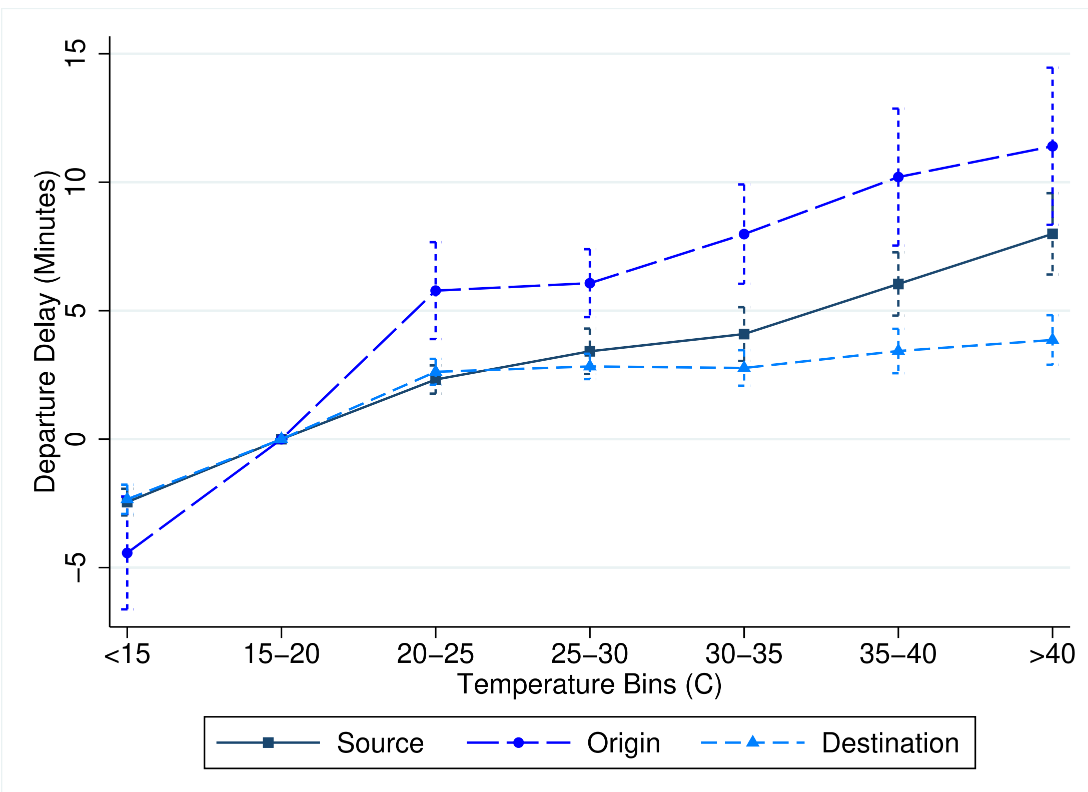
Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Estimation of modified Equation (1) as described in Section 5.2.1 where the outcome is an indicator for departure delays > 15 minutes. Standard errors clustered at the origin airport level.

Figure 8: Before vs. After 2PM: All Departure Delays (Minutes)

(A) Departure Before 2PM



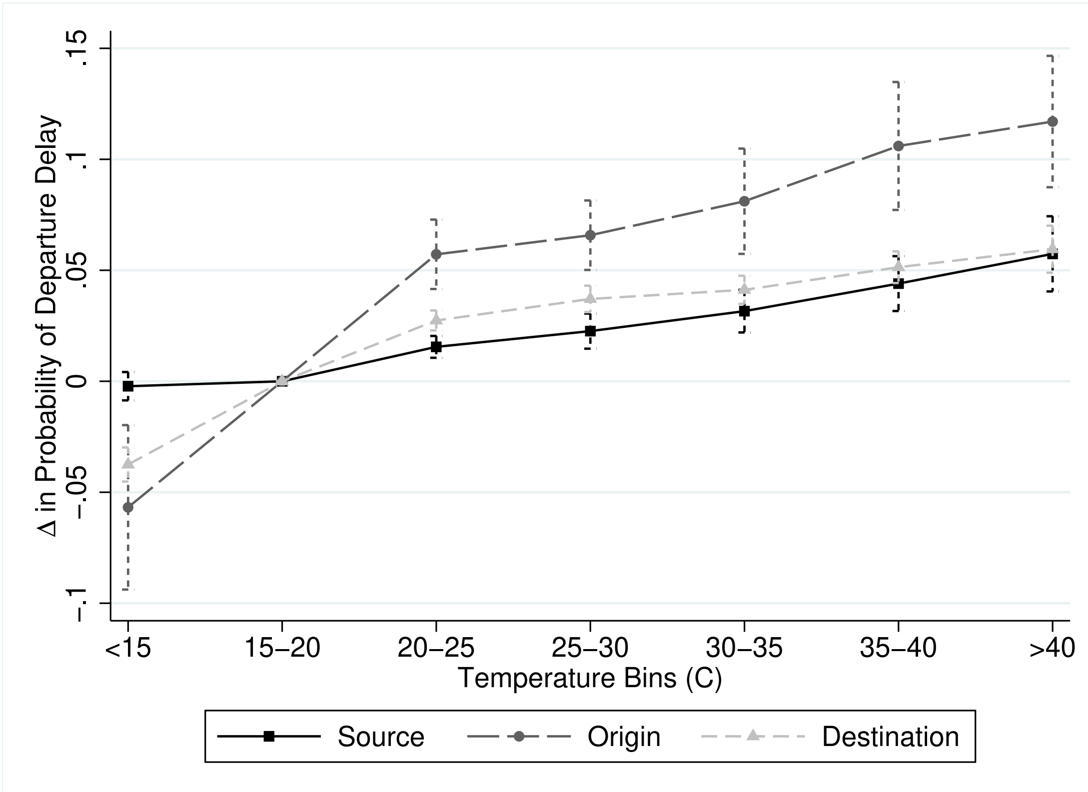
(B) Departure After 2PM



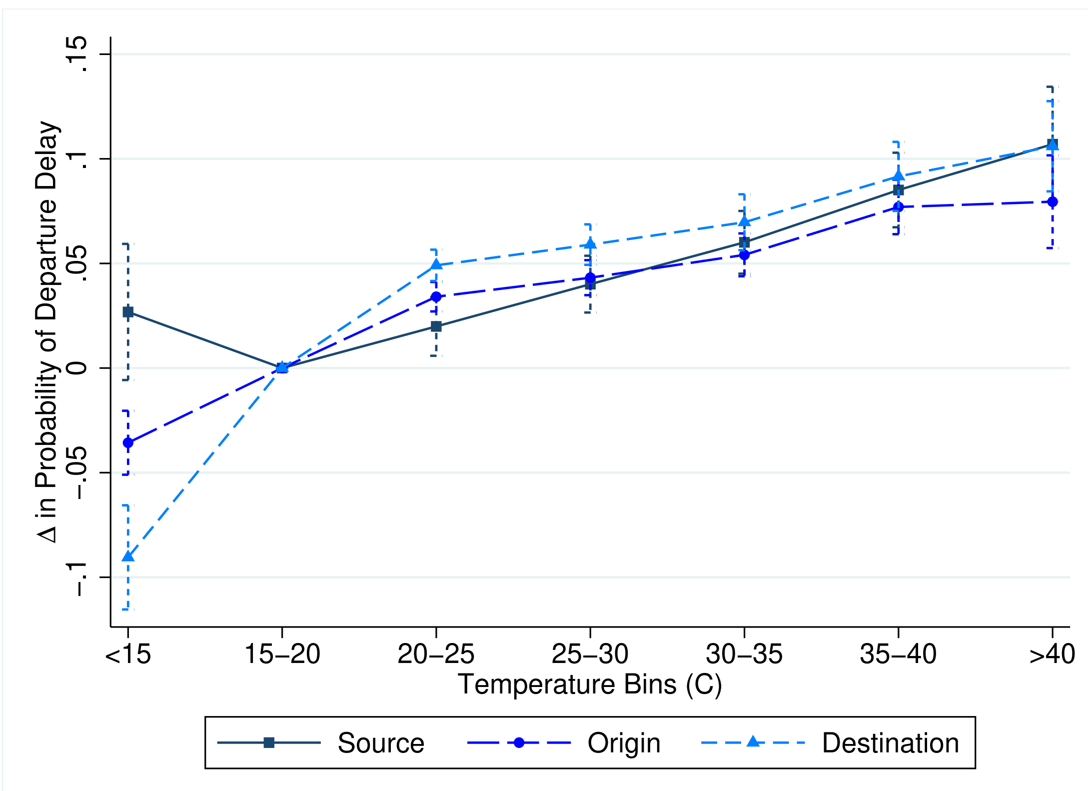
Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Estimation of modified Equation (1) as described in Section 5.2.1 where the outcome is departure delays in minutes. Standard errors clustered at the origin airport level.

Figure 9: Hub vs. Non-Hub Airports: Indicator for Departure Delays > 15 Mins.

(A) Hub Airports



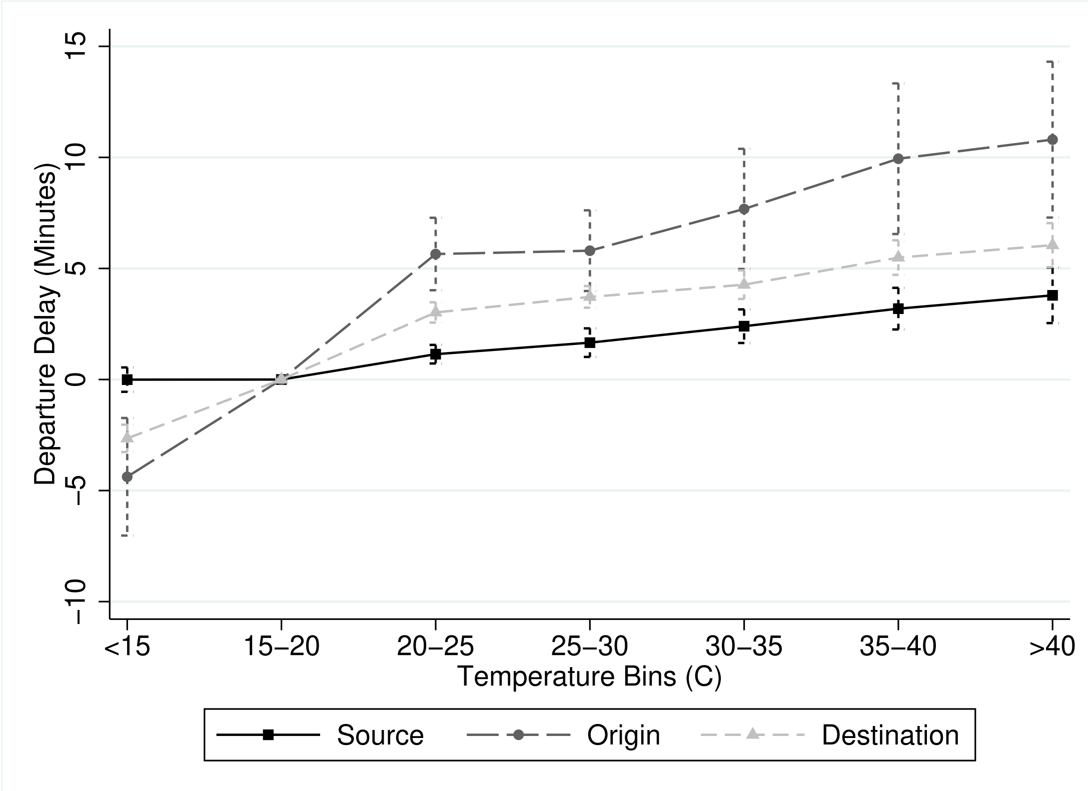
(B) Non-Hub Airports



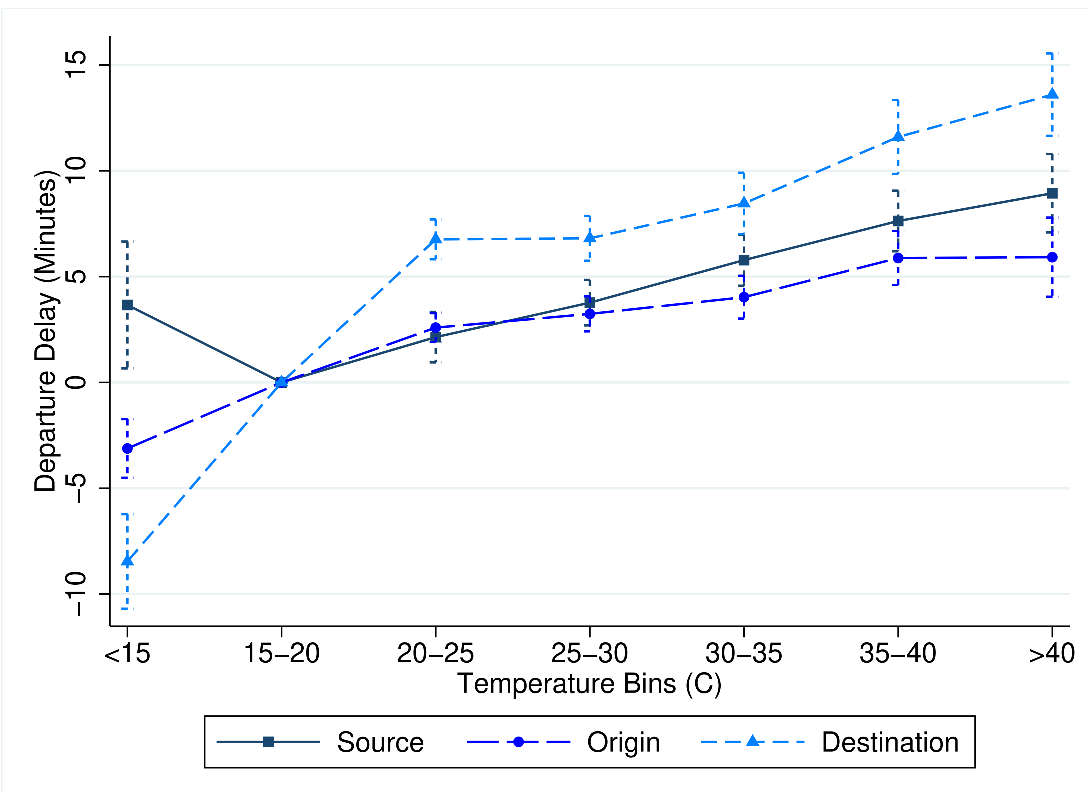
Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Estimation of modified Equation (1) as described in Section 5.2.2 where the outcome is an indicator for departure delays > 15 minutes. Hub based on being above 75th percentile in # of flights per year in 2010 and 2017. Standard errors clustered at the origin airport level.

