Bad weather and flight delays: The impact of sudden and slow onset weather events

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Bad weather and flight delays: The impact of sudden and slow onset weather events

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ABSTRACT

Weather shocks frequently impair the smooth functioning of transportation systems. We use a dataset consisting of 2.14 million flight departures from ten large U.S. airports between January 2012 and September 2017, and estimate the effects sudden onset events, i.e., precipitation and wind, and slow onset events, i.e., temperature, have on departure delay. For sudden onset events, we apply a difference-in-difference framework that allows for inferences at the hourly level. The effects of slow onset events on departure delay are estimated based on a Prais Winstein estimator with panel-corrected standard errors. Our estimates show a significant increase in departure delay of up to 23 min depending on the weather type and intensity of the disturbance. Given the social costs of schedule delays, these results are of high economic importance.

1. Introduction

Modern societies are characterized by a high degree of mobility of goods, services and people. Supply chains are interlinked across countries and continents and people increasingly travel for business and private reasons. As population grows and income increases, the demand for mobility is growing as well (Schafer and Victor, 1997). Overall, the increasing demand for mobility leads to a high dependence on transport systems and their services, with high costs when mobility suddenly is restricted (Wilson, 2007; Ball et al., 2010; Stamos et al., 2015).

When transport systems are interrupted, delays emerge, introducing uncertainty regarding travelers' arrival time. On the one hand, delays directly lead to extra travel time. On the other hand, in reaction to uncertain travel times, travelers may adjust their travelling schedule to ex ante account for potential delays (Noland and Polak, 2002). This represents a disutility and hence additional costs. In general, empirical research shows that individuals have a high preference to avoid delays (Forbes, 2008; Li et al., 2010; Gayle and Yimga, 2018; Luttmann, 2019).

One sector, which is regularly affected by delays, is the air traffic sector. Between 2004 and 2017, around 22% of airline flights within the United States were delayed or cancelled (Bureau of Transport Statistics, 2018). Generally, delays emerge when interactions between air transport players (i.e., carriers, airports and air traffic control entities) and external factors (i.e., adverse weather conditions, strikes and other incidents) lead to airport congestion (Bendinelli et al., 2016). The empirical literature has analyzed two main determinants of airport congestion inherent to the air transport system - congestion externalities in general and how the structure of the airport network (hub vs. non-hub) allows for diverse responses to these externalities. The congestion externality argument explains the emergence of delays as a consequence of airlines' failure to internalize the effect their scheduling decisions have on other airlines (Daniel, 2011; Brueckner 2002, 2009). At hub airports (i.e., airports with one or a few dominant carriers) two contrary forces affect delays. On the one hand, hubs want to provide a maximum of connections to their passengers while facing airports' capacity constraints. Thus there is a trade off between providing additional connections and rising marginal congestion costs (i.e., increase in delays and connecting times) due to higher traffic numbers (Mayer and Sinai, 2003). On the other hand, hub airlines have leeway in their scheduling decisions, which allows to partially offset the increased congestion (Mayer and Sinai, 2003; Brueckner, 2009; Ater, 2012; Bendinelli et al., 2016). Ater (2012) shows evidence that hub-airlines internalize congestion by choosing longer departure and arrival banks. Baumgarten, Malina & Lange (2014) and Miranda and Oliveira (2018) present similar findings, underlining that airlines use buffers to mitigate the propagation of delays as well as the delays perceived by passengers. Additionally, looking at the route level, Mazzeo (2003), Rupp (2009) and Greenfield (2014) show that higher market concentration (i.e., less competition on specific routes) leads to higher delays.

Adverse weather conditions are an important external factor

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affecting delays in the air traffic system (Coy, 2006, Koetse & Rietveld 2009). Depending on the year and month, they account for up to 50 percent of air traffic delays within the U.S. national airspace system (Federal Aviation Administration, 2017). The impact of weather related extremes on delays in the aviation system are only scarcely covered in recent empirical literature. Existing literature suggests that the general impact adverse weather conditions have on airport and airline operations is substantial (Robinson, 1989; Changnon, 1996; Sasse and Hauf, 2003; Hsiao and Hansen, 2006; Markovic et al., 2008). Robinson (1989) analyzed the impact of different weather shocks on airline operations at the Atlanta Hartsfield International Airport for one airline. He finds that annually over 165,000 min of delay are attributable to adverse weather conditions. Changnon (1996) shows that at the end of the 1970s, rainfall substantially increased the number of departures with a delay above 30 min at Chicago O'Hare airport. Sasse and Hauf (2003) examined the impact thunderstorms on delays at Frankfurt Airport during 1997 and 1998. They discover that thunderstorms significantly increase delays by a factor of 6.3 in 1997 and by 1.1 in 1998. Hsiao and Hansen (2006) analyzed the daily average delay in the U.S. domestic transportation system. They find that delays on days with adverse weather conditions are on average 14 min higher than on clear days. Coy (2006) analyzes two million US domestic flights by six airlines in 2004 and shows that poor weather conditions significantly increase block time, i.e., the time an aircraft takes to travel from the departure gate at the originating airport to the arrival gate at the destination.

Against this background, in this paper we examine the impact of adverse weather conditions on flights' departure delays. We differentiate between two types of weather conditions: sudden and slow onset weather events. Sudden onset events occur at a specific point in time in a day, whereas the other hours of this day are mainly unaffected. We identify sudden onset events as the exceedance of particular thresholds for precipitation and wind speed and the occurrence of snowfall. Slow onset events gradually develop in course of a day, often follow a specific trend and are characterized by reaching specific temperature extremes, i.e. frost and heat. We base our econometric analysis on a dataset covering 2.14 million individual flights in 2098 pooled daily cross sections for ten large U.S. airports from January 2012 to September 2017. For sudden onset events, we use a difference-in-difference framework to determine the causal impact on departure delays. To estimate the impact slow onset events have on departure delay, we rely on a Prais Winstein estimator with panel-corrected standard errors.

This paper extends the relevant literature in several ways. First, by differentiating between slow and sudden onset events we are able to disentangle the heterogeneous impact various adverse weather events have on flight departure delays. Information on heterogeneous impacts of adverse weather events on departure delays can guide airlines' block time scheduling decision, leading to more efficient utilization of aircrafts and an improved on time performance (Kang and Hansen, 2017). At the airport level, our estimates provide a reference point for capacity investments (e.g., Gayle and Yimga, 2018) and can inform deliberations about congestion pricing (e.g., Ater, 2012). Second, previous studies analyze flight data either for a single airport (e.g., Changnon, 1996; Sasse and Hauf, 2003) or with a relatively coarse temporal resolution, in general daily. We use a large dataset covering individual flight departures for 10 large U.S. airports at hourly resolution. This allows us to use a large set of different dummy variables to control for potential confounding factors influencing departure delays.

Our results show that adverse weather conditions significantly disturb flight operations. For sudden onset events, we find that flights, which face a weather shock, are additionally delayed by up to 23 min, depending on the type and intensity of the weather shock considered. For slow onset events, we find a significant impact of frost events on flight delays, ranging between 2 and 3 min per flight. For heat events, we do not find any significant impact. These findings remain robust to various robustness exercises. In a further step, we disentangle heterogeneous effects adverse weather conditions potentially have across seasons, airport types (i.e., hub vs. non-hub airports) and airport utilization. We find seasonal variations in the magnitude of shocks. Depending on the type of weather shocks, capacity limits can significantly increase departure delays. Further, our results suggest, that large airports, which often serve as hubs for large airlines, show higher departure delays in response to weather shocks.

There is increasing evidence that extreme precipitation events will intensify and become more frequent (Prein et al., 2017a,b). Projections for future mean wind intensity point towards a reduction across northern mid latitude regions (Karnauskas et al., 2018), whereas the frequency of convective weather and intensity of convective summer storms is expected to increase (Hoogewind et al., 2017; Prein et al., 2017a,b). Therefore, the insights of our study are of high social and economic relevance. Our results highlight the vulnerability of transport systems to the occurrence of adverse weather conditions. Current deliberations regarding ways to contain the impact of adverse weather conditions on the aviation sector range from adapting airport infrastructure (e.g., Burbidge, 2016; Kang and Hansen, 2017) to increasing the precision of weather forecasts and aircraft tracking to improve strategic traffic flow management (e.g., Winston, 2013, Federal Aviation Administration, 2017). As highlighted by Ater (2012), this approach (i.e., allocating resources to improve airline performance under severe weather conditions) at hub airports is more promising than implementing congestion pricing to contain flight delays.

The remainder of the paper is organized as follows. The next section discusses the economic costs of delays. In Section 3 we describe our dataset on departure delays and weather events. Section 4 describes the empirical strategy we follow and the obtained results are presented in Section 5. In Section 6 a series of robustness exercises are presented. Section 7 discusses the results and concludes our analysis.

2. The cost of delays

Travel time delay produces costs. Both for the economy itself, e.g., a delay in delivery of input factors may lead to lost output, and for the individual, e.g., measured in a loss of utility. An essential determinant for the latter cost of delay is the value of travel time, which can be quantified based on two main approaches (Small, 2012). First, those building upon the time allocation framework of Becker (1965) assume that people generally face a time constraint and decide on how to allocate their restricted time among different activities, each of which generates utility. Assuming that leisure as well as time spent at work both affect utility, also the time required to get to work will have an impact. According to Small et al. (2007) the value of travel time depends on the tightness of time and budget constraints and whether the travel activity is enjoyed or not. Additionally, it is shown that the value of travel time hinges on the wage rate. Exceeding it when work is liked and being below it when work is disliked. The second approach is based on production theory. In this setting the value of travel time is inferred by aggregating components, which refer to a loss in productivity for the employer due to employees' travel activity as well as a potential gain in leisure for the employee during travelling (Hensher, 1977).

Generally, when faced with travelling decisions, individuals have a preferred arrival time, i.e., start of work, a meeting or a certain appointment. Departures are planned accordingly, accounting for the travel time required to get to the destination. Irrespective of the approach followed, delays drive an additional wedge between departure and arrival, thus increase travel time and represent a source of disutility. This is particularly true when travelling is considered a derived demand, created by scheduling multiple activities in a way that necessitates movement across locations (Small, 2012).

