Just a Minute

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Abstract

Economic theories suggest that incentive programs can reduce congestion inefficiencies and lead to welfare gains in many markets where congestion is present. The presence and size of any welfare gains rely both on the distribution of user elasticities, as well as the extent to which a marginal user affects the outcome of other users. Quantifying the latter is an empirical challenge for many markets because of the potential endogeneity. In this paper, we present empirical evidence of the latter in the context of air traffic congestion at departing airports. We exploit the exogeneity of unscheduled flights relative to regularly scheduled commercial service as a quasi-experiment and test how an additional flight on the runway affects departure performance for scheduled flights. We find a sizable congestion effect from an unexpected flight on scheduled flights, and with a strong effect during peak hours and when the airport approaches its capacity. Simple simulation exercises suggest sizable time savings if airports and air traffic authorities incentivize or nudge unscheduled flights to change marginal minutes; or if negotiation and trade can be achieved across carriers.

Keywords: Congestion, air transportation, air traffic congestion, unscheduled flights, departure delays, runway waiting, gains from trade

JEL codes: H21, L9, L93, R4

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1 Introduction

Economists have studied congestion and recommended incentive-based interventions such as tolls and critical-time pricing as early as Walters (1961) and Vickrey (1963). Regulating authorities and private companies have adopted and experimented with interventions in many markets such as time-varying tolls on highways, critical-peak pricing by utility companies, tolls and fees for freight congestion, congestion pricing for EV charging stations, and the recent "wait and save" option on Uber to cross-subsidize elastic riders to wait, etc.

The magnitude of the efficiency and welfare gains from those public policy interventions and private company strategies crucially depend on (i) whether a subset of users are elastic enough to respond to incentives, and (ii) how much the marginal user contributes to congestion and affects the quality of the goods and services other users consume. The former has been studied extensively across many markets and industries.[1] Quantifying the latter is an empirical challenge as congestion is endogenous, common in many use cases such as highways, internet, EV stations, and air transportation. In air transportation, this endogeneity can arise when carriers schedule their flights for departure at a congested time to increase profits (e.g., Mayer and Sinai, 2003; Rupp, 2009) or to avoid congested times for better performance.[2] In the ideal setting, for commuter traffic or air transportation, we need to observe how traffic and congestion change as vehicles or flights were introduced into or removed from the traffic at random locations and times. As randomized control trials are rarely feasible to implement, we study this question in a unique scenario with quasi-experiment variation.

This paper focuses on the context of air transportation. Our empirical design and analysis are based on newly collected information on unscheduled flights in major US airports from 2014 to 2017. Commercial passenger service accounts for about 90% of total flights departing from the top 40 US airports during this time period, usually known as *scheduled flights*. The remaining 10% of flights are unscheduled on-demand service, usually known as *unscheduled flights*. They include mostly charter flights for individuals and entities to rent, and also

[1] For commuters, Arnott et al. (1993) studied the congestion pricing theories for elastic commuters and expanded to heterogeneous commuters; Bento et al. (2020) and (Kreindler, 2023) documented heterogeneous willingness-to-pays for waiting and value of time and urgency. For the electricity market, Blonz (2022) documented the heterogeneous response to critical-peak pricing by Pacific Gas & Electric (PG&E) across time and users, and Lijesen (2007) found time-varying demand elasticities using Netherlands data. For air traffic, Daniel (2001) studied the implication of congestion pricing when demand is elastic based on the model of Daniel (1995). For other markets, Huang and Kockelman (2020) studied the time-varying response for EV station congestion.

[2] A substantial body of research has developed the theories and documented evidence that air congestion and delays are correlated with factors of profitability, such as market power and airfare (Bilotkach and Pai, 2020; Bilotkach and Lakew, 2022; Brueckner, 2002, 2005; Forbes, 2008; Mazzeo, 2003).

include private flights, cargo flights (e.g., DHL), military flights (e.g., F18 jets), and very occasionally flights rerouted by scheduled carriers. The nature of the on-demand service makes the timing that a marginal unscheduled flight joins and leaves the runway orthogonal and unpredictable to scheduled flights down to a particular minute. We observe that they neither tend to depart during peak time when scheduled flights cluster to depart, nor tend to avoid the peaks (see Section 2 for the details).