Figure 10: Hub vs. Non-Hub Airports: All Departure Delays (Minutes)

(A) Hub Airports

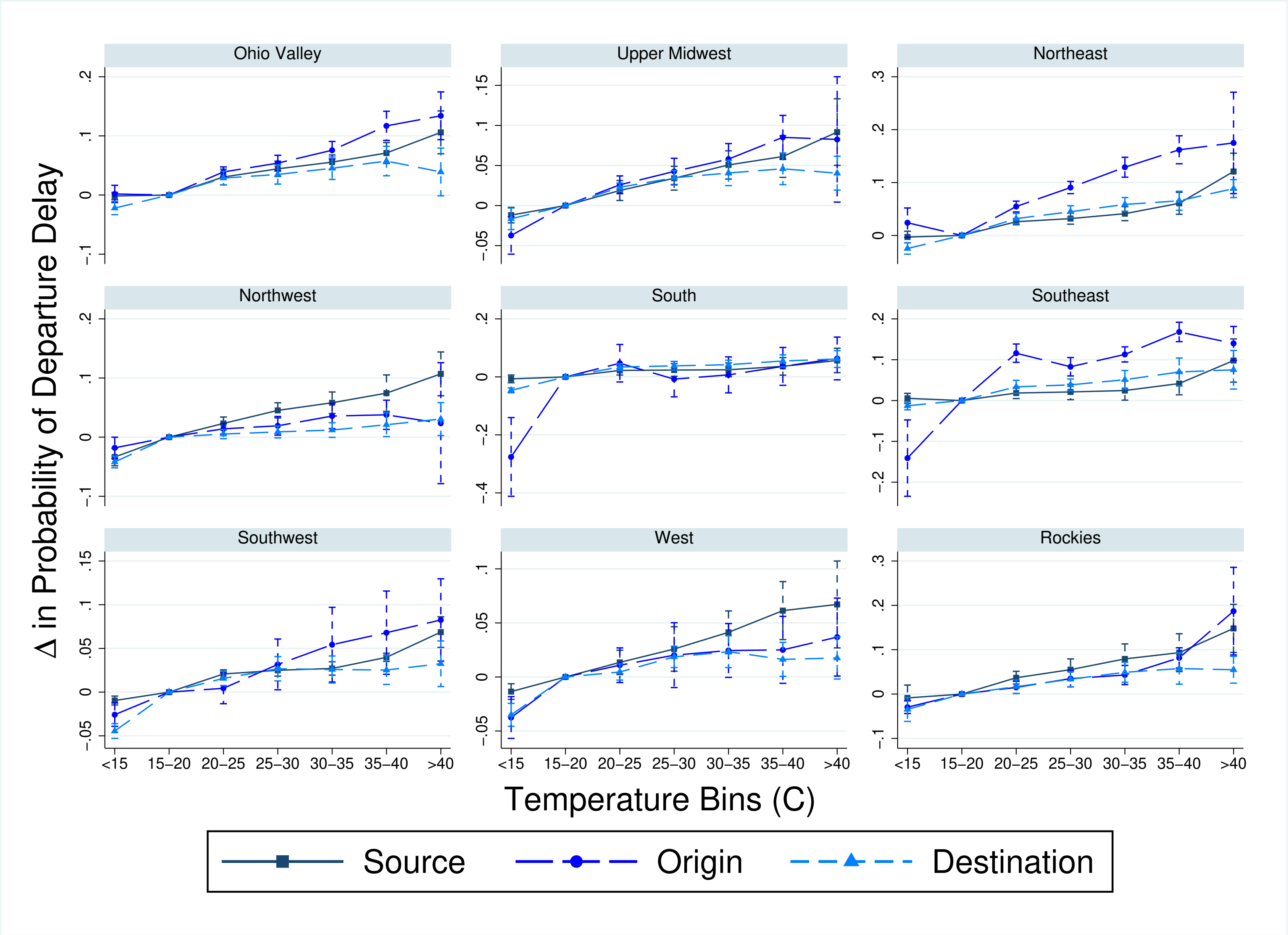


(B) Non-Hub Airports



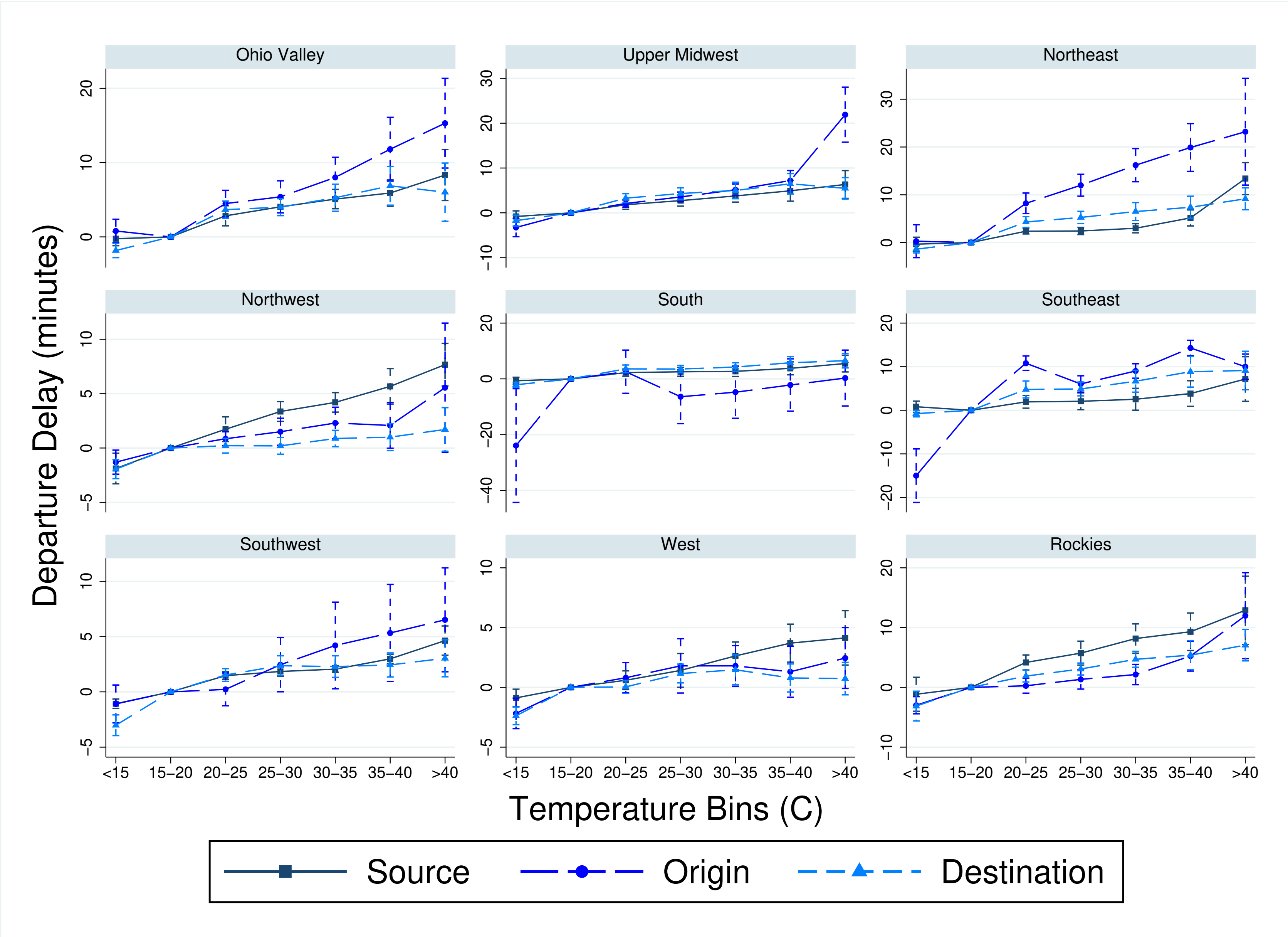
Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Estimation of modified Equation (1) as described in Section 5.2.2 where the outcome is departure delays in minutes. Hub based on being above 75th percentile in # of flights per year in 2010 and 2017. Standard errors clustered at the origin airport level.

Figure 11: Departure Delays >15 Mins. by Climate Region



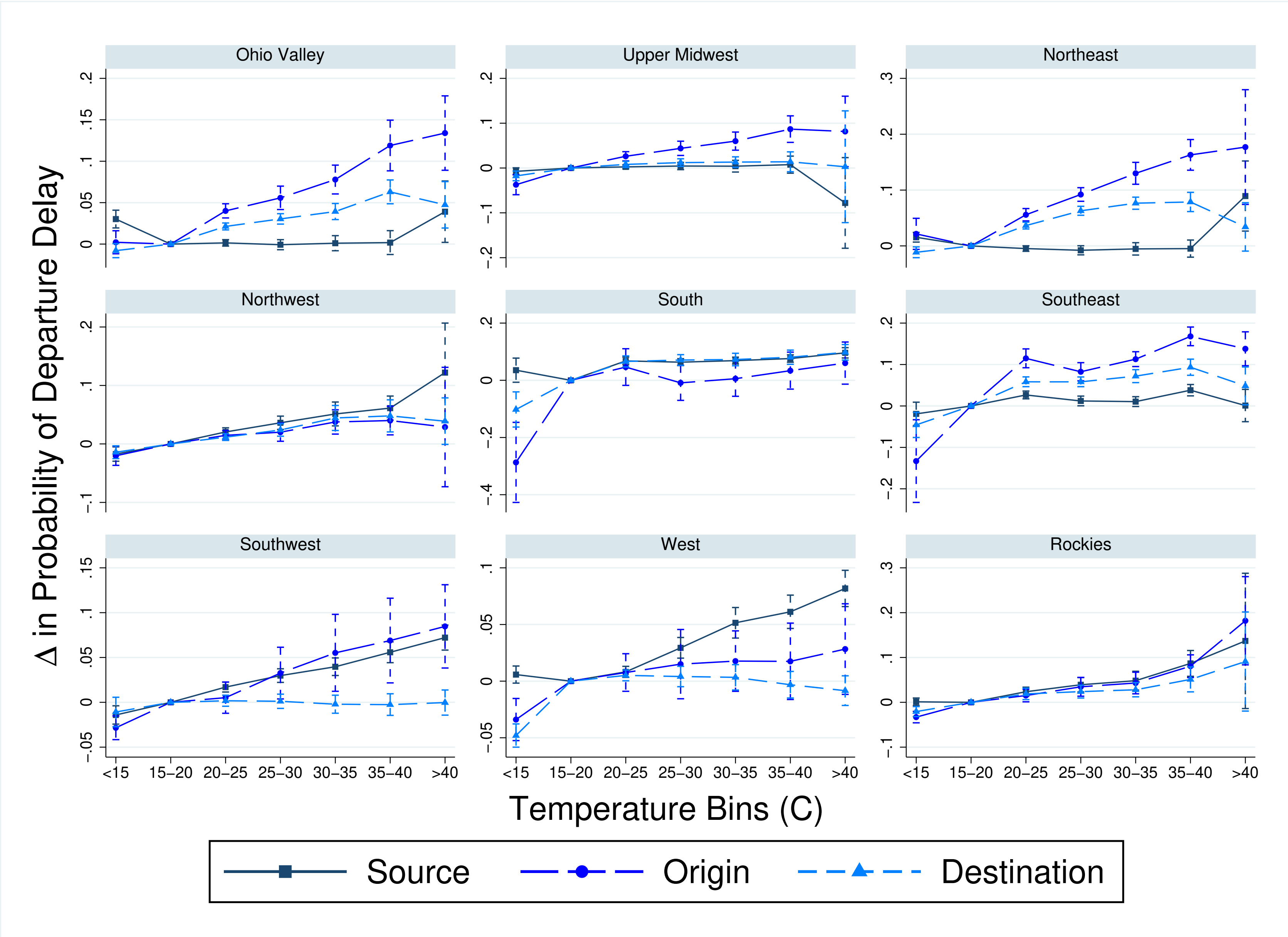
Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Estimation of modified Equation (1) as described in Section 5.2.3 where the outcome is an indicator for departure delays > 15 minutes. Standard errors clustered at the origin airport level.

Figure 12: All Departure Delays by Climate Region (Minutes)



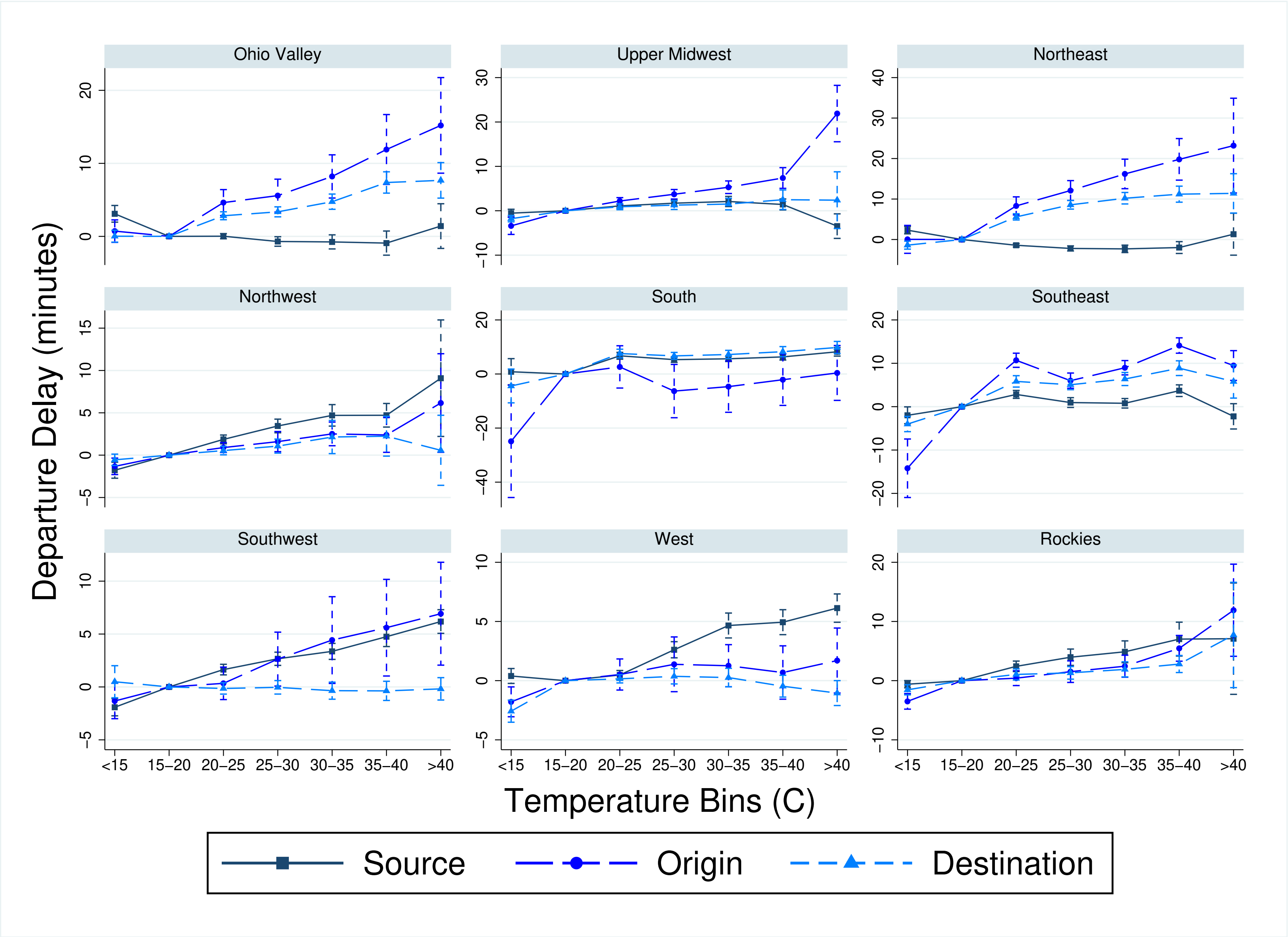
Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Estimation of modified Equation (1) as described in Section 5.2.3 where the outcome is departure delays in minutes. Standard errors clustered at the origin airport level.

Figure 13: Departure Delays >15 Mins. by Nodal Climate Region



Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Estimation of modified Equation (1) as described in Section 5.2.3 where the outcome is an indicator for departure delays > 15 minutes and climate region is defined for each of the source, origin, and destination airports. Standard errors clustered at the origin airport level.

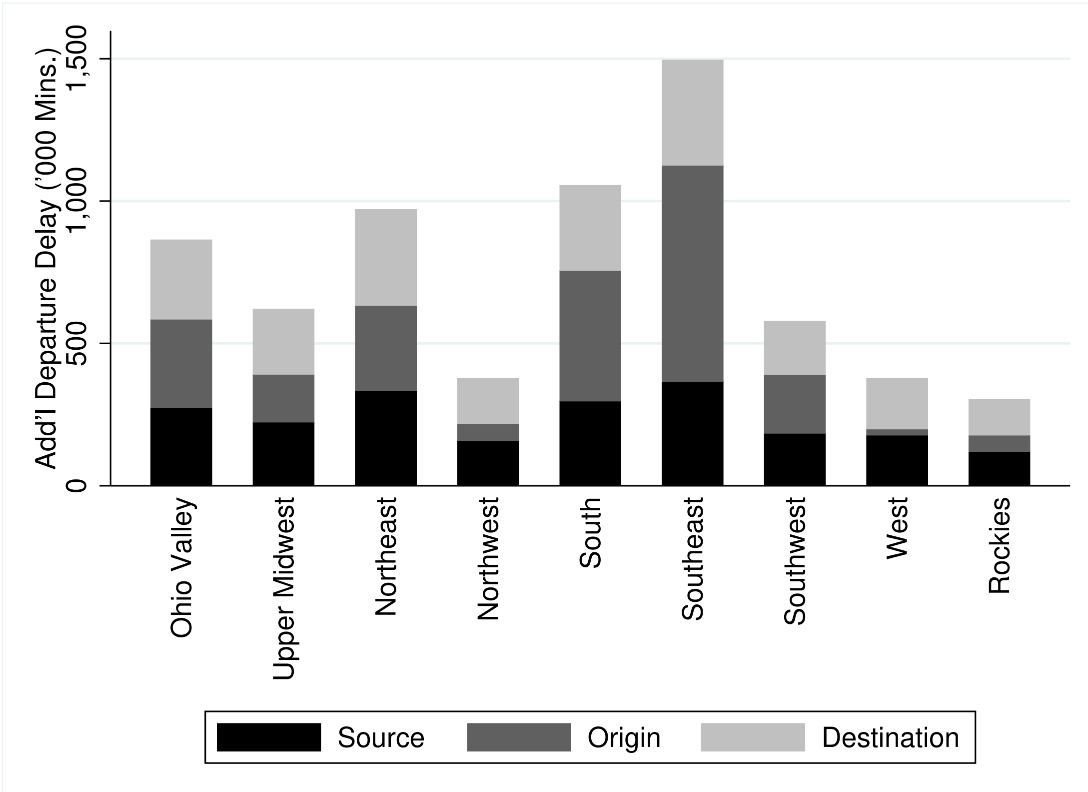
Figure 14: All Departure Delays by Nodal Climate Region (Minutes)