Complementary to theoretic frameworks, the cost of travel time has been empirically estimated. Applying a mixed logit model, Li et al. (2010) report a value of around USD 40 to avoid one hour of delay when travelling by car. For the aviation sector, a hedonic price study by

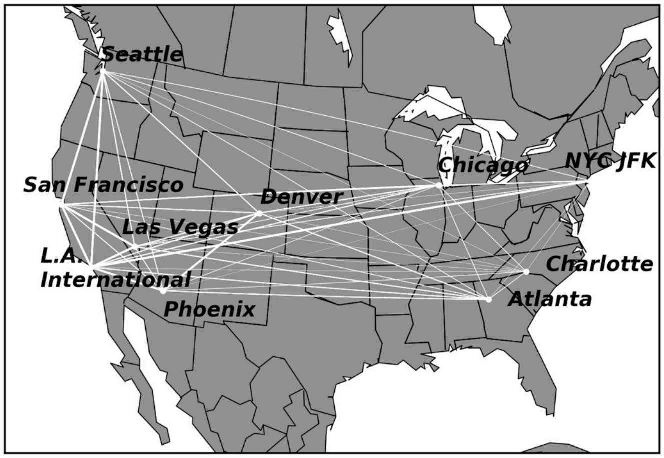

Fig. 1. Flight Connections between 10 large U.S. airports. The linewidth indicates the number of observations. The thickest lines indicate more than 40,000 observations, whereas for the thinnest lines 10,000 or less departures are observed.

Forbes (2008) shows that flight delays lead to an average reduction in ticket prices by USD 1.42 per additional minute of flight delay. This finding is line with a recent study of Gayle and Yimga (2018). They estimate a flight demand model and find that passengers are willing to pay USD 1.56 per minute on average to avoid flight delays. Luttmann (2019) adds further empirical foundations to the theories outlined above by showing that airlines compensate passengers with fares that are USD 42.74 to USD 47.60 cheaper per hour of layover time. It is important to note that some types of trips are more sensitive to delays than others. Obviously, delays are particularly inconvenient when it is vital to keep appointments (e.g., business meetings, accessing flight connections or urgent trips to the hospital). Also, certain categories of freight (e.g., perishable goods) are particularly sensitive to delays. Liu, Yin & Hansen (2016) analyze the cost of flight delay for freight transport by means of a mixed logit model. They estimate that the cost of a 15 min delay is USD 0.77 per package and USD 3.92 per package for a 60 min delay, with a high variance of costs across U.S. airports. These costs accumulate to between USD 12,000 and USD 25,000 per hour of delayed freight per aircraft. The disruption of transport networks generally carries the potential of high economic costs. Ball et al. (2010) estimate the direct cost of U.S. passenger air transport delays in 2007 to amount to USD 28.9 billion, of which, USD 16.7 billion are borne by passengers. Beyond the direct impacts of higher airline costs, flight delays also lead to indirect impacts. For industries that heavily rely on air transportation, flight delays reduce the number of productive hours, which translates to lower labor productivity. This increases the costs and translates to higher prices charged for the goods and services these industries provide. For the United States, Peterson et al. (2013) estimate that the net welfare gain of a reduction in flight delays by 10% would amount to USD 17.61 billion.

3. Data

We analyze hourly flight data for connections between ten large U.S airports (see Fig. 1) from January 2012 to September 2017. Flight connection data was obtained from the United States Department of Transport on-time performance database.[1] For each flight it provides information on the departure and arrival date and time, departure and arrival airport, airline operator, tail and flight number as well as departure and arrival delay in minutes. Based on the tail number, aircraft type and the number of seats for each aircraft were obtained from the webpage of the Federal Aviation Administration.[2] Our sample represents between 4% and 5% of performed annual domestic departures in the United States. To ex ante minimize the impacts of events that are unrelated to weather conditions but lead to large delays, e.g., strikes, problems with infrastructure or technical problems, we disregard observations with delays above 300 min. Delays up to 300 min are assumed to be a credible period in which the impact of weather shocks can be observed. This yields a sample with in total 2,146,500 individual observations. In Section 6.4 we discuss the results for the full sample and other outlier specifications.

The airport specific hourly flight data is combined with hourly weather data for each of the ten airports. Airport specific hourly data on temperature, wind speed and precipitation, which is measured by the weather station at each airport, stems from the local climatological dataset provided by the National Centers for Environmental Information of the National Oceanic and Atmospheric Administration.[3]

3.1. Departure delay data

Based on the flights between the ten airports shown in Fig. 1, we analyze the departure delays for 90 connections.[4] Not all of them are observed with equal frequency. While the connection between the John F. Kennedy Airport in New York City and Los Angeles International Airport is observed 50,638 times, the connection between the Seattle-Tacoma International Airport and Charlotte Douglas International Airport is observed 4038 times in the 6 year period considered.

In our sample, 40% of all departing flights are delayed by on average 12 min with a standard deviation of 29.8 min.[5] For flights that actually exhibit a departure delay, the mean delay is equal to 28 min with a standard deviation of 40.2 min. As shown in Fig. 2 (a), departure delay builds up over the day, peaks at around 8 p.m. and recedes thereafter. This suggests that flight delays are largely handled within the day of occurrence and are hardly transferred to the following day. We do not observe any flights between midnight and 6 a.m. Fig. 2(b) relates departure delays to the day of the week. Generally, flights departing on Mondays, Thursdays and Fridays have slightly higher delays. Further, mean delays are highest during summer months (June, July, August) and December as pictured in Fig. 2(c). The average departure delay in July and August amounts to around 15 min, whereas departure delays in September, October and November on average are around 9 min. This may on the one hand be attributable to an increased volume of travel during holiday seasons. On the other hand, convective weather during summer and snow storms and cold temperatures in December could also increase delays. Fig. 2(d) shows departure delays across the ten airports. The mean departure delay ranges between 9.5 (Seattle-Tacoma International) and 16 min (Chicago O'Hare International). The ranges of the boxplots suggest that delays in Chicago and Denver tend to be more pronounced as for example in Seattle or NYC's JFK Airport.

3.2. Weather data

We focus on the impacts of temperature, precipitation and wind on

[1] https://www.transtats.bts.gov/Fields.asp.

[2] http://registry.faa.gov/aircraftinquiry/NNum_Inquiry.aspx.

[3] https://www.ncdc.noaa.gov/cdo-web/datatools/lcd.

[4] In our dataset, we observe departure delay as well as arrival delay for each flight. The difference between them is then explained by some unobserved in-flight factors, e.g., operating the aircraft with increased fuel-inefficient velocity to reduce the degree of delay. Therefore, we concentrate our analysis on departure delays. Comparing the departure and arrival delay we observe that arrival delay on average is about two minutes higher than departure delay. This difference in the mean delay is small but statistically significant.

[5] According to the Bureau of Transportation Statistics, between 17% and 21% of U.S. domestic flights are delayed. Flights, however, only are considered delayed, if they depart 15 or more minutes late. Applying the same criteria to the delay data presented, the fraction of delayed flights amount to 19.5%.

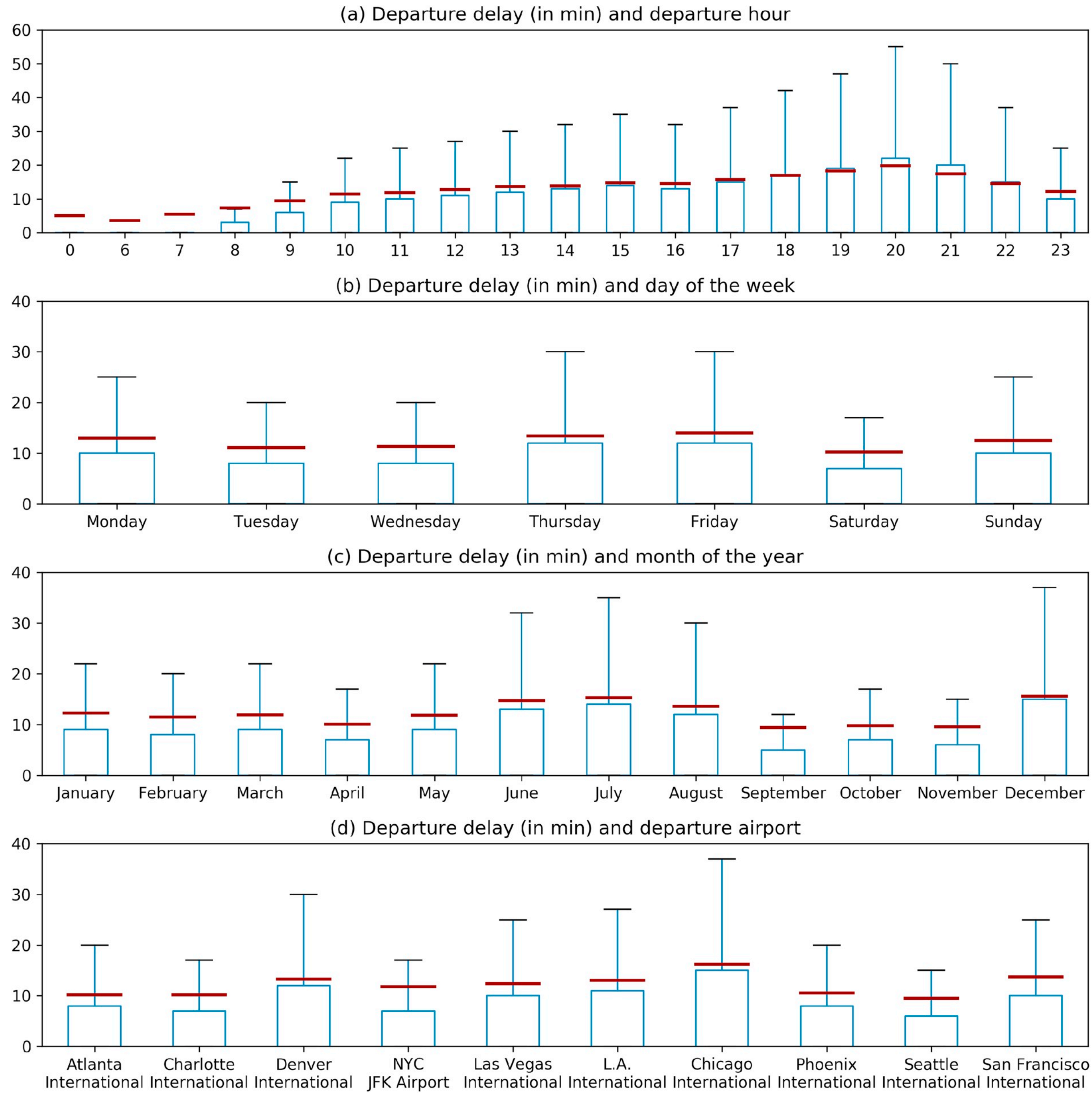

Fig. 2. Departure delay in relation to departure hour (a), day of the week (b), month of departure (c) and departure airport (d). The red lines indicate the mean. The upper and the lower whisker correspond to 1.5 times the interquartile range. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

reported departure delays. Fig. 3 summarizes the hourly weather conditions at each of the airports considered. In general, it can be seen that weather corresponds to the different climatic conditions prevalent at the regions the airports are located in. Fig. 3(a) shows that with 24˚C and 26.1˚C Las Vegas Mc Carran International and Phoenix Sky Harbor International have the highest mean temperature and exhibit the highest range across the airports in our sample. As for negative temperatures, Fig. 3(b) shows that Chicago O'Hare and Denver International have the lowest mean temperature and the highest range. Due to the Mediterranean climate in Los Angeles and San Francisco, no negative temperatures are observed. The average hourly wind speed across all airports is 9 miles per hour, with San Francisco International and NYC's John F Kennedy airport experiencing slightly higher average wind speeds of around 12 miles per hour (see Fig. 3(c)). Fig. 3(d) shows observed hourly precipitation across the ten airports.