Unscheduled flights are not just good candidates for conducting quasi-experiments for scheduled flights, these flights are of great policy importance too. For example, before the FIFA World Cup 2022, air traffic authorities in Qatar were concerned about congestion on scheduled flights as charter flights started to surge in demand in November and December and considered temporary policy options.[3]

Because of its own importance and its exogenous nature relative to scheduled flights, we leverage the variation in unscheduled flights for our empirical design. We estimate (i) how the number of unscheduled flights that have left the gate and are still in the queue to take off at any point in time has affected the departure outcomes of a scheduled flight - departure delays and taxi-out time, and (ii) how such effects vary by time of day. Our sample includes all flights (i.e., all *scheduled* domestic and international flights and all *unscheduled flights*) departing from the Top 40 US airports from 2014 to 2017. Our study focuses on departure flights as past studies suggest potential congestion for departing flights driven by clustering but find no evidence for arrival clustering (Mayer and Sinai, 2003).

In addition to unscheduled flights, our identification also relies on the exhaustive sets of fixed effects that we deploy using high-frequency flight data. Our fixed effects allow us to compare otherwise similar scheduled flights that depart at the same airport, the same year and quarter, the same day of the week, and similar times in the day (down to every 15 minutes), but experience different shocks from unscheduled flights right ahead of them.

We find sizable contemporaneous increases in departure delays and taxi-out time from unscheduled flights, with stronger effects during busier times of the day. If an unexpected flight was added in front of the queue, a scheduled flight would expect a greater departure delay, ranging from 0.2 to 0.9 minutes depending on the time of the day (excluding midnight and very early morning); and a greater taxi-out time, ranging from 0.1 to 0.4 minutes. Moreover, these effects can easily be 10 times stronger when the departing airport is capacity-constrained (above 75% of maximum quarterly capacity).

[3] https://www.businessairportinternational.com/opinion/charter-flights-witness-surge-in-demand-ahead-of-the-fifa-world-cup-2022.html

Our estimates suggest that there are important gains if unscheduled flights can be incentivized to change their departing time with minimum effort. We simulate the time savings for scheduled flights from a shorter departure delay and taxi-out time when unscheduled flights can shift their departure time by up to +/- 1, 2, 3, ... to 20 minutes. We find sizable benefits from marginal changes, hence the title of this paper. For example, if all unscheduled flights can marginally move up to +/- 5 minutes, the time savings on scheduled flights will be 63 minutes per day at an origin airport; and this number can tripple and quadruple on congested days. The time savings will be greater if unscheduled flights can move more such as up to +/- 10 or 15 minutes. These numbers serve as a lower bound of potential benefits, as we only calculate the time savings for scheduled flights that are immediately affected by such change. Gains will also be greater if we allow scheduled flights (90% of all flights) to internalize some of the externality.

Our results suggest there is low-hanging fruit for air regulating authorities when it comes to mitigating congestion, as long as there are unscheduled flights that are elastic enough to move marginally earlier or later. A similar conclusion can be reached if we allow scheduled carriers (e.g., Delta Airlines) and unscheduled carriers (e.g., charter carriers) to trade, subject to some caveats discussed in Section 4.2. Lastly, our policy implications can be further extended to possible trading among scheduled carriers (e.g., Delta Airlines and American Airlines) as there is a missing market of congestion. Scheduled carriers have already started and derived benefits from incentivizing their overbooked passengers to wait. There may be similar gains if, for example, there is a market to allow hub carriers to compensate other carriers for moving departure by a few minutes marginally.

Our study adds to the literature that studies various forms and considerations of congestion pricing in the context of air transportation (e.g., Daniel, 1995, 2001; Daniel and Harback, 2008; Ater, 2012) and its interactions with capacity expansion (e.g., Chu and Zhou, 2022; Zhang and Zhang, 2003, 2006). Our results suggest that implementing previously proposed incentives can be implemented creatively and not just limited to scheduled flights, which has been the focus of the literature to date, but applied to all relatively elastic flights, including unscheduled flights.