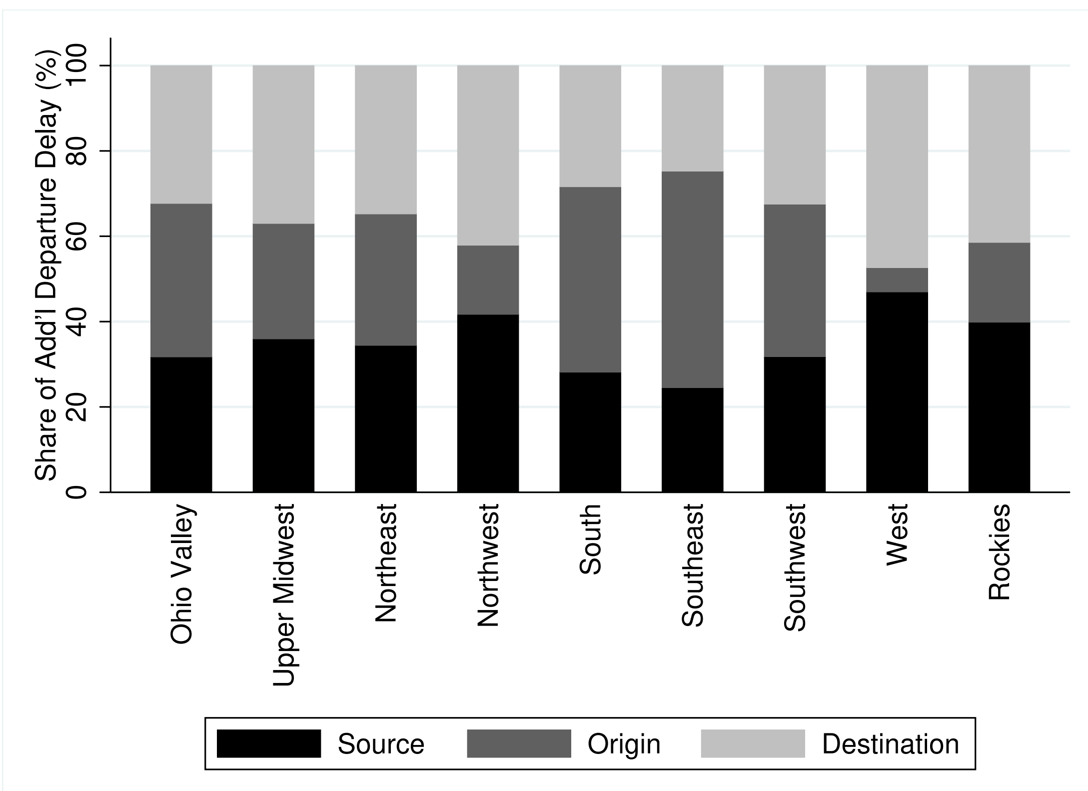
Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Estimation of modified Equation (1) as described in Section 5.2.3 where the outcome is departure delays in minutes and climate region is defined for each of the source, origin, and destination airports. Standard errors clustered at the origin airport level.

Figure 15: Additional Projected Summer Departure Delays (RCP8.5, 2030-2059)

(A) Additional Delays ('000 Minutes)



(B) Share of Additional Delays

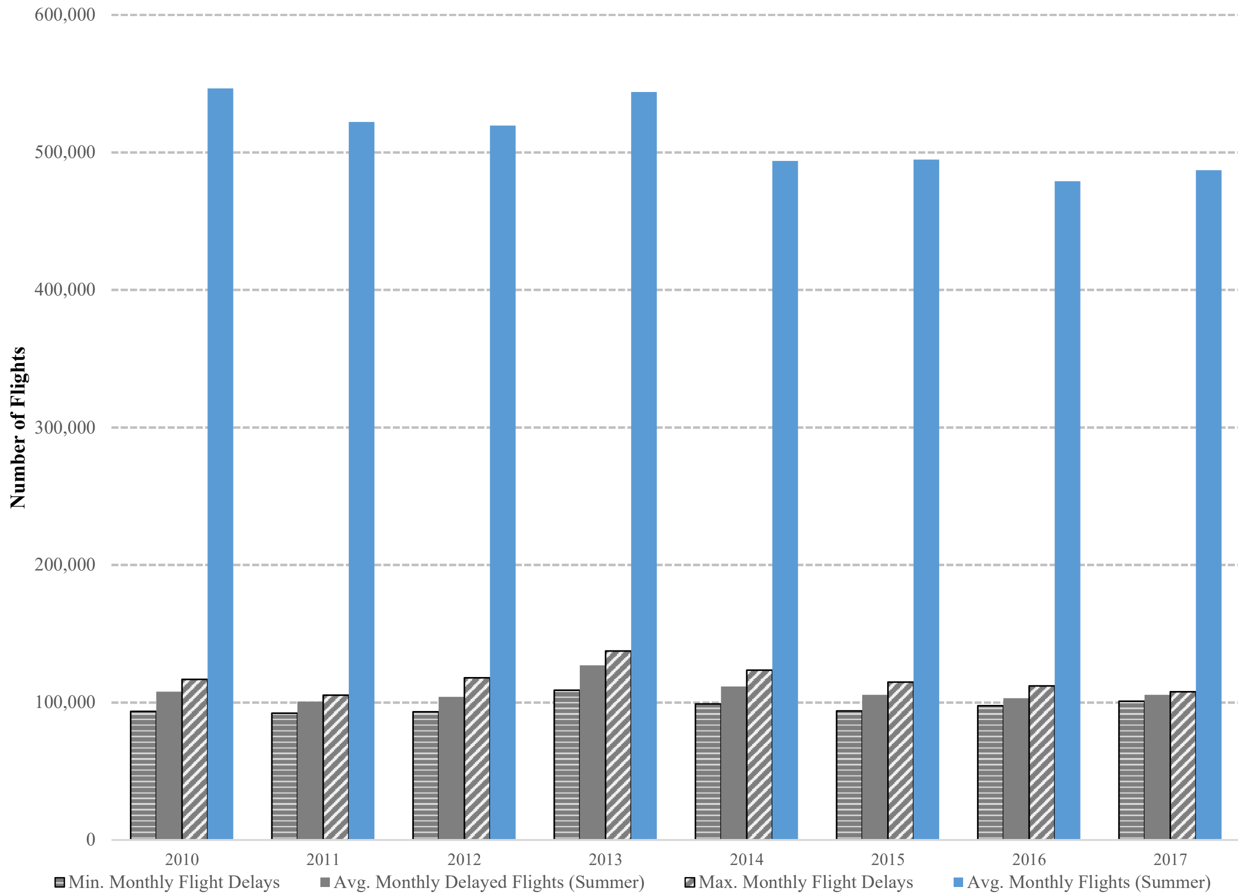


Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017 and NEX-GDDP projection data for 2030-2059 for RCP8.5. Methodology of delay projections as described in Section 6.

A Appendix

A.1 Supplementary Figures

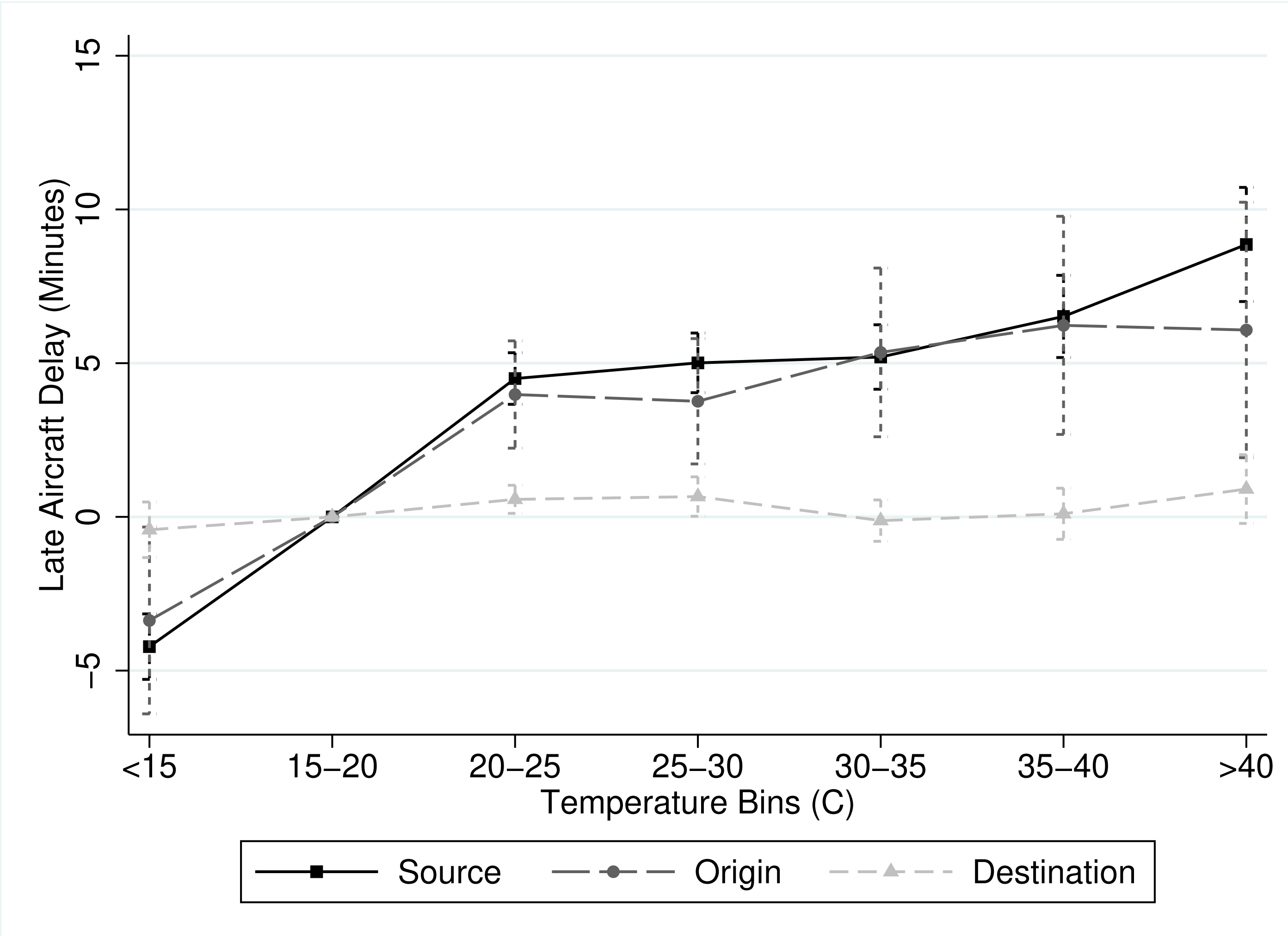
Figure A.1: Monthly Avg. Flights with Departure Delays (Summer 2010–2017)



Notes: This figure displays the monthly average flights over the summer period for 2010–2017, with the minimum, average, and maximum number of flights per month with departure delays of at least 15 minutes.

A.1.1 Extension: Late Aircraft Delays

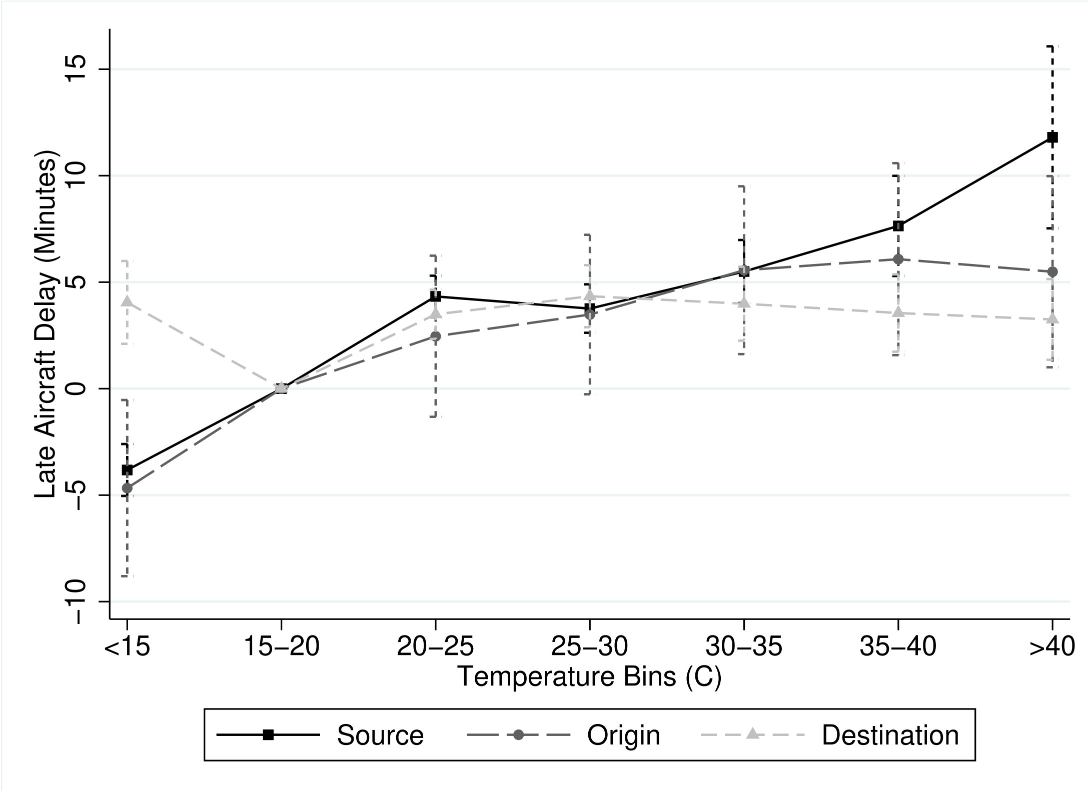
Figure A.2: Late Aircraft Delays (Minutes)



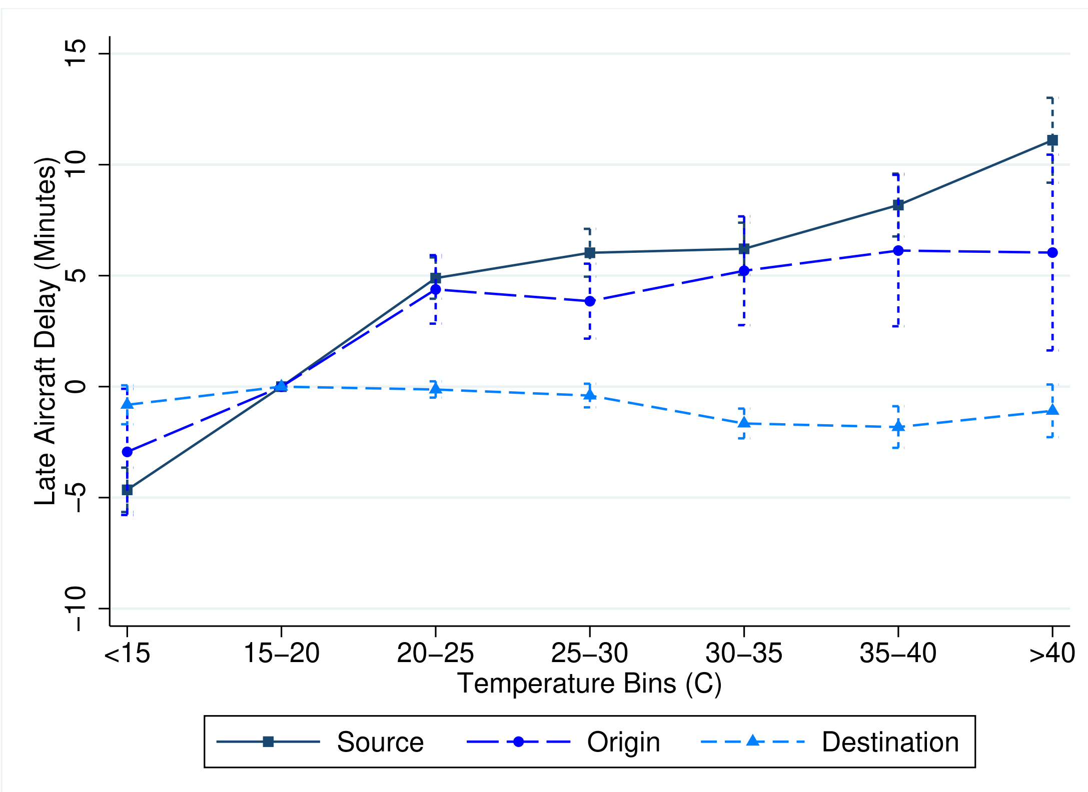
Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Estimation of Equation (1) where the outcome is late aircraft delays in minutes. Standard errors clustered at the origin airport level.