Not all weather events will necessarily induce departure delays. According to the Federal Aviation Administration, most of the delays in winter are due to surface winds, low ceiling and low visibility, whereas during summer the majority of delays is attributable to convective weather, low ceiling and associated low visibility (Federal Aviation Administration, 2017). In our analysis, we use rain, wind, temperature and snowfall as a proxy for these conditions. Typically, weather conditions lying within the boxes shown in Fig. 3 represent regular weather situations, which do not exacerbate the scheduled handling of air traffic. Events that align themselves among the upper (or lower) ends, however, potentially lead to delays either because aircrafts cannot depart at all, have to depart from a reassigned runway or because the weather conditions aggravate preparatory ground work, i.e., maintenance, fueling and loading.

In estimating the impacts weather events have on departure delay, we consider different thresholds for precipitation, wind and temperature. These thresholds are drawn from existing literature or represent high percentiles from the distribution of observed weather conditions. For precipitation we analyze the impacts of rainfall intensities

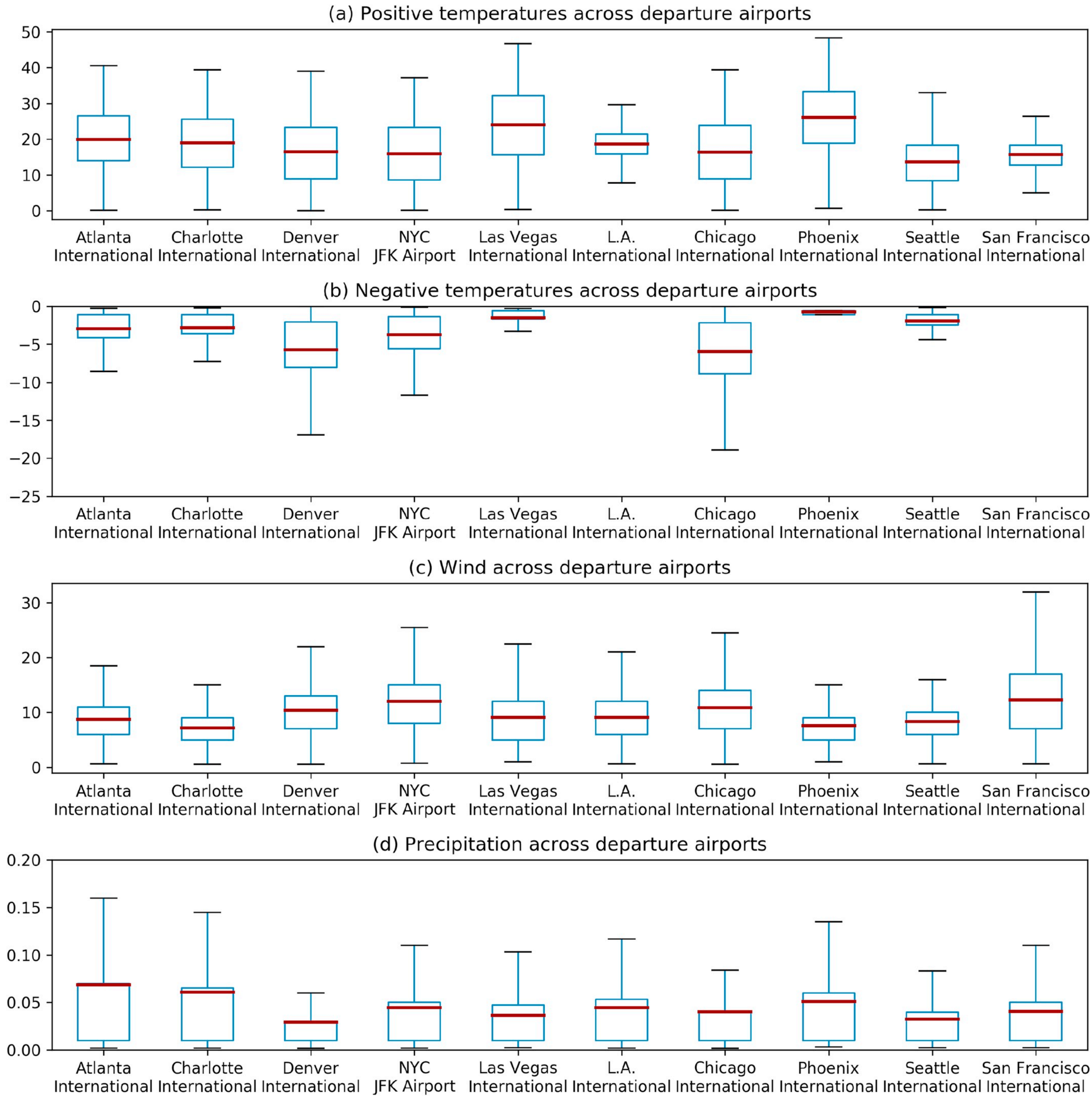

Fig. 3. Positive and negative temperatures (a, b) as well as wind speed (c) and precipitation (d) for each of the analyzed airports. The red lines indicate the mean. The upper and the lower whisker correspond to 1.5 times the interquartile range. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

exceeding the 99th, 99.5th and 99.9th percentile. This corresponds to rainfall in the range of 0.06, 0.11 and 0.25 inches per hour. As an additional threshold, we use precipitation when temperature is below 0˚C to take the impact of snowfall on aircraft operations into account. In categorizing the wind speed variable, we start with a threshold of wind speeds of 10 mph, which corresponds to the 65th percentile. This rather low threshold account for the adverse impacts of tailwinds, which affect aircraft operations at moderate wind conditions. Additionally, we also consider values exceeding the 90th and 99th percentile. The respective thresholds for this are 16 and 25 mph. For temperature we apply the numbers presented in Coffel and Horton (2014) and Coffel et al. (2017). Starting from 35˚C we incrementally increase the threshold by 5˚C until 45˚C. 40˚C correspond to the 90^{th} percentile and 45˚C corresponds to the 99.96th percentile of observed hourly temperatures. Due to different geographic locations and associated different climatic conditions, the frequency of observed weather conditions varies across airports. Fig. 4 visualizes these differences and clearly shows, for example, that the majority of departures during temperature above 35˚C are observed in Las Vegas and Phoenix. Fig. 4 also illustrates that for these airports only few departures during rainy conditions are observed.

When choosing the thresholds there is always the risk that the threshold is set too high, leaving too few observations for robust estimates. Table A1 in the Appendix shows the number of observed departures for each of the specified weather thresholds.

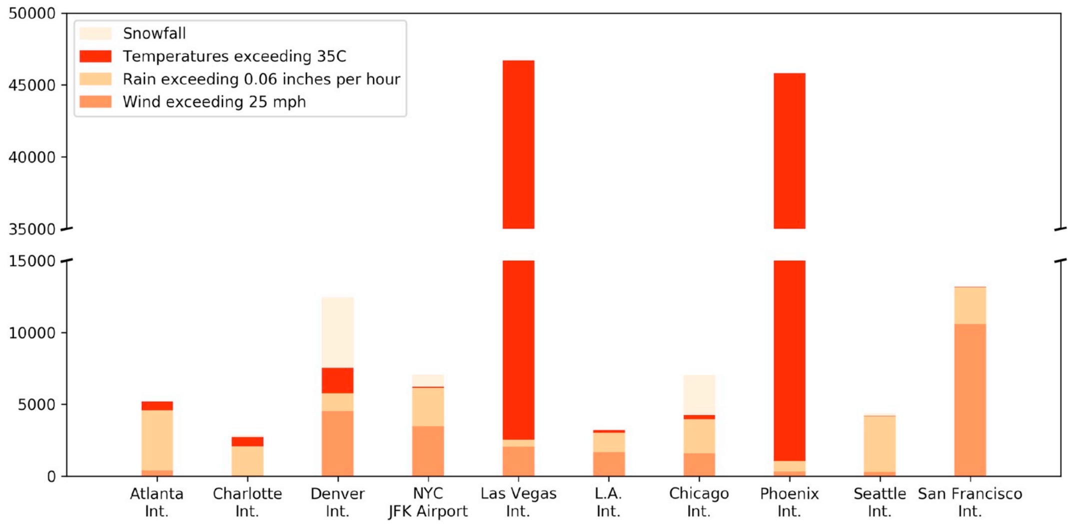

Fig. 4. Number of different weather shocks across airports. Here the intensities used as thresholds are 25 mph for wind, 0.06 inches of rainfall per hour, snowfall and temperatures above 35˚C.

4. Empirical strategy

We differentiate between two types of weather shocks, which require a different empirical strategy. Occurrence of heavy rainfall, strong winds and snowfall can be classified as sudden onset categories. They occur at a specific point in time in a day, whereas the other hours of this day are mainly unaffected by this event. Heat and frost events, however, can be considered as slow onset events. They gradually develop in course of a day and often follow a specific trend. While the hottest hours during summer days generally lie between 3 p.m. and 4.30 p.m., high temperatures will likely be observed for the other hours of the day as well.

For sudden onset weather events, i.e., rainfall, wind and snowfall, we are able to clearly define a period before the weather shock and a period after the shock occurred during one specific day. Moreover, we observe the departure of flights at the airport facing the weather shock as well as for all other airports in the pre- and post-shock period. This setting enables us to infer the impact of these sudden onset weather events on the amount of departure delay based on a difference-in-difference setting as laid out in Section 4.1.

Due to the gradual development of the shock in slow onset events, i.e., heat and frost, we are not able to clearly identify a pre- and post-shock period. For these events we mainly observe days, where some airports in our sample face such a shock and others not. This leaves us to a time-series cross section data structure with a few panels, which are repeatedly observed over a long time period. Therefore, we follow Beck and Katz (1995) and infer the impact of slow onset weather events based on a linear cross-sectional time-series model with panel-corrected standard errors, where the parameters are estimated by a Prais-Winsten regression estimator to account for autocorrelation of the disturbances. This is specified in Section 4.2.