2 Data and background

Scheduled and unscheduled flights. To operate a flight service in US airports, the Federal Aviation Regulation (FAR) mandates carriers obtain either the "Title 14 of the Code of Federal Regulations (CFR) Part 121 Air Carrier Certificate (14 CPF 121 Certificate)" for scheduled operations, or the "Title 14 of the CFR Part 135 Air Carrier Certificate (14 CFR 135 Certificate)" for unscheduled operations.

Civilian commercial airlines such as Delta Airlines (DL) and American Airlines (AA) regularly schedule their flights by reserving and publishing the planned departure and arrival times ahead of time in a scheduled distribution system, such as the Official Airline Guide (OAG), the airline's own timetable, other federal and commercial computer reservation systems (CRS), and global distribution systems (GDS). These airlines hold the 121 Certificate to operate their scheduled flights. We refer to these carriers as *scheduled carriers*; we refer to their flights as *regularly scheduled* or simply *scheduled flights*. This paper focuses on congestion experienced by scheduled flights.

In contrast with scheduled flights, some flights are operated on-demand and added at a particular time on the day of departure. These flights account for 10.2% of our sample, which includes all fights that departed from the Top 40 airports from 2014 to 2017. These flights are known as *unscheduled flights*.[4] Carriers that hold the 14 CPF 135 Certificates are allowed to operate unscheduled, on-demand service, as well as very limited scheduled service.

In our dataset, the majority of unscheduled flights are charter flights. Charter carriers provide rental charter services to individuals and entities. Consumers can purchase single tickets on public charter flights without a pre-determined schedule or rent the whole flight as a private flight. For example, special event tours for sports teams or political campaigns often use charter flights.[5] In addition to charter flights, we observe some private flights (operated with private jets) and cargo flights (such as Amazon and DHL). In rare cases, we observe military flights and government-sponsored flights, inferred by aircraft models (e.g., we observe a few F18 jets). In a very small number of observations, scheduled carriers operate unscheduled flights to make up for cancellation, deadhead flights for next-day allocation, or diverted flights from and/or to an unscheduled airport (these carriers usually hold both the 121 and 135 Certificates to occasionally operate on-demand service).

Dataset and supporting evidence. Our analysis is based on the newly obtained historical flight data from the Official Airline Guide (OAG), which collects the most comprehensive flight data available. Our dataset includes 24 million unique scheduled flights and 2.8 million unscheduled flights departing from a top 40 US airport to any domestic and international

[4] Federal Aviation Administration (FAA) definition:
https://www.faa.gov/licenses_certificates/airline_certification/135_certification.

[5] More examples of charter flights:
https://www.transportation.gov/individuals/aviation-consumer-protection/charter-flights.

destination from 2014 to 2017.[6] Our analysis is conducted on the 24 million scheduled flights. Panel A.1 of Table 1 reports the summary statistics for the outcome variables - the average departure delay is 10 minutes, and the average taxi-out time is 18 minutes, both with a good amount of variation.

To establish supporting evidence of the quasi-randomness of the unscheduled flights experienced by scheduled fights, we examine the distribution of unscheduled flights during different times of the day. Figure 1 plots the total number of unscheduled and scheduled fights by their actual departure time in a day. Two patterns emerge from this figure: (i) scheduled flights appear to have multiple peak times, as documented by Mayer and Sinai (2003), although the peaks do not appear to be very dramatic since we aggregate all flights across 40 airports, which have different peak times; (ii) the distribution of unscheduled flights is much more even compare to scheduled flights. It appears that (a) airports are not busy operating departing unscheduled flights at the same time when scheduled flights are busy departing, and that (b) departing unscheduled flights do not dodge the peak times clustered by scheduled flights.