Figure A.3: Before vs. After 2PM: Late Aircraft Delays (Minutes)

(A) Departure Before 2PM



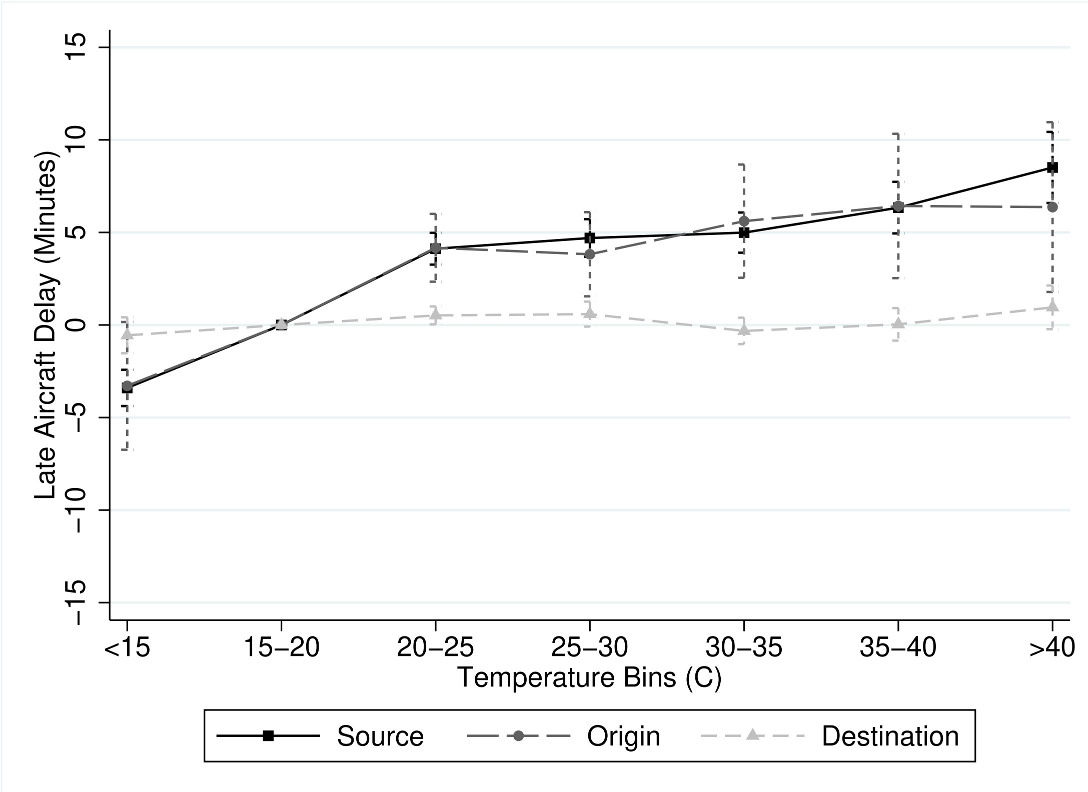
(B) Departure After 2PM



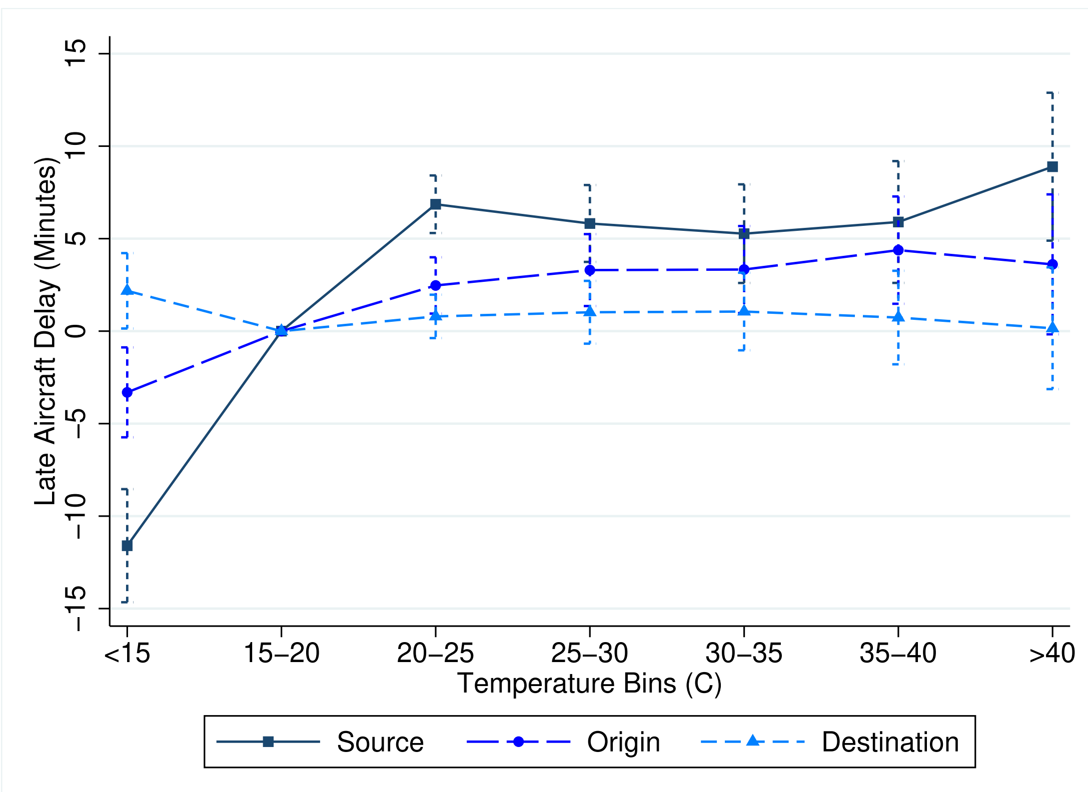
Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Estimation of modified Equation (1) as described in Section 5.2.1 where the outcome is late aircraft delays in minutes. Standard errors clustered at the origin airport level.

Figure A.4: Hub vs. Non-Hub Airports: Late Aircraft Delays (Minutes)

(A) Hub Airports



(B) Non-Hub Airports

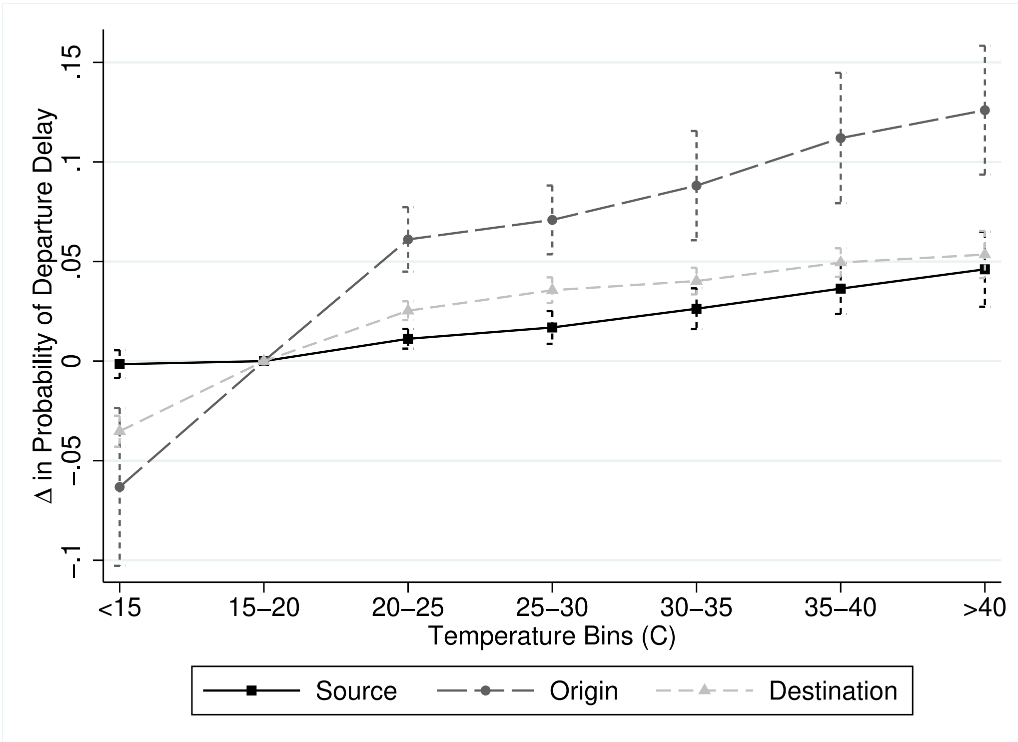


Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Estimation of modified Equation (1) as described in Section 5.2.2 where the outcome is late aircraft delays in minutes. Hub based on being above 75th percentile in # of flights per year in 2010 and 2017. Standard errors clustered at the origin airport level.

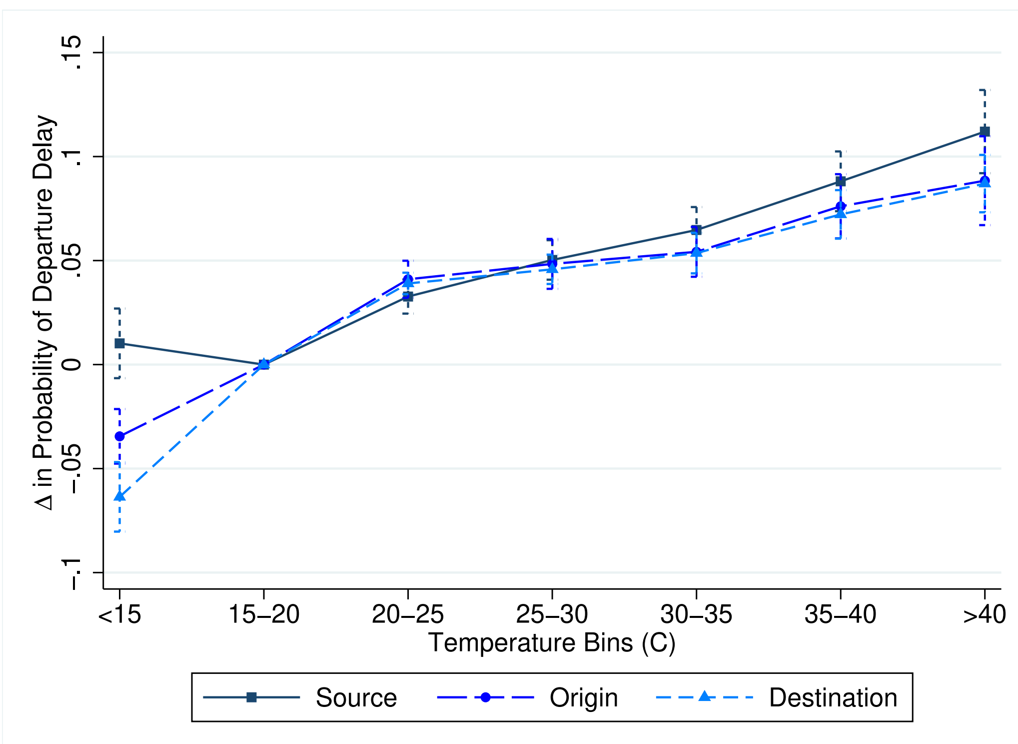
A.1.2 Alternative Hub Definition

Figure A.5: Hub vs. Non-Hub Airports: Indicator for Departure Delays > 15 Mins.

(A) Hub Airports



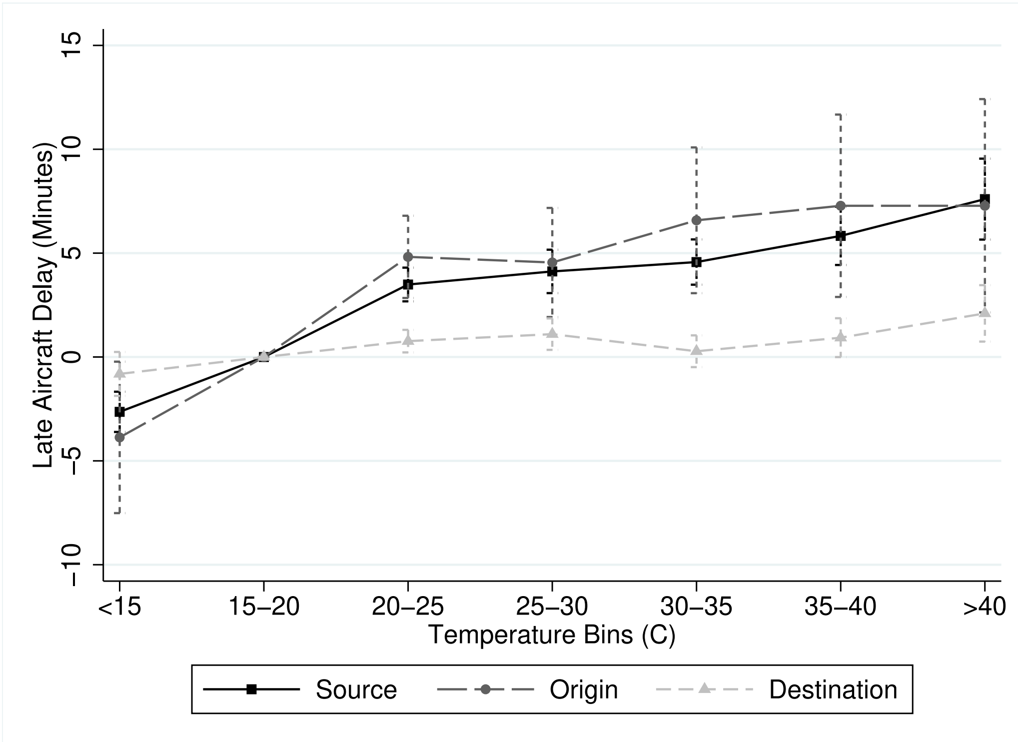
(B) Non-Hub Airports



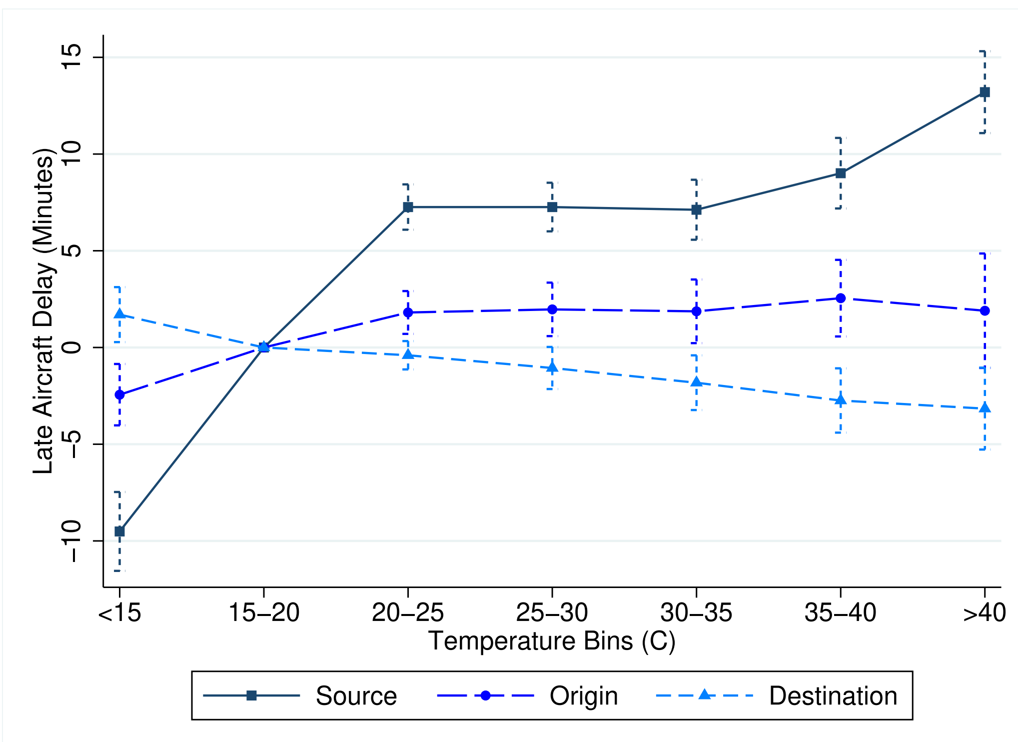
Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Estimation of modified Equation (1) as described in Section 5.2.2 where the outcome is an indicator for departure delays > 15 minutes. Hubs and focus cities as reported for major domestic airlines. Standard errors clustered at the origin airport level.