Based on the insights from Section 3.1 and Section 3.2, we assume that the potential impact of a weather shock is limited by a day, i.e., the potential impact of a shock equals 0 the day after the event. This yields a sample of 2098 pooled daily cross-sections with in total 2,146,500 individual observations. Schematically our approach can be presented as shown in Fig. 5. Departure delays build up between 6 a.m. and 20 p.m. and recede thereafter. Once, an airport is affected by some kind of weather event (treated), the departure delays leave their *”normal”* trajectory and jump to a higher one, which by the end of the day, at latest, approaches *”normal”* conditions again.

4.1. Estimating the impact of sudden onset weather shocks

We estimate the impact of sudden onset weather shocks on the departure delay in minutes for flight, i, at airport, a, at hour, h, at day, d, in a difference-in-difference setting as specified in Equation (1).

$$y_{iahd} = \alpha + \gamma(Treatment)_{ad} + \theta(Post)_{hd} + \beta(DiD)_{ahd} + \kappa X_{iahd} + \mu_a + \delta_d + \zeta_h + \varepsilon_{iahd} \quad (1)$$

where *Treatment* is a dummy indicating, whether the airport has received the treatment, i.e., a weather shock, at day d, or not. *Post* is a dummy variable determining, if an observed flight occurred in the post-treatment period, i.e., in the hours after the weather shock. *DiD*, is our variable of interest, which is a dummy representing airports in the post-treatment period, which received the treatment. X_{iahd} is a set of flight level data controlling for individual flight characteristics, which may influence the amount of departure delay, e.g., size and type of aircraft, number of seats and airline operator. μ is a vector of airport fixed effects controlling for all time invariant airport specific characteristics, e.g., the geographic position and specific outlay of an airport, which can lead to increased delays, or that an airport is in general more exposed to a specific weather type. δ is a vector of day fixed effects, which takes all day specific effects into account, e.g., start of holiday season or large events leading to a general increase in air traffic on a specific day. ζ is a vector of departure hour fixed effects, which controls for all departure hour specific effects, like higher flight demand during business hours. And, ε is the idiosyncratic error term. To account for potential covariance among flight delays within the same airport, we cluster the standard errors at airport level (see, for example, Bertrand et al. (2003)).

To infer the impact of a weather shock, we first calculate the difference in departure delays between the pre- and post-treatment period for all flights starting from the airport facing a weather shock on a specific day. This difference is then compared with the difference in departure delays for the proper control group that involves individual flights at non-treated airports at this specific day. Formally, the additional impact of a weather shock on departure delay is determined by the difference-in-difference parameter, β, which we expect to be positive.

In this setting, the effect of weather shocks on flight delays can be consistently estimated under a set of identifying assumptions (see, for example Angrist and Pischke (2009) and Lechner (2010)). First, we have to assume that the treatment group, i.e., individual flights at airports, which face a weather shock at day, d, and the control group, i.e.,

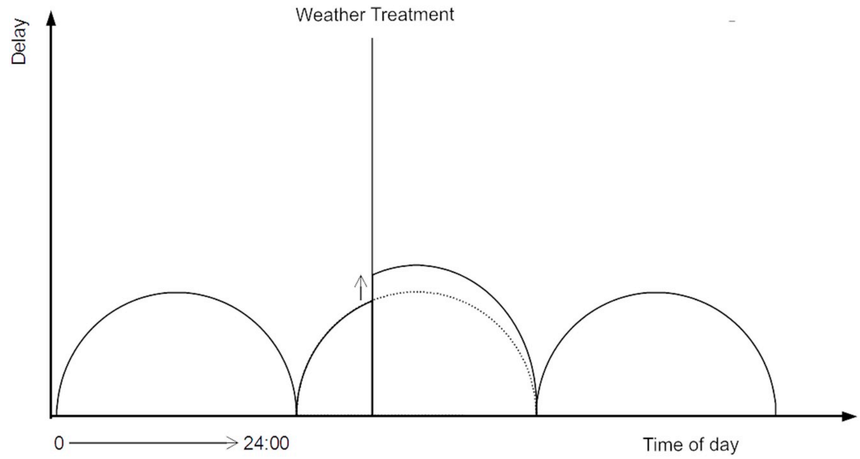

Fig. 5. Schematic representation of the estimation approach.

flights at airports without a weather shock at that day, may have different levels, but follow the same trend in the occurrence of departure delays. Thus, any difference in the differences in departure delays between treatment and control groups can be attributed to the weather shock, rather than to differential pre-existing trends. We control for this assumption later in Section 5.1, where we plot the 5 h leads for each treatment to see, if we find significant differences in the trends between the treatment and control groups before the treatment. Second, we assume that events or factors other than weather shocks occurring at the time of treatment do not differently affect outcomes for treatment and control group, which is also known as the common shock assumption. Randomly occurring frictions in ground operations, for example, may lead to backlogs irrespective of a weather treatment. The same is true for technical problems or workers' absenteeism due to illness. Thirdly, we assume that the incidence of a weather shock is randomly assigned within our sample, i.e., which airports are hit by a weather shock at a specific day is uncorrelated with other determinants of the dependent variables after controlling for airport and day fixed effects. The airport fixed effect accounts for the fact that temperatures in Las Vegas and Phoenix are generally higher or that Denver, Las Vegas and San Francisco are more wind prone than the other airports in our sample. Day fixed effects on the other hand account for confounding factors that are observed over a particular day over all airports like the start of the holiday season. Finally, the stable unit treatment assumption requires that the control group, i.e., airports with no weather shock at the treatment day, remains unaffected by the weather shock. In our setting, this assumption may be violated, since the delay of the treated origin airport may be disseminated through late arriving flights in the untreated destination airport. Generally, airline and airport operators insert buffer times in flight schedules and turnaround operations (Baumgarten et al., 2014, Kafle and Zou, 2016) to mitigate potential propagation effects between arrival and departure delays. Therefore, we assume that the potential spillover bias in our study is not large. This assumption is justified based on the congestion internalization by hub airlines discovered in existing literature (Ater, 2012; Bendinelli et al., 2016 and Miranda and Oliveira, 2018). Further, with the inclusion of day fixed effects we are able to control for any day specific system wide increases in departure delays, which may arise due to daily propagation effects. If there still remains a bias, it would systematically increase the delay in the control group. This would lead to an underestimation of the impact of weather shocks on departure delays, which makes our outcomes a conservative estimate of the potential impact. To assure that our empirical strategy is nevertheless valid, we re-estimate the specification described in Equation (1) (see Section 6), for a varying length of the post-treatment period (one to six hours after the actual treatment) as a robustness exercise. Short post-treatment periods, i.e., 1–2 h should minimize the potential prolongation effect of departure delays.

4.2. Estimating the impact of slow onset weather shocks

To analyze the impact of slow onset weather shocks, i.e., heat and frost, on departure delays we define a linear cross-sectional time-series model as described in Equation (2).

$$y_{ad} = \alpha + \gamma(Treatment)_{ad} + \mu_a + \delta_d + \varepsilon_{ad} \tag{2}$$

where, y_{ad}, is the daily mean of departure delays for each airport, a, at the day, d. *Treatment*, is a dummy indicating whether the airport has received the treatment, i.e., a weather shock, at day d, or not. μ is again a vector of airport fixed effects controlling for all time invariant airport specific characteristics and, δ is a vector of day fixed effects, which takes all day specific effects into account. ε is the error term, which is assumed to be heteroscedastic and contemporaneously correlated across airports, a, and to be, additionally, first-order autocorrelated across days,d. To get a consistent estimate of the auto-correlated parameter we use a Prais-Winsten transformed generalized least squares estimator (Prais and Winsten, 1954). Again, to infer a causal effect of weather shocks on departure delay, we assume that the incidence of a weather shock is randomly assigned within our sample, i.e., which airports are hit by a weather shock at a specific day is uncorrelated with other determinants of the dependent variables after controlling for airport and day fixed effects.

5. Results

5.1. The impact of sudden onset weather events on departure delays

The following tables show the results from the difference-in-difference estimation as described in Equation (1). Each time we present the results for 3 model specifications (1)–(3) for the middle threshold, and the preferred specification for the lower and the higher thresholds. Hereby, (1) represents the basic difference-in-difference specification, which does not account for any fixed effects. Specification (2) includes airport, date and departure hour fixed effects. Specification (3) additionally includes aircraft and airline fixed effects. *Treatment* captures any existing pre-treatment differences in departure delay between those airports that exhibit a weather shock and those that do not. *Post* describes the time trend in the control group, i.e., how departure delay evolves over the day in those airports that do not experience the weather shock. *DiD* reveals, if the departure delay of aircrafts at airports that experience a weather shock is significantly different from the time trend observed in the control group.

Table 1 shows the impact of rainfall on departure delays. For all thresholds, rainfall significantly increases departure delays. The

Table 1
Difference-in-Difference estimates of the impact of rainfall on departure delay.

	Rainfall ≥ 0.1	Rainfall ≥ 0.1	Rainfall ≥ 0.1	Rainfall ≥ 0.06	Rainfall ≥ 0.2
	(1)	(2)	(3)	(3)	(3)
Treatment	1.562	1.733***	1.712***	1.104**	1.699***
	(0.880)	(0.340)	(0.330)	(0.420)	(0.270)
Post	5.093***	2.739***	2.738***	2.023***	3.129***
	(0.210)	(0.280)	(0.282)	(0.226)	(0.780)
DiD	13.450***	13.450***	13.470***	10.050***	23.280***
	(2.470)	(2.170)	(2.150)	(2.290)	(2.030)
Fixed Effects	No	Yes	Yes	Yes	Yes
R^2	0.015	0.078	0.085	0.085	0.083
Observations	2,146,535	2,146,535	2,146,535	2,146,535	2,146,535

Notes: Cluster robust standard errors in parenthesis. Column (1) no fixed effects are included. In Column (2) airport, date and departure hour fixed effects are included. Column (3) additionally includes aircraft and airline fixed effects and the number of seats. The dependent variable in each specification is departure delay in minutes. The intensity of the rainfall event considered as treatment is shown in the headers. Constant not reported. *, **, *** indicate 10, 5, 1% significance levels.

Table 2
Difference-in-Difference estimates of the impact of snowfall on departure delay.