Figure A.6: Hub vs. Non-Hub Airports: Late Aircraft Delays (Minutes)

(A) Hub Airports



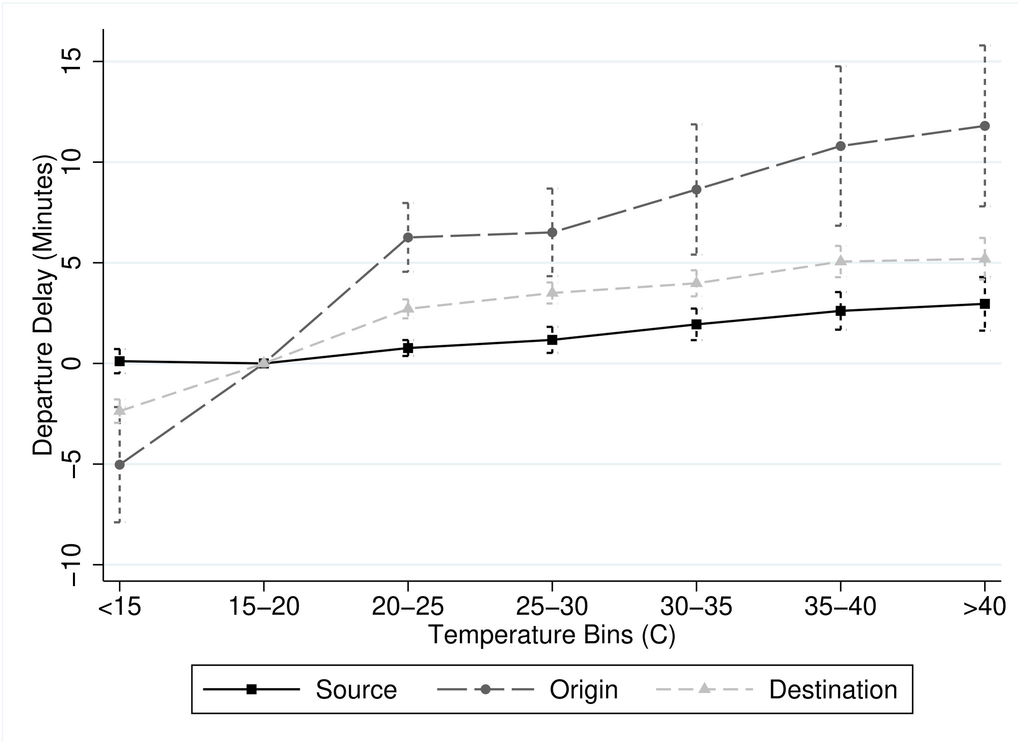
(B) Non-Hub Airports



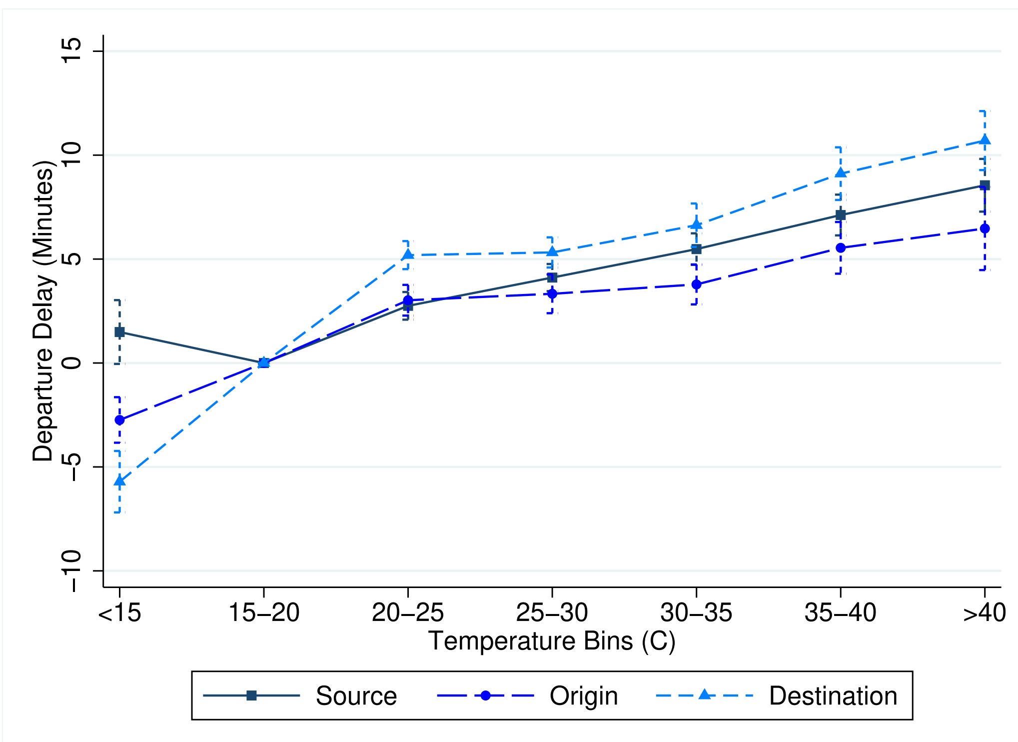
Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Estimation of modified Equation (1) as described in Section 5.2.2 where the outcome is late aircraft delays in minutes. Hubs and focus cities as reported for major domestic airlines. Standard errors clustered at the origin airport level.

Figure A.7: Hub vs. Non-Hub Airports: All Departure Delays (Minutes)

(A) Hub Airports



(B) Non-Hub Airports



Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Estimation of modified Equation (1) as described in Section 5.2.2 where the outcome is departure delays in minutes. Hubs and focus cities as reported for major domestic airlines. Standard errors clustered at the origin airport level.

A.2 Estimates from Main Analyses

Table A.1: Linear Probability Model on Indicator for Departure Delays >15 Mins.

	(1)	(2)	(3)
Panel A. Source			
Below 15 degrees C	-0.00248	-0.00275	-0.00250
	(0.00323)	(0.00312)	(0.00327)
20-25 C	0.0146***	0.0143***	0.0170***
	(0.00262)	(0.00260)	(0.00249)
25-30 C	0.0224***	0.0220***	0.0256***
	(0.00415)	(0.00409)	(0.00400)
30-35 C	0.0299***	0.0294***	0.0353***
	(0.00509)	(0.00497)	(0.00486)
35-40 C	0.0428***	0.0423***	0.0484***
	(0.00653)	(0.00642)	(0.00627)
Above 40 degrees C	0.0557***	0.0551***	0.0628***
	(0.00862)	(0.00854)	(0.00849)
Panel B. Origin			
Below 15 degrees C	-0.0558***	-0.0553***	-0.0546***
	(0.0165)	(0.0166)	(0.0167)
20-25 C	0.0563***	0.0562***	0.0546***
	(0.00761)	(0.00758)	(0.00770)
25-30 C	0.0659***	0.0659***	0.0634***
	(0.00714)	(0.00712)	(0.00731)
30-35 C	0.0817***	0.0817***	0.0786***
	(0.0105)	(0.0105)	(0.0106)
35-40 C	0.107***	0.107***	0.104***
	(0.0129)	(0.0129)	(0.0130)
Above 40 degrees C	0.118***	0.118***	0.114***
	(0.0131)	(0.0133)	(0.0135)
Panel C. Destination			
Below 15 degrees C	-0.0204***	-0.0204***	-0.0418***
	(0.00414)	(0.00412)	(0.00401)
20-25 C	0.0231***	0.0230***	0.0294***
	(0.00247)	(0.00248)	(0.00230)
25-30 C	0.0295***	0.0295***	0.0391***
	(0.00335)	(0.00336)	(0.00298)
30-35 C	0.0288***	0.0288***	0.0438***
	(0.00403)	(0.00405)	(0.00328)
35-40 C	0.0414***	0.0415***	0.0553***
	(0.00524)	(0.00526)	(0.00372)
Above 40 degrees C	0.0491***	0.0494***	0.0632***
	(0.00744)	(0.00741)	(0.00533)
R-squared	0.0863	0.0869	0.0927
N	8,909,720	8,909,719	8,909,718
Day-by-Month-by-Year FE	Yes	Yes	Yes
Origin Meteorological Controls	Yes	Yes	Yes
Source Meteorological Controls	Yes	Yes	Yes
Dest. Meteorological Controls	Yes	Yes	Yes
Carrier FE	Yes	Yes	Yes
Time of Day FE	Yes	Yes	Yes
Origin Airport FE	Yes	Yes	Yes
Source Airport FE		Yes	Yes
Dest. Airport FE			Yes

Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Meteorological controls are precipitation, relative humidity, dewpoint, and wind speed. Standard errors clustered at the origin airport level in parentheses. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table A.2: All Departure Delays (Minutes)

	(1)	(2)	(3)
Panel A. Source			
Below 15 degrees C	0.0826	0.0634	0.00824
	(0.294)	(0.267)	(0.277)
20-25 C	1.18***	1.15***	1.34***
	(0.230)	(0.221)	(0.210)
25-30 C	1.81***	1.74***	1.99***
	(0.347)	(0.331)	(0.323)
30-35 C	2.43***	2.35***	2.82***
	(0.419)	(0.387)	(0.388)
35-40 C	3.32***	3.22***	3.68***
	(0.531)	(0.485)	(0.478)
Above 40 degrees C	3.92***	3.79***	4.39***
	(0.711)	(0.641)	(0.631)
Panel B. Origin			
Below 15 degrees C	-4.30***	-4.29***	-4.27***
	(1.10)	(1.15)	(1.18)
20-25 C	5.43***	5.44***	5.32***
	(0.781)	(0.772)	(0.791)
25-30 C	5.73***	5.75***	5.56***
	(0.788)	(0.786)	(0.813)
30-35 C	7.57***	7.60***	7.36***
	(1.17)	(1.17)	(1.20)
35-40 C	9.81***	9.83***	9.62***
	(1.49)	(1.49)	(1.52)
Above 40 degrees C	10.6***	10.6***	10.4***
	(1.52)	(1.55)	(1.59)
Panel C. Destination			
Below 15 degrees C	-1.31***	-1.30***	-3.12***
	(0.320)	(0.326)	(0.335)
20-25 C	3.07***	3.06***	3.38***
	(0.289)	(0.290)	(0.248)
25-30 C	3.48***	3.46***	4.02***
	(0.300)	(0.301)	(0.257)
30-35 C	3.60***	3.59***	4.65***
	(0.367)	(0.370)	(0.345)
35-40 C	5.27***	5.27***	6.09***
	(0.502)	(0.501)	(0.425)
Above 40 degrees C	6.05***	6.07***	6.71***
	(0.666)	(0.658)	(0.530)
R-squared	0.0693	0.0721	0.0774
N	8,909,720	8,909,719	8,909,718
Day-by-Month-by-Year FE	Yes	Yes	Yes
Origin Meteorological Controls	Yes	Yes	Yes
Source Meteorological Controls	Yes	Yes	Yes
Destination Meteorological Controls	Yes	Yes	Yes
Carrier FE	Yes	Yes	Yes
Time of Day FE	Yes	Yes	Yes
Origin Airport FE	Yes	Yes	Yes
Source Airport FE		Yes	Yes
Destination Airport FE			Yes

Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Meteorological controls are precipitation, relative humidity, dewpoint, and wind speed. Standard errors clustered at the origin airport level in parentheses. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table A.3: Departure Delays >15 Mins. Before/After 2PM

	(1) Before 2PM	(2) After 2PM
Panel A. Source		
Below 15 degrees C	-0.00148	-0.0309***
	(0.00451)	(0.00273)
20-25 C	0.0212***	0.0294***
	(0.00291)	(0.00335)
25-30 C	0.0287***	0.0445***
	(0.00390)	(0.00552)
30-35 C	0.0496***	0.0531***
	(0.00541)	(0.00658)
35-40 C	0.0804***	0.0771***
	(0.00710)	(0.00772)
Above 40 degrees C	0.112***	0.105***
	(0.0153)	(0.0100)
Panel B. Origin		
Below 15 degrees C	-0.0406**	-0.0559***
	(0.0195)	(0.0145)
20-25 C	0.0420***	0.0592***
	(0.0140)	(0.00977)
25-30 C	0.0431**	0.0725***
	(0.0180)	(0.00563)
30-35 C	0.0565***	0.0900***
	(0.0209)	(0.00791)
35-40 C	0.0757***	0.113***
	(0.0245)	(0.0112)
Above 40 degrees C	0.0796***	0.127***
	(0.0254)	(0.0127)
Panel C. Destination		
Below 15 degrees C	-0.0289***	-0.0322***
	(0.00669)	(0.00333)
20-25 C	0.0299***	0.0226***
	(0.00681)	(0.00241)
25-30 C	0.0456***	0.0296***
	(0.00785)	(0.00305)
30-35 C	0.0620***	0.0293***
	(0.00864)	(0.00344)
35-40 C	0.0755***	0.0332***
	(0.00869)	(0.00418)
Above 40 degrees C	0.0821***	0.0366***
	(0.0101)	(0.00505)
R-squared	0.0954	0.0954
N	8,909,718	8,909,718
Day-by-Month-by-Year FE	Yes	Yes
Origin Meteorological Controls	Yes	Yes
Source Meteorological Controls	Yes	Yes
Dest. Meteorological Controls	Yes	Yes
Carrier FE	Yes	Yes
Time of Day FE	Yes	Yes
Origin Airport FE	Yes	Yes
Source Airport FE	Yes	Yes
Dest. Airport FE	Yes	Yes

Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Meteorological controls are precipitation, relative humidity, dewpoint, and wind speed. Standard errors clustered at the origin airport level in parentheses. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table A.4: All Departure Delays Before/After 2PM (Minutes)

	(1) Before 2PM	(2) After 2PM
Panel A. Source		
Below 15 degrees C	-0.112	-2.45***
	(0.378)	(0.265)
20-25 C	1.97***	2.32***
	(0.250)	(0.280)
25-30 C	2.87***	3.42***
	(0.334)	(0.451)
30-35 C	5.28***	4.09***
	(0.486)	(0.533)
35-40 C	7.54***	6.04***
	(0.648)	(0.628)
Above 40 degrees C	10.8***	7.99***
	(1.08)	(0.807)
Panel B. Origin		
Below 15 degrees C	-3.13*	-4.43***
	(1.67)	(1.12)
20-25 C	4.21***	5.78***
	(1.24)	(0.962)
25-30 C	4.46***	6.07***
	(1.58)	(0.674)
30-35 C	6.25***	7.98***
	(1.88)	(0.986)
35-40 C	8.15***	10.2***
	(2.21)	(1.36)
Above 40 degrees C	8.73***	11.4***
	(2.29)	(1.56)
Panel C. Destination		
Below 15 degrees C	-1.96***	-2.34***
	(0.649)	(0.290)
20-25 C	4.18***	2.62***
	(0.636)	(0.257)
25-30 C	5.72***	2.83***
	(0.703)	(0.252)
30-35 C	7.53***	2.77***
	(0.783)	(0.352)
35-40 C	9.08***	3.43***
	(0.793)	(0.441)
Above 40 degrees C	9.34***	3.86***
	(0.830)	(0.492)
R-squared	0.0800	0.0800
N	8,909,718	8,909,718
Day-by-Month-by-Year FE	Yes	Yes
Origin Meteorological Controls	Yes	Yes
Source Meteorological Controls	Yes	Yes
Dest. Meteorological Controls	Yes	Yes
Carrier FE	Yes	Yes
Time of Day FE	Yes	Yes
Origin Airport FE	Yes	Yes
Source Airport FE	Yes	Yes
Dest. Airport FE	Yes	Yes

Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Meteorological controls are precipitation, relative humidity, dewpoint, and wind speed. Standard errors clustered at the origin airport level in parentheses. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table A.5: Hub vs. Non-Hub Airports: Indicator for Departure Delays >15 Mins.

	(1) Hub	(2) NonHub
Panel A. Source		
Below 15 degrees C	-0.00222	0.0268
	(0.00326)	(0.0166)
20-25 C	0.0155***	0.0199***
	(0.00251)	(0.00716)
25-30 C	0.0226***	0.0401***
	(0.00404)	(0.00692)
30-35 C	0.0316***	0.0601***
	(0.00490)	(0.00764)
35-40 C	0.0440***	0.0851***
	(0.00630)	(0.00909)
Above 40 degrees C	0.0574***	0.107***
	(0.00864)	(0.0140)
Panel B. Origin		
Below 15 degrees C	-0.0568***	-0.0357***
	(0.0189)	(0.00780)
20-25 C	0.0572***	0.0341***
	(0.00798)	(0.00359)
25-30 C	0.0658***	0.0432***
	(0.00798)	(0.00427)
30-35 C	0.0811***	0.0541***
	(0.0121)	(0.00522)
35-40 C	0.106***	0.0770***
	(0.0147)	(0.00664)
Above 40 degrees C	0.117***	0.0795***
	(0.0151)	(0.0113)
Panel C. Destination		
Below 15 degrees C	-0.0375***	-0.0905***
	(0.00392)	(0.0127)
20-25 C	0.0274***	0.0491***
	(0.00230)	(0.00382)
25-30 C	0.0371***	0.0590***
	(0.00304)	(0.00494)
30-35 C	0.0412***	0.0697***
	(0.00324)	(0.00681)
35-40 C	0.0514***	0.0916***
	(0.00364)	(0.00842)
Above 40 degrees C	0.0595***	0.106***
	(0.00540)	(0.0110)
R-squared	0.0937	0.0937
N	8,905,484	8,905,484
Day-by-Month-by-Year FE	Yes	Yes
Origin Meteorological Controls	Yes	Yes
Source Meteorological Controls	Yes	Yes
Dest. Meteorological Controls	Yes	Yes
Carrier FE	Yes	Yes
Time of Day FE	Yes	Yes
Origin Airport FE	Yes	Yes
Source Airport FE	Yes	Yes
Dest. Airport FE	Yes	Yes

Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Hub based on being above 75th percentile in of flights per year in 2010 and 2017. Meteorological controls are precipitation, relative humidity, dewpoint, and wind speed. Standard errors clustered at the origin airport level in parentheses. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table A.6: Hub vs. Non-Hub: All Departure Delays (Mins.)

	(1) Hub	(2) NonHub
Panel A. Source		
Below 15 degrees C	-0.00517	3.66**
	(0.280)	(1.53)
20-25 C	1.14***	2.14***
	(0.213)	(0.609)
25-30 C	1.66***	3.77***
	(0.328)	(0.549)
30-35 C	2.40***	5.78***
	(0.386)	(0.617)
35-40 C	3.19***	7.63***
	(0.478)	(0.732)
Above 40 degrees C	3.79***	8.94***
	(0.638)	(0.945)
Panel B. Origin		
Below 15 degrees C	-4.38***	-3.12***
	(1.35)	(0.707)
20-25 C	5.65***	2.59***
	(0.832)	(0.349)
25-30 C	5.80***	3.24***
	(0.927)	(0.422)
30-35 C	7.68***	4.03***
	(1.38)	(0.516)
35-40 C	9.94***	5.88***
	(1.73)	(0.651)
Above 40 degrees C	10.8***	5.92***
	(1.79)	(0.954)
Panel C. Destination		
Below 15 degrees C	-2.65***	-8.46***
	(0.314)	(1.14)
20-25 C	3.02***	6.76***
	(0.233)	(0.480)
25-30 C	3.72***	6.81***
	(0.249)	(0.540)
30-35 C	4.27***	8.46***
	(0.328)	(0.739)
35-40 C	5.49***	11.6***
	(0.397)	(0.891)
Above 40 degrees C	6.05***	13.6***
	(0.505)	(0.993)
R-squared	0.0788	0.0788
N	8,905,484	8,905,484
Day-by-Month-by-Year FE	Yes	Yes
Origin Meteorological Controls	Yes	Yes
Source Meteorological Controls	Yes	Yes
Dest. Meteorological Controls	Yes	Yes
Carrier FE	Yes	Yes
Time of Day FE	Yes	Yes
Origin Airport FE	Yes	Yes
Source Airport FE	Yes	Yes
Dest. Airport FE	Yes	Yes

Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Hub based on being above 75th percentile in of flights per year in 2010 and 2017. Meteorological controls are precipitation, relative humidity, dewpoint, and wind speed. Standard errors clustered at the origin airport level in parentheses. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table A.7: Effects of Temperature by Climate Region on Indicator for Departure Delays >15 Mins.

	(1) All Regions	(2) Ohio Valley	(3) Upper Midwest	(4) Northeast	(5) Northwest	(6) South	(7) Southeast	(8) Southwest	(9) West	(10) Rockies
Panel A. Source										
Below 15 degrees C	-0.00250	-0.00161	-0.0119**	-0.00286	-0.0336***	-0.00686	0.00541	-0.00963***	-0.0135***	-0.00875
	(0.00327)	(0.00313)	(0.00493)	(0.00557)	(0.00752)	(0.00677)	(0.00622)	(0.00259)	(0.00369)	(0.0148)
20 - 25 C	0.0170***	0.0305***	0.0188***	0.0260***	0.0232***	0.0223***	0.0184***	0.0208***	0.0135**	0.0368***
	(0.00249)	(0.00679)	(0.00634)	(0.00296)	(0.00551)	(0.00800)	(0.00689)	(0.00239)	(0.00572)	(0.00736)
25 - 30 C	0.0256***	0.0443***	0.0341***	0.0319***	0.0453***	0.0237**	0.0211**	0.0250***	0.0259**	0.0551***
	(0.00400)	(0.00660)	(0.00756)	(0.00538)	(0.00654)	(0.0111)	(0.00965)	(0.00344)	(0.0105)	(0.0123)
30 - 35 C	0.0353***	0.0557***	0.0507***	0.0412***	0.0582***	0.0246**	0.0245**	0.0271***	0.0413***	0.0793***
	(0.00486)	(0.00618)	(0.00898)	(0.00674)	(0.00928)	(0.0121)	(0.0120)	(0.00389)	(0.0101)	(0.0172)
35 - 40 C	0.0484***	0.0711***	0.0612***	0.0608***	0.0744***	0.0364**	0.0417***	0.0398***	0.0614***	0.0933***
	(0.00627)	(0.00899)	(0.0133)	(0.0106)	(0.0157)	(0.0155)	(0.0141)	(0.00238)	(0.0137)	(0.0218)
Above 40 degrees C	0.0628***	0.106***	0.0917***	0.121***	0.107***	0.0566***	0.0980***	0.0687***	0.0671***	0.148***
	(0.00849)	(0.0185)	(0.0212)	(0.0176)	(0.0189)	(0.0215)	(0.0270)	(0.00893)	(0.0205)	(0.0277)
Panel B. Origin										
Below 15 degrees C	-0.0546***	0.00185	-0.0373***	0.0241*	-0.0181**	-0.276***	-0.141***	-0.0258***	-0.0375***	-0.0296***
	(0.0167)	(0.00743)	(0.0119)	(0.0142)	(0.00917)	(0.0692)	(0.0477)	(0.00682)	(0.00985)	(0.00732)
20 - 25 C	0.0546***	0.0390***	0.0259***	0.0547***	0.0141***	0.0471	0.116***	0.00443	0.0109	0.0150**
	(0.00770)	(0.00435)	(0.00565)	(0.00522)	(0.00448)	(0.0330)	(0.0115)	(0.00902)	(0.00816)	(0.00698)
25 - 30 C	0.0634***	0.0540***	0.0426***	0.0906***	0.0192**	-0.00769	0.0828***	0.0317**	0.0202	0.0349***
	(0.00731)	(0.00673)	(0.00835)	(0.00588)	(0.00803)	(0.0312)	(0.0115)	(0.0148)	(0.0153)	(0.00959)
30 - 35 C	0.0786***	0.0758***	0.0580***	0.129***	0.0357***	0.00698	0.113***	0.0543**	0.0245*	0.0429***
	(0.0106)	(0.00754)	(0.00988)	(0.00963)	(0.0109)	(0.0316)	(0.00944)	(0.0218)	(0.0127)	(0.0110)
35 - 40 C	0.104***	0.117***	0.0851***	0.162***	0.0378***	0.0362	0.168***	0.0680***	0.0251	0.0816***
	(0.0130)	(0.0126)	(0.0140)	(0.0135)	(0.0126)	(0.0333)	(0.0121)	(0.0243)	(0.0158)	(0.0116)
Above 40 degrees C	0.114***	0.134***	0.0825**	0.175***	0.0236	0.0636*	0.140***	0.0826***	0.0369**	0.187***
	(0.0135)	(0.0206)	(0.0399)	(0.0489)	(0.0522)	(0.0376)	(0.0212)	(0.0240)	(0.0184)	(0.0504)
Panel C. Destination										
Below 15 degrees C	-0.0418***	-0.0220***	-0.0165**	-0.0246***	-0.0419***	-0.0464***	-0.0127**	-0.0445***	-0.0350***	-0.0346**
	(0.00401)	(0.00573)	(0.00688)	(0.00546)	(0.00507)	(0.00424)	(0.00508)	(0.00430)	(0.00541)	(0.0138)
20 - 25 C	0.0294***	0.0287***	0.0228***	0.0319***	0.00521	0.0342***	0.0336***	0.0157***	0.00461	0.0166**
	(0.00230)	(0.00583)	(0.00265)	(0.00504)	(0.00398)	(0.00583)	(0.00810)	(0.00416)	(0.00381)	(0.00772)
25 - 30 C	0.0391***	0.0348***	0.0347***	0.0449***	0.00888*	0.0383***	0.0384***	0.0267***	0.0186***	0.0335***
	(0.00298)	(0.00835)	(0.00463)	(0.00579)	(0.00516)	(0.00763)	(0.00732)	(0.00709)	(0.00502)	(0.00888)
30 - 35 C	0.0438***	0.0453***	0.0407***	0.0587***	0.0120*	0.0420***	0.0511***	0.0259***	0.0234***	0.0491***
	(0.00328)	(0.00966)	(0.00805)	(0.00664)	(0.00630)	(0.00797)	(0.0115)	(0.00788)	(0.00749)	(0.0115)
35 - 40 C	0.0553***	0.0575***	0.0459***	0.0656***	0.0211**	0.0550***	0.0700***	0.0253***	0.0163**	0.0575***
	(0.00372)	(0.0127)	(0.0101)	(0.00918)	(0.0103)	(0.0107)	(0.0174)	(0.00841)	(0.00802)	(0.0180)
Above 40 degrees C	0.0632***	0.0390*	0.0404***	0.0886***	0.0306**	0.0616***	0.0754***	0.0325**	0.0176*	0.0548***
	(0.00533)	(0.0206)	(0.0108)	(0.00864)	(0.0142)	(0.0148)	(0.0241)	(0.0133)	(0.00996)	(0.0154)
N	8,909,722	8,909,722	8,909,722	8,909,722	8,909,722	8,909,722	8,909,722	8,909,722	8,909,722	8,909,722
R-squared	0.093	0.097	0.097	0.097	0.097	0.097	0.097	0.097	0.097	0.097
Day-by-Month-by-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Origin Meteorological Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Source Meteorological Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Dest. Meteorological Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Carrier FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Origin Airport FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Source Airport FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Destination Airport FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Meteorological controls are precipitation, relative humidity, dewpoint, and wind speed. Standard errors clustered at the origin airport level in parentheses. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

A.3 Supplementary Tables

Table A.8: Airports with Most Departure Delays (Summer, 2010–2017)

Rank	Airport Name	# of Flights Delayed/Year	% of Total Flights
1	Atlanta, GA: Hartsfield-Jackson Atlanta International	23,195	22.8%
2	Chicago, IL: Chicago O'Hare International	21,092	26.6%
3	Dallas/Fort Worth, TX: Dallas/Fort Worth International	16,016	24.7%
4	Denver, CO: Denver International	14,851	24.1%
5	Los Angeles, CA: Los Angeles International	12,612	21.7%
6	San Francisco, CA: San Francisco International	10,999	25.2%
7	Houston, TX: George Bush Intercontinental/Houston	9,913	22.7%
8	Las Vegas, NV: McCarran International	8,997	24.0%
9	Phoenix, AZ: Phoenix Sky Harbor International	8,588	19.7%
10	Newark, NJ: Newark Liberty International	8,073	26.9%
11	Orlando, FL: Orlando International	7,413	23.8%
12	Baltimore, MD: Baltimore/Washington International Thurgood Marshall	7,327	27.4%
13	Chicago, IL: Chicago Midway International	7,180	30.3%
14	Charlotte, NC: Charlotte Douglas International	6,639	21.2%
15	New York, NY: John F. Kennedy International	6,582	24.5%
16	Boston, MA: Logan International	6,354	20.7%
17	Detroit, MI: Detroit Metro Wayne County	6,189	18.7%
18	Minneapolis, MN: Minneapolis-St Paul International	5,770	16.9%
19	New York, NY: LaGuardia	5,501	21.0%
20	Seattle, WA: Seattle/Tacoma International	5,162	15.5%
21	Miami, FL: Miami International	4,772	25.5%
22	Philadelphia, PA: Philadelphia International	4,274	20.9%
23	Houston, TX: William P Hobby	4,153	28.8%
24	Fort Lauderdale, FL: Fort Lauderdale-Hollywood International	4,077	23.2%
25	Salt Lake City, UT: Salt Lake City International	3,944	13.0%

Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017.

Table A.9: Alt. Specification – LPM on Indicator for Departure Delays >15 Mins.

	(1)	(2)
Panel A. Source		
Below 15 degrees C	-0.00405	-0.00203
	(0.00363)	(0.00349)
20-25 C	0.0213***	0.0179***
	(0.00258)	(0.00248)
25-30 C	0.0318***	0.0271***
	(0.00401)	(0.00401)
30-35 C	0.0443***	0.0368***
	(0.00495)	(0.00497)
35-40 C	0.0653***	0.0509***
	(0.00617)	(0.00642)
Above 40 degrees C	0.0830***	0.0656***
	(0.00823)	(0.00842)
Panel B. Origin		
Below 15 degrees C	-0.0528***	-0.0522***
	(0.0159)	(0.0167)
20-25 C	0.0565***	0.0534***
	(0.00755)	(0.00751)
25-30 C	0.0647***	0.0609***
	(0.00787)	(0.00755)
30-35 C	0.0832***	0.0746***
	(0.0121)	(0.0111)
35-40 C	0.116***	0.0987***
	(0.0151)	(0.0136)
Above 40 degrees C	0.131***	0.108***
	(0.0161)	(0.0138)
Panel C. Destination		
Below 15 degrees C	-0.0395***	-0.0366***
	(0.00427)	(0.00389)
20-25 C	0.0338***	0.0297***
	(0.00241)	(0.00237)
25-30 C	0.0444***	0.0394***
	(0.00312)	(0.00295)
30-35 C	0.0533***	0.0445***
	(0.00351)	(0.00327)
35-40 C	0.0732***	0.0562***
	(0.00410)	(0.00372)
Above 40 degrees C	0.0866***	0.0649***
	(0.00524)	(0.00529)
R-squared	0.0873	0.105
N	9,056,076	9,056,076
Day-by-Month-by-Year FE		Yes
Origin Meteorological Controls	Yes	Yes
Source Meteorological Controls	Yes	Yes
Destination Meteorological Controls	Yes	Yes
Carrier FE	Yes	Yes
Time of Day FE	Yes	Yes
Source × Origin × Destination × Month FE	Yes	Yes

Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Meteorological controls are precipitation, relative humidity, dewpoint, and wind speed. Standard errors clustered at the origin airport level in parentheses. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table A.10: Alt. Specification – All Departure Delays (Minutes)

	(1)	(2)
Panel A. Source		
Below 15 degrees C	0.0596	0.0224
	(0.325)	(0.293)
20-25 C	1.66***	1.38***
	(0.214)	(0.205)
25-30 C	2.57***	2.08***
	(0.326)	(0.326)
30-35 C	3.67***	2.92***
	(0.409)	(0.407)
35-40 C	5.14***	3.83***
	(0.489)	(0.500)
Above 40 degrees C	6.14***	4.56***
	(0.643)	(0.639)
Panel B. Origin		
Below 15 degrees C	-3.87***	-4.06***
	(1.09)	(1.12)
20-25 C	5.49***	5.18***
	(0.772)	(0.777)
25-30 C	5.86***	5.32***
	(0.862)	(0.814)
30-35 C	7.99***	6.96***
	(1.29)	(1.19)
35-40 C	10.9***	9.03***
	(1.66)	(1.51)
Above 40 degrees C	11.9***	9.51***
	(1.75)	(1.54)
Panel C. Destination		
Below 15 degrees C	-2.89***	-2.82***
	(0.327)	(0.306)
20-25 C	3.80***	3.35***
	(0.250)	(0.250)
25-30 C	4.56***	3.93***
	(0.256)	(0.253)
30-35 C	5.66***	4.62***
	(0.345)	(0.337)
35-40 C	7.81***	6.04***
	(0.449)	(0.417)
Above 40 degrees C	8.91***	6.65***
	(0.550)	(0.519)
R-squared	0.0991	0.117
N	9,056,076	9,056,076
Day-by-Month-by-Year FE		Yes
Origin Meteorological Controls	Yes	Yes
Source Meteorological Controls	Yes	Yes
Destination Meteorological Controls	Yes	Yes
Carrier FE	Yes	Yes
Time of Day FE	Yes	Yes
Source × Origin × Destination × Month FE	Yes	Yes

Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Meteorological controls are precipitation, relative humidity, dewpoint, and wind speed. Standard errors clustered at the origin airport level in parentheses. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table A.11: Late Aircraft Delays (Minutes)