	Snowfall	Snowfall	Snowfall
	(1)	(2)	(3)
Treatment	0.381	1.832*	1.996*
	(1.540)	(0.910)	(0.884)
Post	1.430***	− 0.073	− 0.093
	(0.330)	(0.360)	(0.350)
DiD	14.870***	11.730***	11.500***
	(1.290)	(1.580)	(1.590)
Fixed Effects	No	Yes	Yes
R^2	0.003	0.073	0.080
Observations	2,146,535	2,146,535	2,146,535

Notes: Cluster robust standard errors in parenthesis. Column (1) no fixed effects are included. In Column (2) airport, date and departure hour fixed effects are included. Column (3) additionally includes aircraft and airline fixed effects and the number of seats. The dependent variable in each specification is departure delay in minutes. Constant not reported. *, **, *** indicate 10, 5, 1% significance levels.

Table 3
Difference-in-Difference estimates of the impacts of wind on departure delay.

	Wind ≥ 16	Wind ≥ 16	Wind ≥ 16	Wind ≥ 10	Wind ≥ 25
	(1)	(2)	(3)	(3)	(3)
Treatment	− 0.267	− 0.608***	− 0.501**	− 0.029	0.170
	(0.260)	(0.210)	(0.206)	(0.660)	(0.310)
Post	4.740***	− 0.665	− 0.637	− 1.875**	0.495*
	(0.330)	(0.400)	(0.410)	(0.670)	(0.230)
DiD	2.694***	2.113***	2.016***	1.247	3.422***
	(0.480)	(0.320)	(0.310)	(0.770)	(0.660)
Fixed Effects	No	Yes	Yes	Yes	Yes
R^2	0.006	0.072	0.079	0.079	0.079
Observations	2,146,535	2,146,535	2,146,535	2,146,535	2,146,535

Notes: Cluster robust standard errors in parenthesis. Column (1) no fixed effects are included. In Column (2) airport, date and departure hour fixed effects are included. Column (3) additionally includes aircraft and airline fixed effects and the number of seats. The dependent variable in each specification is departure delay in minutes. The intensity of the wind speed considered as treatment as treatment is shown in the headers. Constant not reported. *, **, *** indicate 10, 5, 1% significance levels.

significant positive coefficient on the *Treatment* variable implies that flights departing from airports that experience rainfall above the threshold generally have higher delays. While departure delays increase over the day, as shown by the positive coefficients on the *Post* variable in Table 1, rainfall causes additional delays at the affected airports. This is indicated by the significant positive coefficient for the *DiD* parameter. For intensities that exceed 0.1 inches per hour, the results suggest that rainfall increases departure delays by on average 13 min. For stronger intensities, we find an increase by around 23 min.

To account for potential differences between rain- and snowfall we explicitly look at precipitation when temperatures are below zero. As indicated by the significant positive coefficients on the *DiD* parameter in Table 2, snowfall on average causes an additional delay of around 11 min.[6]

Table 3 presents the results for the impact wind has on departure delay. The significant positive DiD coefficient suggests that wind speeds above 16 mph increase departure delays by on average between 2 and 3 min. For 10 mph we do not find any difference in departure delays between treatment and control group. This suggests that wind speeds of 10 mph are too low to lead to delayed departures.

Generally, the results for wind suggest that wind speeds below 25 mph are no major impediment for smooth airport operations. While we do find an increase in departure delays for wind speeds above 16 mph the magnitude is small when compared to rain or snowfall. Runways generally are aligned along the main wind directions, and airport traffic control typically organizes traffic flows so that aircrafts start and land into headwinds. As long as winds only have a headwind component, aircraft operation is possible up to wind speeds of around 50 mph. As for crosswind, aircrafts are a lot more sensitive. Here the maximum allowable wind speeds are around 31 miles per hour. Considering the magnitude of our estimates, the findings suggest that airports' runways are largely aligned with the main wind directions and wind currently has a minor impact on delays.

In a further step, we analyze the development of the impacts of sudden onset weather shocks on departure delay over time by looking at the lead and lag effects of the treatment. This serves two purposes. First, it decomposes the overall effect reported in Table 1, Tables 2 and 3 in hourly steps and, thereby, gives us the possibility to investigate how the effect of the weather shock develops over time, e.g., if it accumulates in the hours after the treatment. Second, it provides a visual inspection of the parallel trend assumption as discussed in Section 4.1. As shown in Fig. 6, neither for rain (Fig. 6(a)) nor for snowfall (Fig. 6(b)) any systematic differences in the pre-treatment trend is apparent and the coefficients on the leads of the treatment largely are not significantly different from zero. Regarding the temporal development of the treatment effect, we observe values significantly different from zero, which accumulate over the following 2–4 h after the treatment

[6] The reason for the overall smaller impacts estimated for snowfall is, that we do not apply thresholds to the amount of snowfall in order to account for the effects already small amounts of snow coverage have.

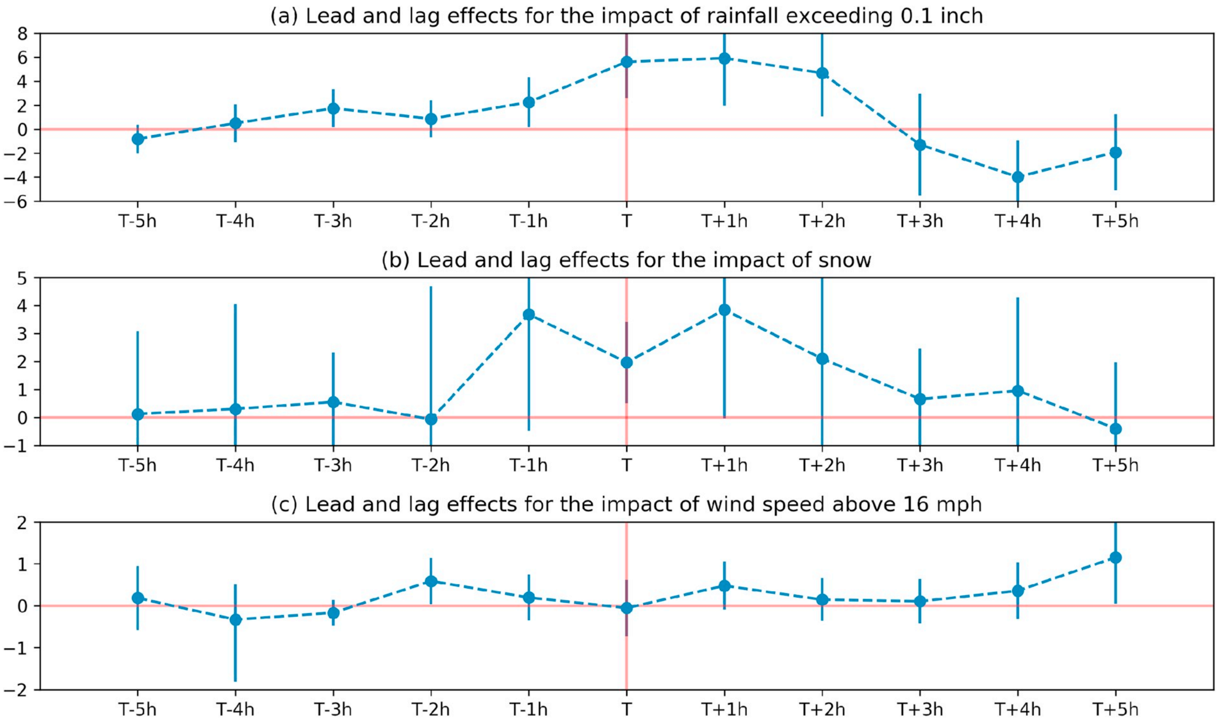

Fig. 6. Lead and lag effects of the rain, snowfall and wind treatment. The dots correspond to the estimates for the specific lead and lag effects of the treatment. The bars indicate the 95 percent confidence interval surrounding them.

and then begin to return to pre-treatment levels. Considering the evolution of the treatment effect of wind speed over time, Fig. 6(c) shows, no significant differences in the pre-treatment trend. For the lags of the treatment we observe values significantly different from zero and with positive tendency. This suggests an accumulating effect over time.

5.2. *The impact of slow onset weather events on departure delays*

For the slow onset events we present the estimation results from the linear cross-sectional time-series model represented in Equation (2). The results of three specifications (1)–(3) are shown for the middle threshold. The basic specification (1) shows the results for the Prais-Winsten estimation described in Section 4.2 without controlling for any fixed effects. Again, specification (2) extends the baseline estimate and additionally accounts for airport and date fixed effects. Specification (3), for comparison reason, shows the results for the fixed effects estimation with airport and day fixed effects. For the lower and the higher thresholds, only the results for our preferred specification (2) are presented.

Looking at cold temperatures, our results reveal that as temperatures go below 0°C, mean daily departure delays per flight increase. This is indicated by the significant positive coefficient on the Temp variables in Table 4. Controlling for airport and day fixed effects, the average daily increase in departure delays amounts to around 2 min per flight for temperatures below −3°C. As one might expect, the colder the temperatures get, the higher the impact on delays.

Looking at the impact high temperatures have on departure delays, we find no significant effect after controlling for airport and date fixed effects. As shown by the coefficients in Table 5, days with temperatures above 40°C exhibit no significant change in departure delays. For temperatures above 45°C, the coefficient suggests a positive tendency but is not significant. In our dataset, there are only 586 observations with temperatures above 45°C. For 47°C only 64 observations out of more than 2,000,000 are available. Hence, for extreme heat there are insufficient observations available to report robust inference.

Table 4
Estimates of the impacts of cold temperatures on departure delay.

	P−W	P−W	FX Effects	P−W	P−W
	(1)	(2)	(3)	(2)	(2)
Temp ≤[-3°C]	3.339***	2.058***	2.700***		
	(0.400)	(0.330)	(0.680)		
Temp ≤[0°C]				1.694***	
				(0.260)	
Temp ≤[-8°C]					3.426***
					(0.490)
Constant	12.090***	7.282***	9.351***	7.137***	7.479*
	(10.110)	(2.290)	(1.430)	(2.290)	(2.280)
Fixed Effects	No	Yes	Yes	Yes	Yes
R^2	0.005	0.435	0.460	0.435	0.436
Observations	20,085	20,085	20,085	20,085	20,085

Notes: Cluster robust standard errors in parenthesis. Column (1) Prais-Winsten estimation with no fixed effects are included. In Column (2) Prais-Winsten estimation airport and day fixed effects are included. Column (3) fixed effects estimator with airport and day fixed effects. The dependent variable in each specification is mean departure delay in minutes.The intensity of the respective weather condition considered as treatment is shown in the first left columns. *, **, *** indicate 10, 5, 1% significance levels.

5.3. *Differential effects*

The impact of weather shocks may differ depending on the specific prevailing circumstances at the airport. We conduct a series of extension exercises to disentangle heterogeneous effects adverse weather conditions potentially have across seasons, airport and aircraft types (i.e., hub vs. non-hub airports) and airport utilization.