	(1)	(2)	(3)
Panel A. Source			
Below 15 degrees C	-3.93***	-4.00***	-4.22***
	(0.616)	(0.607)	(0.543)
20-25 C	4.47***	4.45***	4.50***
	(0.437)	(0.437)	(0.428)
25-30 C	4.96***	4.92***	5.01***
	(0.493)	(0.498)	(0.495)
30-35 C	5.16***	5.14***	5.20***
	(0.524)	(0.520)	(0.535)
35-40 C	6.61***	6.66***	6.52***
	(0.696)	(0.679)	(0.682)
Above 40 degrees C	8.66***	8.82***	8.86***
	(0.970)	(0.937)	(0.947)
Panel B. Origin			
Below 15 degrees C	-3.50**	-3.50**	-3.37**
	(1.59)	(1.64)	(1.55)
20-25 C	3.97***	3.99***	3.98***
	(0.903)	(0.899)	(0.890)
25-30 C	3.73***	3.77***	3.76***
	(1.05)	(1.06)	(1.04)
30-35 C	5.31***	5.36***	5.35***
	(1.43)	(1.43)	(1.40)
35-40 C	6.25***	6.29***	6.23***
	(1.84)	(1.86)	(1.81)
Above 40 degrees C	6.16***	6.17***	6.08***
	(2.12)	(2.19)	(2.12)
Panel C. Destination			
Below 15 degrees C	0.367	0.356	-0.419
	(0.313)	(0.310)	(0.461)
20-25 C	0.0503	0.0585	0.571**
	(0.246)	(0.244)	(0.233)
25-30 C	-0.123	-0.117	0.661**
	(0.307)	(0.313)	(0.327)
30-35 C	-1.08***	-1.04***	-0.121
	(0.325)	(0.335)	(0.343)
35-40 C	-1.32***	-1.30***	0.101
	(0.434)	(0.437)	(0.424)
Above 40 degrees C	-1.70***	-1.69***	0.905
	(0.557)	(0.555)	(0.570)
R-squared	0.0607	0.0652	0.0681
N	2,189,137	2,189,136	2,189,136
Day-by-Month-by-Year FE	Yes	Yes	Yes
Origin Meteorological Controls	Yes	Yes	Yes
Source Meteorological Controls	Yes	Yes	Yes
Destination Meteorological Controls	Yes	Yes	Yes
Carrier FE	Yes	Yes	Yes
Time of Day FE	Yes	Yes	Yes
Origin Airport FE	Yes	Yes	Yes
Source Airport FE		Yes	Yes
Destination Airport FE			Yes

Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Meteorological controls are precipitation, relative humidity, dewpoint, and wind speed. Standard errors clustered at the origin airport level in parentheses. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table A.12: Late Aircraft Delays Before/After 2PM (Minutes)

	(1) Before 2PM	(2) After 2PM
Panel A. Source		
Below 15 degrees C	-3.82***	-4.65***
	(0.622)	(0.510)
20-25 C	4.33***	4.89***
	(0.497)	(0.475)
25-30 C	3.76***	6.03***
	(0.580)	(0.550)
30-35 C	5.50***	6.21***
	(0.754)	(0.600)
35-40 C	7.64***	8.18***
	(1.20)	(0.722)
Above 40 degrees C	11.8***	11.1***
	(2.18)	(0.975)
Panel B. Origin		
Below 15 degrees C	-4.67**	-2.94**
	(2.11)	(1.45)
20-25 C	2.46	4.38***
	(1.93)	(0.787)
25-30 C	3.48*	3.85***
	(1.91)	(0.861)
30-35 C	5.56***	5.22***
	(2.01)	(1.25)
35-40 C	6.08***	6.13***
	(2.30)	(1.74)
Above 40 degrees C	5.49**	6.04***
	(2.29)	(2.25)
Panel C. Destination		
Below 15 degrees C	4.05***	-0.818*
	(0.992)	(0.447)
20-25 C	3.49***	-0.128
	(0.590)	(0.187)
25-30 C	4.34***	-0.402
	(0.743)	(0.271)
30-35 C	3.99***	-1.66***
	(0.885)	(0.342)
35-40 C	3.55***	-1.82***
	(0.926)	(0.478)
Above 40 degrees C	3.25***	-1.09*
	(0.967)	(0.605)
R-squared	0.0691	0.0691
N	2,189,136	2,189,136
Day-by-Month-by-Year FE	Yes	Yes
Origin Meteorological Controls	Yes	Yes
Source Meteorological Controls	Yes	Yes
Dest. Meteorological Controls	Yes	Yes
Carrier FE	Yes	Yes
Time of Day FE	Yes	Yes
Origin Airport FE	Yes	Yes
Source Airport FE	Yes	Yes
Dest. Airport FE	Yes	Yes

Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Meteorological controls are precipitation, relative humidity, dewpoint, and wind speed. Standard errors clustered at the origin airport level in parentheses. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table A.13: Hub vs. Non-Hub: Late Aircraft Delays (Mins.)

	(1) Hub	(2) NonHub
Panel A. Source		
Below 15 degrees C	-3.40***	-11.6***
	(0.500)	(1.56)
20-25 C	4.12***	6.86***
	(0.438)	(0.794)
25-30 C	4.70***	5.82***
	(0.519)	(1.06)
30-35 C	4.99***	5.27***
	(0.554)	(1.36)
35-40 C	6.34***	5.90***
	(0.711)	(1.68)
Above 40 degrees C	8.51***	8.89***
	(0.980)	(2.04)
Panel B. Origin		
Below 15 degrees C	-3.29*	-3.31***
	(1.76)	(1.24)
20-25 C	4.17***	2.47***
	(0.934)	(0.776)
25-30 C	3.82***	3.30***
	(1.16)	(0.992)
30-35 C	5.61***	3.33***
	(1.56)	(1.20)
35-40 C	6.43***	4.38***
	(1.99)	(1.48)
Above 40 degrees C	6.37***	3.61*
	(2.34)	(1.93)
Panel C. Destination		
Below 15 degrees C	-0.558	2.18**
	(0.495)	(1.04)
20-25 C	0.517**	0.797
	(0.247)	(0.598)
25-30 C	0.587*	1.02
	(0.344)	(0.866)
30-35 C	-0.321	1.06
	(0.365)	(1.07)
35-40 C	0.0339	0.735
	(0.448)	(1.29)
Above 40 degrees C	0.953	0.157
	(0.602)	(1.68)
R-squared	0.0693	0.0693
N	2,188,069	2,188,069
Day-by-Month-by-Year FE	Yes	Yes
Origin Meteorological Controls	Yes	Yes
Source Meteorological Controls	Yes	Yes
Dest. Meteorological Controls	Yes	Yes
Carrier FE	Yes	Yes
Time of Day FE	Yes	Yes
Origin Airport FE	Yes	Yes
Source Airport FE	Yes	Yes
Dest. Airport FE	Yes	Yes

Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Hub based on being above 75th percentile in of flights per year in 2010 and 2017. Meteorological controls are precipitation, relative humidity, dewpoint, and wind speed. Standard errors clustered at the origin airport level in parentheses. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table A.14: Late Aircraft Delays (Minutes, Delayed Flights Only)

	(1)	(2)	(3)
Panel A. Source			
Below 15 degrees C	-4.52***	-4.60***	-4.73***
	(0.681)	(0.679)	(0.614)
20-25 C	4.54***	4.53***	4.46***
	(0.461)	(0.466)	(0.458)
25-30 C	4.98***	4.95***	4.90***
	(0.511)	(0.523)	(0.514)
30-35 C	5.31***	5.30***	5.19***
	(0.558)	(0.563)	(0.572)
35-40 C	6.72***	6.78***	6.49***
	(0.739)	(0.724)	(0.728)
Above 40 degrees C	8.59***	8.80***	8.67***
	(0.989)	(0.958)	(0.968)
Panel B. Origin			
Below 15 degrees C	-3.07**	-3.08**	-2.94**
	(1.36)	(1.41)	(1.33)
20-25 C	4.13***	4.16***	4.16***
	(0.946)	(0.942)	(0.925)
25-30 C	3.80***	3.85***	3.86***
	(1.12)	(1.12)	(1.10)
30-35 C	5.14***	5.20***	5.23***
	(1.51)	(1.51)	(1.47)
35-40 C	5.78***	5.83***	5.80***
	(1.99)	(2.01)	(1.96)
Above 40 degrees C	5.19**	5.20**	5.10**
	(2.25)	(2.34)	(2.27)
Panel C. Destination			
Below 15 degrees C	-0.0996	-0.112	-0.0937
	(0.363)	(0.357)	(0.478)
20-25 C	0.308	0.315	0.517**
	(0.239)	(0.238)	(0.226)
25-30 C	0.443	0.451	0.636**
	(0.282)	(0.289)	(0.322)
30-35 C	-0.453	-0.409	-0.373
	(0.286)	(0.295)	(0.346)
35-40 C	-0.638	-0.601	-0.374
	(0.413)	(0.414)	(0.454)
Above 40 degrees C	-0.837	-0.825	0.202
	(0.541)	(0.536)	(0.593)
R-squared	0.0608	0.0653	0.0690
N	1,796,382	1,796,381	1,796,381
Day-by-Month-by-Year FE	Yes	Yes	Yes
Origin Meteorological Controls	Yes	Yes	Yes
Source Meteorological Controls	Yes	Yes	Yes
Destination Meteorological Controls	Yes	Yes	Yes
Carrier FE	Yes	Yes	Yes
Time of Day FE	Yes	Yes	Yes
Origin Airport FE	Yes	Yes	Yes
Source Airport FE		Yes	Yes
Destination Airport FE			Yes

Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Meteorological controls are precipitation, relative humidity, dewpoint, and wind speed. Standard errors clustered at the origin airport level in parentheses. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table A.15: All Departure Delays (Minutes, Delayed Flights Only)

	(1)	(2)	(3)
Panel A. Source			
Below 15 degrees C	0.00424	-0.0301	-0.319
	(0.528)	(0.457)	(0.457)
20-25 C	1.80***	1.79***	2.02***
	(0.356)	(0.327)	(0.304)
25-30 C	2.52***	2.45***	2.66***
	(0.463)	(0.425)	(0.407)
30-35 C	3.33***	3.23***	3.64***
	(0.557)	(0.479)	(0.478)
35-40 C	4.42***	4.32***	4.64***
	(0.800)	(0.646)	(0.621)
Above 40 degrees C	5.36***	5.17***	5.65***
	(1.15)	(0.865)	(0.827)
Panel B. Origin			
Below 15 degrees C	-2.82***	-2.87***	-3.03***
	(0.821)	(0.830)	(0.860)
20-25 C	5.58***	5.61***	5.66***
	(1.04)	(1.03)	(1.05)
25-30 C	4.78***	4.82***	4.89***
	(1.24)	(1.23)	(1.26)
30-35 C	7.20***	7.25***	7.34***
	(1.66)	(1.64)	(1.67)
35-40 C	9.40***	9.39***	9.65***
	(2.24)	(2.25)	(2.28)
Above 40 degrees C	10.9***	10.6***	10.9***
	(2.37)	(2.45)	(2.50)
Panel C. Destination			
Below 15 degrees C	-0.231	-0.229	-1.95***
	(0.352)	(0.361)	(0.384)
20-25 C	4.37***	4.34***	3.84***
	(0.470)	(0.478)	(0.389)
25-30 C	4.37***	4.30***	3.95***
	(0.417)	(0.441)	(0.435)
30-35 C	4.33***	4.29***	4.31***
	(0.478)	(0.504)	(0.596)
35-40 C	6.52***	6.51***	5.69***
	(0.677)	(0.684)	(0.796)
Above 40 degrees C	7.25***	7.31***	5.59***
	(0.833)	(0.838)	(0.980)
R-squared	0.0632	0.0686	0.0721
N	2,196,714	2,196,713	2,196,712
Day-by-Month-by-Year FE	Yes	Yes	Yes
Origin Meteorological Controls	Yes	Yes	Yes
Source Meteorological Controls	Yes	Yes	Yes
Destination Meteorological Controls	Yes	Yes	Yes
Carrier FE	Yes	Yes	Yes
Time of Day FE	Yes	Yes	Yes
Origin Airport FE	Yes	Yes	Yes
Source Airport FE		Yes	Yes
Destination Airport FE			Yes

Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Meteorological controls are precipitation, relative humidity, dewpoint, and wind speed. Standard errors clustered at the origin airport level in parentheses. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table A.16: Hub vs. Non-Hub: Late Aircraft Delays (Mins., Delayed Flights)

	(1) Hub	(2) NonHub
Panel A. Source		
Below 15 degrees C	-3.83***	-12.3***
	(0.544)	(1.72)
20-25 C	4.12***	6.64***
	(0.480)	(0.864)
25-30 C	4.68***	5.37***
	(0.550)	(1.12)
30-35 C	5.08***	4.69***
	(0.602)	(1.46)
35-40 C	6.41***	5.29***
	(0.771)	(1.75)
Above 40 degrees C	8.40***	8.42***
	(1.01)	(2.14)
Panel B. Origin		
Below 15 degrees C	-2.89*	-2.65**
	(1.48)	(1.32)
20-25 C	4.39***	2.30***
	(0.964)	(0.825)
25-30 C	3.99***	2.84***
	(1.22)	(1.09)
30-35 C	5.57***	2.53*
	(1.62)	(1.33)
35-40 C	6.09***	3.24*
	(2.12)	(1.71)
Above 40 degrees C	5.48**	2.88
	(2.46)	(2.04)
Panel C. Destination		
Below 15 degrees C	-0.230	2.54**
	(0.507)	(1.21)
20-25 C	0.479**	0.624
	(0.236)	(0.649)
25-30 C	0.551*	1.13
	(0.333)	(0.911)
30-35 C	-0.555	0.688
	(0.362)	(1.13)
35-40 C	-0.333	-0.420
	(0.473)	(1.33)
Above 40 degrees C	0.335	-1.07
	(0.620)	(1.75)
R-squared	0.0701	0.0701
N	1,795,506	1,795,506
Day-by-Month-by-Year FE	Yes	Yes
Origin Meteorological Controls	Yes	Yes
Source Meteorological Controls	Yes	Yes
Dest. Meteorological Controls	Yes	Yes
Carrier FE	Yes	Yes
Time of Day FE	Yes	Yes
Origin Airport FE	Yes	Yes
Source Airport FE	Yes	Yes
Dest. Airport FE	Yes	Yes

Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Hub based on being above 75th percentile in of flights per year in 2010 and 2017. Meteorological controls are precipitation, relative humidity, dewpoint, and wind speed. Standard errors clustered at the origin airport level in parentheses. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table A.17: Hub vs. Non-Hub: All Departure Delays (Mins., Delayed Flights)

	(1) Hub	(2) NonHub
Panel A. Source		
Below 15 degrees C	-0.543	3.50*
	(0.466)	(1.84)
20-25 C	1.76***	2.44***
	(0.329)	(0.901)
25-30 C	2.37***	3.14***
	(0.444)	(1.04)
30-35 C	3.19***	5.82***
	(0.495)	(1.29)
35-40 C	4.18***	7.19***
	(0.660)	(1.66)
Above 40 degrees C	5.02***	8.72***
	(0.860)	(2.09)
Panel B. Origin		
Below 15 degrees C	-3.13***	-2.26
	(0.897)	(1.37)
20-25 C	6.17***	0.750
	(1.10)	(0.811)
25-30 C	5.23***	1.06
	(1.42)	(1.01)
30-35 C	7.89***	1.04
	(1.89)	(1.28)
35-40 C	10.2***	2.49
	(2.56)	(1.62)
Above 40 degrees C	11.6***	2.10
	(2.80)	(2.68)
Panel C. Destination		
Below 15 degrees C	-1.43***	-7.39***
	(0.367)	(1.41)
20-25 C	3.22***	10.5***
	(0.367)	(0.882)
25-30 C	3.55***	8.93***
	(0.424)	(1.06)
30-35 C	3.87***	10.7***
	(0.584)	(1.36)
35-40 C	4.97***	14.6***
	(0.798)	(1.67)
Above 40 degrees C	4.66***	18.3***
	(0.949)	(2.24)
R-squared	0.0732	0.0732
N	2,195,740	2,195,740
Day-by-Month-by-Year FE	Yes	Yes
Origin Meteorological Controls	Yes	Yes
Source Meteorological Controls	Yes	Yes
Dest. Meteorological Controls	Yes	Yes
Carrier FE	Yes	Yes
Time of Day FE	Yes	Yes
Origin Airport FE	Yes	Yes
Source Airport FE	Yes	Yes
Dest. Airport FE	Yes	Yes

Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Hub based on being above 75th percentile in of flights per year in 2010 and 2017. Meteorological controls are precipitation, relative humidity, dewpoint, and wind speed. Standard errors clustered at the origin airport level in parentheses. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table A.18: Hub vs. Non-Hub Airports: Indicator for Departure Delays >15 Mins.