First, the impacts of the analyzed weather shocks may differ across seasons. Rain during winter months, when outside temperatures tend to be colder, can be more problematic due to ice formation. Generally, the included date fixed effects control for any present time effect that may bias our estimates. Nevertheless, the seasonal effects of weather shocks on departure delays affect the magnitude of the estimators. Therefore,

Table 5
Estimates of the impacts of warm temperatures on departure delay.

	P—W	P—W	FX Effects	P—W	P—W
	(1)	(2)	(3)	(2)	(2)
Temp ≥[40°C]	0.956***	− 0.427	− 0.354		
	(0.370)	(0.300)	(0.470)		
Temp ≥[35°C]				− 0.199	
				(0.250)	
Temp ≥[45°C]					0.512
					(0.990)
Constant	12.250***	7.402***	9.621***	7.403***	7.417***
	(0.110)	(2.290)	(1.490)	(2.290)	(2.290)
Fixed Effects	No	Yes	Yes	Yes	Yes
R^2	0.001	0.433	0.457	0.433	0.433
Observations	20,085	20,085	20,085	20,085	20,085

Notes: Cluster robust standard errors in parenthesis. Column (1) Prais-Winsten estimation with no fixed effects are included. In Column (2) Prais-Winsten estimation airport and day fixed effects are included. Column (3) fixed effects estimator with airport and day fixed effects. The dependent variable in each specification is mean departure delay in minutes.The intensity of the respective weather condition considered as treatment is shown in the first left columns. *, **, *** indicate 10, 5, 1% significance levels.

seasonal disaggregation provides additional insights. This is particularly relevant in view of seasonally varying effects. Intensities and frequencies of rainfall, for example, vary considerably among seasons. We therefore split the dataset into two six month periods. One includes spring and summer months (April–September) and is referred to as ”warm season”, the other is termed ”cold season” and includes the remaining months (October–March). Table A2 in the appendix shows the results for the sudden onset weather shocks for the two periods considered. In both seasons rainfall significantly increases delays. One reason for the discovered higher impacts during the warm season is that the rainfall events observed during this time of the year are generally stronger than during the cold season. For snowfall we also find a significant positive impact in both seasons, whereas the effects are more pronounced during the colder months. This again is due to the more intense snowfall events observed during cold seasons. For wind, the effects are more equally spread over the year, suggesting that there is no major seasonal difference regarding the impacts wind has on departure delays. Table A3 in the appendix presents the seasonal results for the slow onset events. Generally, there are only very few observations that oppose to the conventional expectations that there are barely any hot days during the cold season and cold days during the warm season. Our sample contains 25 departures at temperatures above 40°C during the cold season and 540 departures at temperatures below −3°C during the warm season. The results suggest that the effects cold temperatures have on average daily departure delay per flight is more pronounced between April and September. As for temperatures above 40°C we do not find any significant impact between October and March.

Second, to link our analysis to the congestion literature we analyze the role of capacity utilization in the impact of weather shocks on departure delays. We differentiate between peak capacity and non-peak capacity hours. Peak capacity hours are defined as hours at a specific airport that exhibit departures above the 75th percentile of the sum of hourly departures. The remaining flights are grouped into the ”other” group. Table A4 in the appendix shows the results for the sudden onset weather shocks when taking capacity limits into account. Table A5 in the appendix presents the results for the slow onset impacts. The impact of rainfall is significantly higher in the group with high capacity utilization. For wind, the effects are more equally spread over the two groups. With regard to snowfall, we find in case of hourly capacity limits a less pronounced delay. We do not find clear evidence of differences in the impact of slow onset events on departure delays depending on the degree of capacity utilization. The results suggest that the effects cold temperatures have on average daily departure delay per flight is more pronounced in the off-peak hours. As for temperatures above 40°C we do not find any significant impact in the group with high capacity utilization and a negative but slightly significant effect for the other group.

Third, to account for potential airline and airport specific factors that affect airport congestion and delays (e.g., Rupp, 2009; Ater, 2012; Greenfield, 2014) we differentiate between flights departing in hours with high airline concentration and other flights. Table A6 in the appendix shows the results for the sudden onset weather shocks and Table A7 presents the results for the slow onset impacts when taking the degree of airline concentration into account. For rain, wind and temperature weather shocks we do not find differences in the resulting departure delay for the two groups considered. For snowfall, we find a slightly larger departure delay in the group with higher airline concentration.

Fourth, we compare the estimates presented in Section 5 to those received when conducting the similar analysis to a sample of departing flights between ten smaller U.S airports[7] (see Tables A8 and A9). This allows us to take the role of hub airports into account (Mayer and Sinai, 2003; Forbes, 2008), as most of the airports contained in the large airport sample are main hubs for several large U.S. airlines. This is not true for airports in the small airport sample. At large, we find a less pronounced effect of weather shocks on departure delays in smaller airports. For rainfall and wind we find a positive significant effect on departure delay, whilst smaller in magnitude. For snowfall, we do not find any significant impact on departure delays in smaller airports. For slow onset events, our comparison between large and small airports reveals that cold temperatures have no significant impact on departure delays of flights from the smaller airports. For temperatures above 40°C, the estimate is insignificant for both samples. This is shown in Table A9.

Fifth, we test, if the effect of weather shocks on departure delays is heterogeneous across different aircraft types, i.e., has a more pronounced effect on small aircrafts (see Table A10). Coffel et al. (2017), for example, show that the impact of rising temperature on aircraft take-off performance depends on the size and type of the aircraft. Therefore, we additionally allow an individual weather treatment for each aircraft type. We differentiate between small and large aircrafts, with large referring to aircrafts with 300 and more seats. As presented in Table A10, we again find a general treatment effect, which means that aircrafts, which face a weather shock, have a higher delay on average as shown by the positive significant coefficient of the *DiD* variable. With regard to the type of aircraft our results suggest, that in general large aircrafts have a significant higher departure delay of around 3 min than small aircrafts (see columns (2)). But, after facing a weather shock, we do not find any significant difference in departure delay between large and small aircrafts. This result can be seen for all three different sudden onset weather shocks.

6. Robustness tests

To assure the robustness of our results we conduct a series of robustness exercises. First, we analyze the impact of varying the length of the post-treatment period to account for a potential violation of the stable unit treatment assumption (see Table A11 in the Appendix). Generally, rain and snowfall significantly increase departure delays across all periods studied. There is an initial amplifying effect on departure delays of around 16 min, which recedes the longer the considered post-treatment period becomes. The fact that the overall estimate presented in Section 5.1 is lower indicates that the effects fade the

[7] The following airports are considered: St. Louis Lambert Int., Nashville Int., Austin-Bergstrom Int., Metropolitan Oakland Int., New Orleans Int., Raleigh-Durham Int., Kansas City Int., Southwest Florida Int., Cleveland-Hopkins Int., Pittsburgh Int.

longer the time span between weather shock and departure. This suggests that even if there would be a violation of the stable unit treatment assumption, as discussed in Section 5.1, any bias due to prolongation effects will lead to an underestimation of the impact. To limit redundancies we only report results for rainfall exceeding 0.1 inches, snowfall and wind speed above 16 mph. The results for the other intensities of the sudden onset events are qualitatively similar. While for precipitation the initial effect was higher than the effect over all hours, for wind the analysis shows that the effect on departure delays accumulates over time. In light of the stable unit treatment assumption, it has to be noted that prolongation effects for this type of weather shock may lead to a slight overestimation of the impact.

Second, to account for potential impacts of weather conditions at the arrival airport, we include them into our analysis and compare the results to our initial ones (see Table A12). Both estimations lead to similar results. This implies that the weather conditions at the arrival airport do not introduce any systematic bias, which our estimation strategy not already accounts for.

Third, our results could be susceptible to outliers. Therefore, we look at different subsamples of our dataset. In our main estimations, we disregard all observations with delays above 300 min. To assure that this discretionary threshold does not influence our results, we also conducted the analysis for the full sample, for observations with delays up to 500 min and up to 150 min (see Table A13). To avoid unnecessary repetitions Table A13 presents only the results for rainfall. The presented pattern is representative for the other sudden and slow onset weather shocks. The coefficient on the *DiD* variable is significantly positive across all the subsamples. The changes in magnitude directly arise due to the deletion of very large departure delay values. This suggests that our results are robust with respect to the choice of subsamples.

Finally, it may be that both the intensity and frequency of weather shocks correlates with other airport specific time trends, e.g., increase in passenger numbers over time, which influences the amount of departure delay for an airport. To disentangle the causal effect of the weather shock from potential underlying trends we re-estimate our model as specified in Equation (1) for all three weather shocks, i.e., rainfall, snowfall and wind, and additionally include an airport specific parametric day trend. The results of this robustness exercise are reported in Table A14. For all three different weather shocks our findings stay robust. Thus potential time trends do not confound our estimates.

7. Conclusion

Our analysis shows that weather shocks like rainfall, snow and wind have a significant impact on departure delays within the U.S. aviation system. Depending on the intensity of the weather shock considered, rain- and snowfall lead to additional departure delays between 10 and 23 min. For wind, the discovered effects are smaller in magnitude, ranging from 1 to 3 min. While the impact of rainfall is more pronounced between April and September, the effect of wind is more evenly distributed across the year. With regard to slow onset weather shocks, our results reveal that cold conditions lead to additional departure delays. For temperatures below 0°C, our analysis shows an increase in delay on average by around 2 min per departure. For heat, we do not discover any significant amplifying impacts on departure delay. While our results indicate a tendency of higher average departure delays when temperatures go beyond 45°C, the results are not statistically significant. Considering the recent experiences from Phoenix, where temperatures of 49°C on June 20th, 2017 lead to the cancellation of more than 40 regional flights, together with the projections by Coffel et al. (2017), we expect extreme temperatures to increase departure delays.[8] Our observations for temperatures beyond 45°C, however, are insufficient for robust estimates.

Generally, the magnitude of the effect should be considered jointly with the frequency the impacts emerge with. The estimated small impact of wind may accumulate considerably due to a higher frequency of occurrence. In our sample, windy conditions are observed 23 times more frequently than rainy ones.[9] Mutual consideration of magnitude and frequency of estimated impacts is particularly relevant in connections with future changes in frequency and intensity of adverse weather conditions due to climate change (Prein et al., 2017a,b).

Delays lead to uncertainty in the travel time faced. Travelers may thus decide to adjust the time of departure in order to create a safety-margin with respect to the desired time of arrival. Empirical studies reveal that travelers have high preferences to avoid the adverse effects of delays (Carrion and Levinson, 2012). Further, industries, which rely on air transportation, carry large costs of delays due to a decrease in productivity. According to the U.S. Bureau of Transportation Statistics, in 2017 more than 720 million passengers boarded a domestic flight within the United States.[10] Of them around 20 percent experienced some kind of delay, with adverse weather conditions having a share of around 31 percent.[11] Hence, 44,640,000 passengers experience some kind of weather related delay. According to Forbes (2008) and Gayle & Yimga (2018), passengers value the avoidance of a flight delay with around USD 1.50 per minute. Our results reveal, that the additional average delay varies across the different weather shocks and the specific intensities considered. Assuming that all of the encountered weather related delays in 2017 were due to precipitation, i.e., delays range between 10 and 23 min, this corresponds to costs between USD 670 million and USD 1.54 billion. For wind the numbers range from USD 180 million to 229 million, whereas for cold conditions between USD 113 million and USD 229 million. It is important to note that these numbers only reflect the value of time from passengers' perspective. For airlines, delays cause additional costs due to expenses for crews, fuel and maintenance.

Considering these costs together with the projected doubling of passenger numbers (IATA, 2017), strategies are called for to contain the impact this double burden potentially has on delays (Burbidge, 2016). In addition to further investment in transport infrastructure, forward looking traffic planning that anticipates delays and proactively provides flexibility to passengers will be essential. To predict delays and pre-emptively provide alternative routes to passengers, detailed information regarding the connection between weather and flight delays is required. The presented results reveal that already nowadays adverse weather conditions introduce significant uncertainty to journey times. In this respect our results highlight the particular importance of evaluating the heterogeneous impacts weather shocks have on transport systems. Being aware of the heterogeneous effects adverse weather conditions have across seasons and airport types provides decision support for congestion management and capacity planning (e.g., Burbidge, 2016; Kang and Hansen, 2017). As highlighted by Ater (2012) the allocation of resources to improve airline performance under severe weather condition is a promising way to contain flight delays, particularly at hub airports. Whilst our analysis is based on observations from the aviation network, the insights equally apply to other modes of transport. Thus, an interesting track for future research could be to explore the impact of weather extremes on other modes of

[8] https://www.washingtonpost.com/news/capital-weather-gang/wp/2017/

(*footnote continued*)
06/20/its-so-hot-in-phoenix-that-airplanes-cant-fly/?utm_term=.8abc36ddd8de.

[9] See Table A1 in the Appendix for the frequencies of our weather shock categories being considered.

[10] https://www.transtats.bts.gov/TRAFFIC/.

[11] https://www.transtats.bts.gov/OT_Delay/ot_delaycause1.asp?type=3&pn=1.

transport, like rail or maritime transport. This would give a more comprehensive picture of the vulnerability of the transport sector to weather extremes.

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Appendix

Table A1
Number of observed departures under the specified weather thresholds

Event	Number of observed departures
Rainfall ≥ 0.067 inch	21,343
Rainfall ≥ 0.11 inch	11,122
Rainfall ≥ 0.26 inch	2,122
Snowfall	8,810
Wind speed ≥ 10 mph	823,938
Wind speed ≥ 16 mph	264,325
Wind speed ≥ 25 mph	25,909
Temperature ≤ [0°C]	81,669
Temperature ≤ [-3°C]	43,691
Temperature ≤ [-8°C]	16,495
Temperature ≥ [35°C]	92,604
Temperature ≥ [40°C]	25,177
Temperature ≥ [45°C]	878

Table A2
Seasonal differences in the impacts of sudden onset weather shocks.

	Rainfall ≥ 0.1	Rainfall ≥ 0.1	Snowfall	Snowfall	Wind ≥ 16	Wind ≥ 16
	Warm season	Cold season	Warm season	Cold season	Warm season	Cold season
Treatment	1.118**	2.445***	2.851	2.420**	− 0.384	− 0.142
	(0.380)	(0.340)	(1.830)	(0.450)	(0.370)	(0.410)
Post	2.703***	2.028***	2.642**	0.571	− 0.470	− 1.309**
	(0.400)	(0.307)	(1.120)	(0.460)	(0.280)	(0.470)
DiD	16.570***	10.200***	4.660***	12.200***	1.516**	2.205***
	(1.650)	(3.340)	(1.020)	(1.440)	(0.540)	(0.540)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.080	0.093	0.072	0.092	0.072	0.088
Observations	1,104,807	1,041,728	1,104,807	1,041,728	1,104,807	1,041,728

Notes: Cluster robust standard errors in parenthesis. The whole sample is split into two seasons. The warm season includes the months from April to September and the cold season entails the months from October to March. Airport, date, departure hour, aircraft and airline fixed effects and the number of seats are included in the regressions. The dependent variable in each specification is departure delay in minutes. The intensity of the respective weather condition considered as treatment is shown in the headers. Constant not reported. *, **, *** indicate 10, 5, 1% significance levels.

Table A3
Seasonal differences in the impacts of slow onset weather shocks.

	Temp ≤[-3 °C]	Temp ≤[-3 °C]	Temp ≥[40 °C]	Temp ≥[40 °C]
	Warm season	Cold season	Warm season	Cold season
Treatment	5.917***	2.288**	− 0.742**	− 0.551
	(1.950)	(0.370)	(0.320)	(4.890)
Constant	6.143***	7.228***	6.087***	7.300***
	(2.130)	(2.440)	(2.130)	(2.460)
Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.434	0.437	0.434	0.432
Observations	10,070	10,015	10,070	10,015

Notes: Cluster robust standard errors in parenthesis. The whole sample is split into two seasons. The warm season includes the months from April to September and the cold season entails the months from October to March. Airport, day fixed effects are included in the regressions. The dependent variable in each specification is mean departure delay in minutes. The intensity of the respective weather condition considered as treatment is shown in the headers. Constant not reported. *, **, *** indicate 10, 5, 1% significance levels.

Table A4
Peak capacity differences in the impacts of sudden onset weather shocks.

	Rainfall ≥ 0.1	Rainfall ≥ 0.1	Snowfall	Snowfall	Wind ≥ 16	Wind ≥ 16
	Peak capacity	Other	Peak capacity	Other	Peak capacity	Other
Treatment	0.684	1.988***	2.557**	2.001	− 1.216**	− 0.203
	(0.805)	(0.421)	(0.986)	(1.099)	(0.377)	(0.259)
Post	2.522***	2.759***	− 0.447	− 0.005	− 0.670*	− 0.603
	(0.473)	(0.237)	(0.728)	(0.377)	(0.413)	(0.467)
DiD	17.920***	12.520***	4.220**	11.810***	2.151***	1.877***
	(1.641)	(2.598)	(1.483)	(1.854)	(0.566)	(0.353)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.077	0.091	0.071	0.087	0.071	0.086
Observations	551,747	1,594,788	551,747	1,594,788	551,747	1,594,788

Notes: Cluster robust standard errors in parenthesis. Airport, date and departure hour fixed effects aircraft and airline fixed effects and the number of seats are included but not reported. The dependent variable in each specification is departure delay in minutes. The intensity of the respective weather condition considered as treatment is shown in the column header. The airport specific peak capacity is defined as flights departing at hours, which are above the 75th percentile in the total sum of hourly departures for each airport. *, **, *** indicate 10, 5, 1% significance levels.

Table A5
Peak capacity differences in the impacts of slow onset weather shocks.

	Temp ≤[-3 °C]	Temp ≤[-3 °C]	Temp ≥[40 °C]	Temp ≥[40 °C]
	Peak capacity	Other	Peak capacity	Other
Treatment	1.255	2.031***	− 0.163	− 0.634*
	(0.850)	(0.357)	(0.496)	(0.369)
Constant	8.387***	7.419***	8.356***	7.525***
	(2.972)	(2.338)	(2.973)	(2.345)
Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.577	0.467	0.577	0.465
Observations	5316	14,769	5316	14,769

Notes: Cluster robust standard errors in parenthesis. Prais-Winsten estimation airport and day fixed effects are included. The dependent variable in each specification is mean departure delay in minutes. The intensity of the respective weather condition considered as treatment is shown in the column header. The airport specific peak capacity is defined as flights departing at days which are above the 75th percentile in the total sum of daily departures for each airport. *, **, *** indicate 10, 5, 1% significance levels.

Table A6
Airline concentration differences in the impacts of sudden onset weather shocks.

	Rainfall ≥ 0.1	Rainfall ≥ 0.1	Snowfall	Snowfall	Wind ≥ 16	Wind ≥ 16
	High Conc.	Other	High Conc.	Other	High Conc.	Other
Treatment	0.776	1.554***	1.815	2.038*	− 0.415	− 0.633**
	(0.692)	(0.358)	(1.073)	(0.809)	(0.397)	(0.264)
Post	3.221***	2.509***	0.396	− 0.219	0.438	− 1.009*
	(0.369)	(0.267)	(0.750)	(0.292)	(0.306)	(0.449)
DiD	13.900***	13.520***	13.200***	10.400***	2.367***	2.021***
	(1.612)	(2.545)	(1.409)	(1.544)	(0.432)	(0.393)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.102	0.086	0.095	0.082	0.092	0.080
Observations	442,607	1,703,928	442,607	1,703,928	442,607	1,703,928

Notes: Cluster robust standard errors in parenthesis. Airport, date and departure hour fixed effects aircraft and airline fixed effects and the number of seats are included but not reported. The dependent variable in each specification is departure delay in minutes. The intensity of the respective weather condition considered as treatment is shown in the column header. High concentration departure hours are operated at maximum by 2 airlines. *, **, *** indicate 10, 5, 1% significance levels.

Table A7
Airline concentration differences in the impacts of slow onset weather shocks.

	Temp ≤[-3 °C]	Temp ≤[-3 °C]	Temp ≥[40 °C]	Temp ≥[40 °C]
	High Conc.	Other	High Conc.	Other
Treatment	2.800***	1.568***	− 0.947*	0.126

(*continued on next page*)

Table A7 (*continued*)

	Temp ≤[-3 °C]	Temp ≤[-3 °C]	Temp ≥[40 °C]	Temp ≥[40 °C]
	High Conc.	Other	High Conc.	Other
	(0.501)	(0.372)	(0.522)	(0.358)
Constant	8.990**	5.531**	8.791***	5.780**
	(3.615)	(2.433)	(3.622)	(2.434)
Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.481	0.611	0.478	0.610
Observations	8514	11,571	8514	11,571

Notes: Cluster robust standard errors in parenthesis. Prais-Winsten estimation airport and day fixed effects are included. The dependent variable in each specification is mean departure delay in minutes. The intensity of the respective weather condition considered as treatment is shown in the column header. High concentration departure days are operated at average by less than 3 airlines. *, **, *** indicate 10, 5, 1% significance levels.