	(1) Hub	(2) NonHub
Panel A. Source		
Below 15 degrees C	-0.00153	0.0102
	(0.00356)	(0.00854)
20-25 C	0.0112***	0.0327***
	(0.00251)	(0.00418)
25-30 C	0.0169***	0.0503***
	(0.00418)	(0.00484)
30-35 C	0.0263***	0.0647***
	(0.00522)	(0.00562)
35-40 C	0.0364***	0.0881***
	(0.00648)	(0.00733)
Above 40 degrees C	0.0461***	0.112***
	(0.00959)	(0.0102)
Panel B. Origin		
Below 15 degrees C	-0.0632***	-0.0345***
	(0.0202)	(0.00669)
20-25 C	0.0611***	0.0410***
	(0.00825)	(0.00455)
25-30 C	0.0709***	0.0484***
	(0.00882)	(0.00612)
30-35 C	0.0881***	0.0542***
	(0.0140)	(0.00612)
35-40 C	0.112***	0.0761***
	(0.0167)	(0.00787)
Above 40 degrees C	0.126***	0.0884***
	(0.0165)	(0.0109)
Panel C. Destination		
Below 15 degrees C	-0.0352***	-0.0636***
	(0.00397)	(0.00852)
20-25 C	0.0253***	0.0390***
	(0.00241)	(0.00264)
25-30 C	0.0356***	0.0458***
	(0.00329)	(0.00360)
30-35 C	0.0402***	0.0536***
	(0.00342)	(0.00498)
35-40 C	0.0495***	0.0722***
	(0.00365)	(0.00595)
Above 40 degrees C	0.0535***	0.0870***
	(0.00605)	(0.00704)
R-squared	0.0945	0.0945
N	8,909,718	8,909,718
Day-by-Month-by-Year FE	Yes	Yes
Origin Meteorological Controls	Yes	Yes
Source Meteorological Controls	Yes	Yes
Dest. Meteorological Controls	Yes	Yes
Carrier FE	Yes	Yes
Time of Day FE	Yes	Yes
Origin Airport FE	Yes	Yes
Source Airport FE	Yes	Yes
Dest. Airport FE	Yes	Yes

Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Hubs and focus cities as reported for major domestic airlines. Meteorological controls are precipitation, relative humidity, dewpoint, and wind speed. Standard errors clustered at the origin airport level in parentheses. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table A.19: Hub vs. Non-Hub: Late Aircraft Delays (Mins., Delayed Flights)

	(1) Hub	(2) NonHub
Panel A. Source		
Below 15 degrees C	-2.95***	-10.5***
	(0.518)	(1.16)
20-25 C	3.51***	6.93***
	(0.478)	(0.683)
25-30 C	4.13***	6.77***
	(0.583)	(0.703)
30-35 C	4.74***	6.47***
	(0.635)	(0.871)
35-40 C	6.08***	8.07***
	(0.827)	(0.992)
Above 40 degrees C	7.52***	12.4***
	(1.05)	(1.16)
Panel B. Origin		
Below 15 degrees C	-3.63**	-1.58*
	(1.51)	(0.929)
20-25 C	5.17***	1.52**
	(1.04)	(0.609)
25-30 C	4.86***	1.50*
	(1.41)	(0.775)
30-35 C	6.62***	1.23
	(1.84)	(0.957)
35-40 C	6.99***	1.54
	(2.34)	(1.17)
Above 40 degrees C	6.49**	0.402
	(2.71)	(1.57)
Panel C. Destination		
Below 15 degrees C	-0.444	1.96**
	(0.554)	(0.786)
20-25 C	0.682***	-0.359
	(0.261)	(0.391)
25-30 C	0.993***	-0.768
	(0.361)	(0.577)
30-35 C	-0.0171	-1.81**
	(0.367)	(0.739)
35-40 C	0.513	-3.11***
	(0.488)	(0.881)
Above 40 degrees C	1.45**	-3.71***
	(0.696)	(1.16)
R-squared	0.0716	0.0716
N	1,796,381	1,796,381
Day-by-Month-by-Year FE	Yes	Yes
Origin Meteorological Controls	Yes	Yes
Source Meteorological Controls	Yes	Yes
Dest. Meteorological Controls	Yes	Yes
Carrier FE	Yes	Yes
Time of Day FE	Yes	Yes
Origin Airport FE	Yes	Yes
Source Airport FE	Yes	Yes
Dest. Airport FE	Yes	Yes

Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Hubs and focus cities as reported for major domestic airlines. Meteorological controls are precipitation, relative humidity, dewpoint, and wind speed. Standard errors clustered at the origin airport level in parentheses. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table A.20: Hub vs. Non-Hub: All Departure Delays (Mins., Delayed Flights)

	(1) Hub	(2) NonHub
Panel A. Source		
Below 15 degrees C	-0.351	1.30
	(0.487)	(1.22)
20-25 C	1.39***	3.04***
	(0.327)	(0.599)
25-30 C	1.92***	3.89***
	(0.467)	(0.655)
30-35 C	2.79***	5.52***
	(0.499)	(0.779)
35-40 C	3.89***	6.68***
	(0.698)	(0.933)
Above 40 degrees C	4.48***	8.56***
	(0.930)	(1.10)
Panel B. Origin		
Below 15 degrees C	-3.94***	-1.31
	(0.912)	(0.907)
20-25 C	7.09***	1.44**
	(1.16)	(0.574)
25-30 C	6.21***	1.07
	(1.69)	(0.667)
30-35 C	9.13***	1.25*
	(2.24)	(0.747)
35-40 C	11.3***	2.84***
	(2.96)	(1)
Above 40 degrees C	12.9***	3.63*
	(3.19)	(2.09)
Panel C. Destination		
Below 15 degrees C	-1.07***	-4.90***
	(0.353)	(0.849)
20-25 C	2.78***	7.10***
	(0.387)	(0.717)
25-30 C	3.28***	6.12***
	(0.451)	(0.721)
30-35 C	3.45***	7.54***
	(0.594)	(0.982)
35-40 C	4.42***	10.4***
	(0.861)	(1.22)
Above 40 degrees C	3.81***	11.7***
	(1)	(1.60)
R-squared	0.0744	0.0744
N	2,196,712	2,196,712
Day-by-Month-by-Year FE	Yes	Yes
Origin Meteorological Controls	Yes	Yes
Source Meteorological Controls	Yes	Yes
Dest. Meteorological Controls	Yes	Yes
Carrier FE	Yes	Yes
Time of Day FE	Yes	Yes
Origin Airport FE	Yes	Yes
Source Airport FE	Yes	Yes
Dest. Airport FE	Yes	Yes

Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Hubs and focus cities as reported for major domestic airlines. Meteorological controls are precipitation, relative humidity, dewpoint, and wind speed. Standard errors clustered at the origin airport level in parentheses. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table A.21: Indicator for Arrival Delays >15 Mins.

	(1)	(2)	(3)
Panel A. Source			
Below 15 degrees C	0.00217	0.00188	0.00216
	(0.00276)	(0.00264)	(0.00281)
20-25 C	0.00819***	0.00796***	0.0101***
	(0.00243)	(0.00240)	(0.00226)
25-30 C	0.0161***	0.0157***	0.0183***
	(0.00398)	(0.00390)	(0.00376)
30-35 C	0.0265***	0.0260***	0.0308***
	(0.00483)	(0.00470)	(0.00454)
35-40 C	0.0372***	0.0367***	0.0424***
	(0.00620)	(0.00605)	(0.00588)
Above 40 degrees C	0.0455***	0.0449***	0.0519***
	(0.00850)	(0.00833)	(0.00818)
Panel B. Origin			
Below 15 degrees C	-0.0538***	-0.0534***	-0.0531***
	(0.0131)	(0.0132)	(0.0135)
20-25 C	0.0607***	0.0607***	0.0593***
	(0.00759)	(0.00756)	(0.00776)
25-30 C	0.0696***	0.0696***	0.0676***
	(0.00815)	(0.00814)	(0.00848)
30-35 C	0.0833***	0.0834***	0.0812***
	(0.0121)	(0.0121)	(0.0125)
35-40 C	0.106***	0.106***	0.105***
	(0.0158)	(0.0158)	(0.0162)
Above 40 degrees C	0.115***	0.115***	0.112***
	(0.0167)	(0.0169)	(0.0175)
Panel C. Destination			
Below 15 degrees C	-0.0297***	-0.0296***	-0.0461***
	(0.00380)	(0.00381)	(0.00389)
20-25 C	0.0365***	0.0364***	0.0371***
	(0.00310)	(0.00312)	(0.00269)
25-30 C	0.0508***	0.0508***	0.0498***
	(0.00368)	(0.00371)	(0.00341)
30-35 C	0.0551***	0.0551***	0.0557***
	(0.00437)	(0.00440)	(0.00394)
35-40 C	0.0754***	0.0755***	0.0696***
	(0.00577)	(0.00578)	(0.00446)
Above 40 degrees C	0.0854***	0.0857***	0.0734***
	(0.00800)	(0.00796)	(0.00598)
R-squared	0.0900	0.0905	0.0973
N	8,873,686	8,873,685	8,873,685
Day-by-Month-by-Year FE	Yes	Yes	Yes
Origin Meteorological Controls	Yes	Yes	Yes
Source Meteorological Controls	Yes	Yes	Yes
Destination Meteorological Controls	Yes	Yes	Yes
Carrier FE	Yes	Yes	Yes
Time of Day FE	Yes	Yes	Yes
Origin Airport FE	Yes	Yes	Yes
Source Airport FE		Yes	Yes
Destination Airport FE			Yes

Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Meteorological controls are precipitation, relative humidity, dewpoint, and wind speed. Standard errors clustered at the origin airport level in parentheses. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table A.22: All Arrival Delays (Mins.)

	(1)	(2)	(3)
Panel A. Source			
Below 15 degrees C	0.392	0.373	0.314
	(0.291)	(0.264)	(0.269)
20-25 C	0.818***	0.788***	0.943***
	(0.231)	(0.222)	(0.208)
25-30 C	1.45***	1.39***	1.57***
	(0.360)	(0.342)	(0.331)
30-35 C	2.25***	2.17***	2.59***
	(0.427)	(0.393)	(0.391)
35-40 C	2.98***	2.90***	3.33***
	(0.539)	(0.490)	(0.481)
Above 40 degrees C	3.42***	3.30***	3.86***
	(0.748)	(0.673)	(0.656)
Panel B. Origin			
Below 15 degrees C	-4.43***	-4.42***	-4.42***
	(0.902)	(0.954)	(0.983)
20-25 C	5.71***	5.72***	5.61***
	(0.791)	(0.782)	(0.807)
25-30 C	6.07***	6.08***	5.92***
	(0.892)	(0.890)	(0.925)
30-35 C	7.89***	7.91***	7.71***
	(1.30)	(1.29)	(1.33)
35-40 C	10.1***	10.1***	9.94***
	(1.68)	(1.68)	(1.72)
Above 40 degrees C	10.7***	10.6***	10.4***
	(1.75)	(1.78)	(1.84)
Panel C. Destination			
Below 15 degrees C	-1.76***	-1.75***	-3.40***
	(0.316)	(0.322)	(0.344)
20-25 C	3.95***	3.94***	3.98***
	(0.365)	(0.367)	(0.304)
25-30 C	4.71***	4.69***	4.75***
	(0.353)	(0.356)	(0.305)
30-35 C	5.18***	5.17***	5.58***
	(0.429)	(0.433)	(0.410)
35-40 C	7.34***	7.33***	7.19***
	(0.585)	(0.586)	(0.507)
Above 40 degrees C	8.20***	8.22***	7.54***
	(0.754)	(0.745)	(0.603)
R-squared	0.0783	0.0809	0.0871
N	8,873,686	8,873,685	8,873,685
Day-by-Month-by-Year FE	Yes	Yes	Yes
Origin Meteorological Controls	Yes	Yes	Yes
Source Meteorological Controls	Yes	Yes	Yes
Destination Meteorological Controls	Yes	Yes	Yes
Carrier FE	Yes	Yes	Yes
Time of Day FE	Yes	Yes	Yes
Origin Airport FE	Yes	Yes	Yes
Source Airport FE		Yes	Yes
Destination Airport FE			Yes

Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Meteorological controls are precipitation, relative humidity, dewpoint, and wind speed. Standard errors clustered at the origin airport level in parentheses. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table A.23: Effects of Weather at Origin and Destination on an Indicator for Departure Delays

	(1)	(2)
Panel A. Origin		
Below 15 degrees C	-0.0359***	-0.0349***
	(0.00892)	(0.00895)
20-25 C	0.0380***	0.0369***
	(0.00700)	(0.00700)
25-30 C	0.0445***	0.0431***
	(0.00603)	(0.00604)
30-35 C	0.0534***	0.0519***
	(0.00836)	(0.00832)
35-40 C	0.0660***	0.0648***
	(0.0105)	(0.0104)
Above 40 degrees C	0.0697***	0.0681***
	(0.0110)	(0.0110)
Panel B. Destination		
Below 15 degrees C	-0.0173***	-0.0337***
	(0.00380)	(0.00343)
20-25 C	0.0191***	0.0253***
	(0.00191)	(0.00171)
25-30 C	0.0237***	0.0325***
	(0.00288)	(0.00222)
30-35 C	0.0280***	0.0419***
	(0.00366)	(0.00252)
35-40 C	0.0405***	0.0534***
	(0.00439)	(0.00287)
Above 40 degrees C	0.0432***	0.0566***
	(0.00620)	(0.00448)
R-squared	0.0886	0.0931
N	11,529,955	11,529,954
Day-by-Month-by-Year FE	Yes	Yes
Origin Meteorological Controls	Yes	Yes
Destination Meteorological Controls	Yes	Yes
Carrier FE	Yes	Yes
Time of Day FE	Yes	Yes
Origin Airport FE	Yes	Yes
Destination Airport FE		Yes

Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Meteorological controls are precipitation, relative humidity, dewpoint, and wind speed. Standard errors clustered at the origin airport level in parentheses. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table A.24: Effects of Weather at Origin and Destination on Late Aircraft Delays

	(1)	(2)
Panel A. Origin		
Below 15 degrees C	-3.36***	-3.24***
	(1.14)	(1.09)
20-25 C	3.76***	3.74***
	(0.925)	(0.919)
25-30 C	3.80***	3.80***
	(0.938)	(0.923)
30-35 C	4.99***	4.99***
	(1.20)	(1.18)
35-40 C	5.06***	5.01***
	(1.62)	(1.59)
Above 40 degrees C	4.08**	4.00**
	(1.80)	(1.75)
Panel B. Destination		
Below 15 degrees C	0.146	-0.553
	(0.273)	(0.403)
20-25 C	0.270	0.705***
	(0.229)	(0.217)
25-30 C	0.0214	0.717**
	(0.277)	(0.286)
30-35 C	-0.591**	0.215
	(0.289)	(0.303)
35-40 C	-0.763**	0.495
	(0.368)	(0.404)
Above 40 degrees C	-1.28**	1.09*
	(0.528)	(0.618)
R-squared	0.0648	0.0673
N	2,517,628	2,517,628
Day-by-Month-by-Year FE	Yes	Yes
Origin Meteorological Controls	Yes	Yes
Destination Meteorological Controls	Yes	Yes
Carrier FE	Yes	Yes
Time of Day FE	Yes	Yes
Origin Airport FE	Yes	Yes
Destination Airport FE		Yes

Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Meteorological controls are precipitation, relative humidity, dewpoint, and wind speed. Standard errors clustered at the origin airport level in parentheses. ***, **, and * represent significance at 1%, 5% and 10%, respectively.

Table A.25: Effects of Weather at Origin and Destination on All Departure Delays

	(1)	(2)
Panel A. Origin		
Below 15 degrees C	-2.65***	-2.58***
	(0.658)	(0.663)
20-25 C	3.52***	3.44***
	(0.651)	(0.656)
25-30 C	3.63***	3.54***
	(0.571)	(0.583)
30-35 C	4.72***	4.62***
	(0.827)	(0.839)
35-40 C	5.69***	5.63***
	(1.06)	(1.08)
Above 40 degrees C	5.76***	5.66***
	(1.06)	(1.09)
Panel B. Destination		
Below 15 degrees C	-1.06***	-2.46***
	(0.303)	(0.288)
20-25 C	2.62***	2.90***
	(0.223)	(0.186)
25-30 C	2.92***	3.34***
	(0.252)	(0.197)
30-35 C	3.42***	4.32***
	(0.330)	(0.279)
35-40 C	4.87***	5.52***
	(0.420)	(0.339)
Above 40 degrees C	5.09***	5.61***
	(0.545)	(0.432)
R-squared	0.0595	0.0635
N	11,529,955	11,529,954
Day-by-Month-by-Year FE	Yes	Yes
Origin Meteorological Controls	Yes	Yes
Destination Meteorological Controls	Yes	Yes
Carrier FE	Yes	Yes
Time of Day FE	Yes	Yes
Origin Airport FE	Yes	Yes
Destination Airport FE		Yes

Notes: Data from U.S. BTS On-Time Performance Dataset and NOAA's QCLCD database for Summer 2010–2017. Meteorological controls are precipitation, relative humidity, dewpoint, and wind speed. Standard errors clustered at the origin airport level in parentheses. ***, **, and * represent significance at 1%, 5% and 10%, respectively.