Table A8
Estimates for the sudden onset events for large and small airports.

	Rainfall ≥ 0.1	Rainfall ≥ 0.1	Snowfall	Snowfall	Wind ≥ 16	Wind ≥ 16
	Large	Small	Large	Small	Large	Small
Treatment	1.712***	0.174	1.996*	2.144	− 0.501**	− 0.382
	(0.330)	(0.450)	(0.884)	(2.020)	(0.210)	(0.304)
Post	2.738***	2.534**	− 0.0927	− 0.166	− 0.637	0.339
	(0.280)	(0.520)	(0.350)	(0.825)	(0.410)	(0.260)
DiD	13.470***	7.114***	11.500***	1.207	2.016***	1.407**
	(2.150)	(1.080)	(1.588)	(2.305)	(0.310)	(0.520)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.085	0.131	0.080	0.128	0.079	0.128
Observations	2,146,535	142,719	2,146,535	142,719	2,146,535	142,719

Notes: Cluster robust standard errors in parenthesis. Airport, date, departure hour, aircraft and airline fixed effects and the number of seats are included in the regressions. The dependent variable in each specification is departure delay in minutes. The intensity of the respective weather condition considered as treatment is shown in the headers. Constant not reported. *, **, *** indicate 10, 5, 1% significance levels.

Table A9
Estimates of the slow onset events for large and small airports.

	Temp ≤[-3 °C]	Temp ≤[-3 °C]	Temp ≥[40 °C]	Temp ≥[40 °C]
	Large	Small	Large	Small
Treatment	2.058***	0.248	− 0.427	− 1.537
	(0.330)	(0.470)	(0.030)	(2.470)
Constant	7.282***	8.413**	7.402***	8.401**
	(2.290)	(3.740)	(2.290)	(3.740)
Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.434	0.265	0.433	0.265
Observations	20,085	20,018	20,085	10,015

Notes: Cluster robust standard errors in parenthesis. Airport, day fixed effects are included in the regressions. The dependent variable in each specification is mean departure delay in minutes. The intensity of the respective weather condition considered as treatment is shown in the headers. Constant not reported. *, **, *** indicate 10, 5, 1% significance levels.

Table A10
Estimates for heterogeneous treatment effect for different aircrafts.

	Rainfall ≥ 0.1	Rainfall ≥ 0.1	Snowfall	Snowfall	Wind ≥ 16	Wind ≥ 16
	(1)	(2)	(1)	(2)	(1)	(2)
Treatment	1.712***	1.799***	1.996*	1.901**	− 0.501***	− 0.534**
	(0.330)	(0.360)	(0.880)	(0.784)	(0.210)	(0.220)
Post	2.738***	2.742***	− 0.093	− 0.046	− 0.637	− 0.647
	(0.280)	(0.290)	(0.350)	(0.350)	(0.410)	(0.410)
DiD	13.470***	13.600***	11.500***	11.390***	2.016***	2.021***
	(−2.150)	(−2.220)	(−1.590)	(−1.560)	(−0.310)	(−0.300)
Large aircraft		3.430***		3.216***		2.633***

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Table A10 (*continued*)

	Rainfall ≥ 0.1	Rainfall ≥ 0.1	Snowfall	Snowfall	Wind ≥ 16	Wind ≥ 16
	(1)	(2)	(1)	(2)	(1)	(2)
		(0.760)		(0.820)		(0.710)
Treatment * large aircraft		− 2.035		4.359		0.815
		(1.190)		(5.280)		(1.040)
Post * large aircraft		− 0.265		− 1.048		0.229
		(0.680)		(0.600)		(0.390)
DiD * large aircraft		− 2.477		2.691		− 0.117
		(1.790)		(3.250)		(0.840)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.085	0.085	0.080	0.080	0.079	0.079
Observations	2,146,535	2,146,535	2,146,535	2,146,535	2,146,535	2,146,535

Notes: Cluster robust standard errors in parenthesis. Airport, date, departure hour, aircraft and airline fixed effects and the number of seats are included in the regressions. In Columns (2) it is additionally accounted for heterogeneous treatment effects across aircraft types. The dependent variable in each specification is departure delay in minutes. The intensity of the respective weather condition considered as treatment is shown in the headers. Constant not reported. *, **, *** indicate 10, 5, 1% significance levels.

Table A11
Difference-in-Difference estimates with varying length of post-treatment period.

	Length of the post-treatment period				
	all hours	+ 1h	+ 2h	+ 4h	+ 6h
Panel A: Varying post-treatment period for Rainfall ≥ 0.1					
Treatment	1.712**	1.717**	1.711**	1.707**	1.624***
	(0.330)	(0.520)	(0.480)	(0.380)	(0.320)
Post	2.738***	0.216***	0.433***	0.793***	1.041***
	(0.280)	(0.120)	(0.130)	(0.160)	(0.150)
DiD	13.470***	15.660***	16.440***	16.340***	16.300***
	(2.150)	(2.240)	(2.320)	(2.310)	(2.320)
Panel B: Varying post-treatment period for Snowfall					
Treatment	1.996*	2.039**	2.011*	1.995*	1.856*
	(0.880)	(0.620)	(0.630)	(0.380)	(0.780)
Post	− 0.093	− 0.265	− 0.261	− 0.026	0.0326***
	(0.350)	(0.450)	(0.420)	(0.350)	(0.350)
DiD	11.500***	16.570***	16.140***	15.880***	15.180***
	(1.590)	(2.070)	(1.990)	(2.120)	(2.240)
Panel C: Varying post-treatment period for Wind ≥ 16					
Treatment	− 0.501**	− 0.355	− 0.403	− 0.410	− 0.429
	(0.210)	(0.200)	(0.210)	(0.190)	(0.220)
Post	− 0.637	− 0.008	0.089	0.112	0.060
	(0.410)	(0.160)	(0.170)	(0.160)	(0.260)
DiD	2.016***	1.508***	1.678***	1.844***	1.929***
	(0.310)	(0.400)	(0.420)	(0.410)	(0.410)

Notes: Number of observations is 2,146,535. Cluster robust standard errors in parenthesis. The length of the post-treatment period is varied between one and six hours after the event. As a reference, the estimate for the whole day is reported in column (1). Airport, date, departure hour, aircraft and airline fixed effects and the number of seats are included in the regressions. The dependent variable in each specification is departure delay in minutes. The intensity of rainfall considered as treatment is shown in the headers. Constant not reported. *, **, *** indicate 10, 5, 1% significance levels.

Table A12
Weather at arrival airport.

	Rainfall ≥ 0.1	Rainfall ≥ 0.1	Snowfall	Snowfall	Wind ≥ 16	Wind ≥ 16
	(1)	(2)	(1)	(2)	(1)	(2)
Treatment	1.712***	1.876***	1.996*	2.083**	− 0.501***	− 0.452*
	(0.330)	(0.330)	(0.880)	(0.890)	(0.206)	(0.210)
Post	2.738***	2.889***	− 0.093	− 0.074	− 0.637	− 0.684
	(0.280)	(0.280)	(0.350)	(0.360)	(0.410)	(0.410)
DiD	13.470***	13.390***	11.500***	11.520***	2.016***	2.033***
	(2.150)	(2.170)	(1.590)	(1.590)	(0.310)	(0.320)
Weather Arrival	No	Yes	No	Yes	No	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.085	0.087	0.080	0.082	0.079	0.080

(*continued on next page*)

Table A12 (*continued*)

	Rainfall ≥ 0.1	Rainfall ≥ 0.1	Snowfall	Snowfall	Wind ≥ 16	Wind ≥ 16
	(1)	(2)	(1)	(2)	(1)	(2)
Observations	2,146,535	2,146,535	2,146,535	2,146,535	2,146,535	2,146,535

Notes: Cluster robust standard errors in parenthesis. Airport, date, departure hour, aircraft and airline fixed effects and the number of seats are included in the regressions. Columns (2) include weather conditions at the arrival airport at projected arrival time. The dependent variable in each specification is departure delay in minutes. The intensity of the respective weather condition considered as treatment is shown in the headers. Constant not reported. *, **, *** indicate 10, 5, 1% significance levels.

Table A13
Results for the full sample as well as different outlier thresholds

	Rainfall ≥ 0.1	Rainfall ≥ 0.1	Rainfall ≥ 0.1	Rainfall ≥ 0.1
	Full	Delay < 500min	Delay < 150min	Delay < 300min
Treatment	2.221***	2.144***	1.009***	1.712***
	(0.390)	(0.360)	(0.270)	(0.330)
Post	2.902***	2.886***	1.868***	2.738***
	(0.310)	(0.310)	(0.180)	(0.280)
DiD	14.710***	14.400***	9.298***	13.470***
	(2.540)	(2.450)	(1.290)	(2.150)
Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.073	0.080	0.087	0.085
Observations	2,150,015	2,149,435	2,122,764	2,146,535

Notes: Cluster robust standard errors in parenthesis. Airport, date, departure hour, aircraft and airline fixed effects and the number of seats are included in the regressions. The dependent variable in each specification is departure delay in minutes. The departure delay considered as threshold for outliers is shown in the headers. Constant not reported. *, **, *** indicate 10, 5, 1% significance levels.

Table A14
Weather at arrival airport.

	Rainfall ≥ 0.1	Rainfall ≥ 0.1	Snowfall	Snowfall	Wind ≥ 16	Wind ≥ 16
	(1)	(2)	(1)	(2)	(1)	(2)
Treatment	1.712***	1.737***	1.996*	2.008**	− 0.501***	− 0.515**
	(0.330)	(0.320)	(0.880)	(0.270)	(0.210)	(0.210)
Post	2.738***	2.734***	− 0.093	− 0.078	− 0.637	− 0.633
	(0.280)	(0.280)	(0.350)	(0.360)	(0.410)	(0.410)
DiD	13.470***	13.470***	11.500***	11.340***	2.016***	2.010***
	(2.150)	(2.140)	(1.590)	(1.560)	(0.310)	(0.310)
Time Trend	No	Yes	No	Yes	No	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.085	0.086	0.080	0.081	0.079	0.079
Observations	2,146,535	2,146,535	2,146,535	2,146,535	2,146,535	2,146,535

Notes: Cluster robust standard errors in parenthesis. Airport, date, departure hour, aircraft and airline fixed effects and the number of seats are included in the regressions. Columns (2) additionally include an airport specific parametric time trend. The dependent variable in each specification is departure delay in minutes. The intensity of the respective weather condition considered as treatment is shown in the headers. Constant not reported. *, **, *** indicate 10, 5, 1% significance levels.

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