To assess the distribution of these two types of flights within an airport, we examine two specific airports on an arbitrary day, Friday, July 1st, 2016, and repeat the same exercise. Figure 2 shows the distribution of departing unscheduled and scheduled flights at Dallas-Fort Worth International Airport (DFW) and Charlotte International Airport (CLT). Panels A and B show clear clustering patterns of scheduled flights consistent with Figure 1. In contrast, we do not observe a clear pattern of unscheduled flights. Panel A shows that while there are some earlier unscheduled flights at DFW on that particular day, they may depart both outside of peak hours (e.g., 6:15-6:45 am) and also coincident with peak hours (e.g., 6:45-7:15 am). Similarly in Panel B, unscheduled flights appear to depart at random times relative to scheduled flights, whether there is no peak (e.g., 12:00-12:30 pm), or a peak (e.g., 11:30-11:45 am). We find similar patterns at other airports on this day and other arbitrary days. In some cases, the clustering pattern of scheduled flights may be less dramatic if the market is less concentrated (as documented in Mayer and Sinai, 2003); we still observe a similar even and seemingly random distribution of unscheduled flights relative to scheduled flights.

3 Empirical approach

Constructing the measure of unexpected flight shocks. We begin by measuring the degree of unexpected flights that a scheduled flight i experiences measured by unscheduled

[6] Appendix Section A.1 describes the OAG dataset and lists the airports in our sample.

flights. For a scheduled flight i that is scheduled to depart from airport o at a particular minute τ, we count the number of departed unscheduled flights $n_{o\tau}$ that are ahead of flight i in the queue to take off: $n_{o\tau}$ equals the number of unscheduled flights that have already departed from the gate and have not taken off yet based on the timestamps of their departure (i.e., outgate) time and in-air (i.e., wheel-off) time.

On average, a scheduled flight experiences 0.5 unscheduled flights by its scheduled outgate time (Table 1 Panel A.2). We see a lot of variation in $n_{o\tau}$ - the standard deviation is 0.9, with 36% of scheduled flights experiencing at least 1 unscheduled flight, 12% at least 2, 1% at least 4, and 0.1% at least 6.

Departure delay analysis. We begin by estimating how an unexpected flight affects the departure delay of a scheduled flight. We illustrate the thought exercise in Appendix Figure A.1 Panel A. For a scheduled flight i that is scheduled to depart from the gate at the airport o at time τ, the realized (actual) outgate time is distributed around τ without additional shock, illustrated in the black dotted line. When flight i experiences $n_{o\tau}$ unscheduled flights ahead of it to take off at time τ, these unexpected flights will shock the distribution of realized outgate time of flight i to a new distribution, illustrated in the red dashed line. The difference between realized and scheduled outgate time is the departure delay.

Based on this thought exercise, we specify and estimate the following equation. For a scheduled flight i departing from an origin airport o in a given year y, month m, and a scheduled outgate time τ (down to a particular minute):

$$\text{departure delay}_{io\tau} = \beta_{1h} n_{o\tau} + \phi_{ob} + \phi_{ym} + \varepsilon_{io\tau} \quad (1)$$

The key parameter of interest is β_{1h}, which we allow to vary, every two hours h, to capture heterogeneity arising from the plausible peak and less busy times in a day. The main identifying fixed effects are the airport by time block fixed effects ϕ_{ob}. We construct ϕ_{ob} by interacting the origin airport o, with year y, quarter q, day-of-a-week, (scheduled) hour-of-a-day, and (scheduled) 15-minute slot in of an hour. These very fine fixed effects allow us to compare the departure delay of otherwise similar flights. For example, (i) one that departed from Atlanta (ATL) on Sunday, November 1st, 2015, during the 12:00–12:15 pm block of time versus (ii) another flight that departed from ATL also during 12:00–12:15 pm on Sunday, November 22nd, 2015 within the same quarter of 2015, but experienced a different number of shocks from unscheduled flights $n_{o\tau}$. Also, we remove potential temporal unobservables by including year-by-month fixed effects ϕ_{ym}.

One may specify a naive version of our baseline using the total number of scheduled flights $r_{o\tau}$ (instead of $n_{o\tau}$) due to data availability constraints (e.g., using the DOT publicly available data). The challenge, common in other contexts such as commuter traffic, is that the number of flights at a given minute $r_{o\tau}$ potentially congesting a flight i behind them in the queue can be correlated to the departure delay and the taxi-out time of flight i. Our empirical design allows us to overcome this endogeneity challenge by exploiting both (i) the relative quasi-random variation that arises from unscheduled flights and (ii) very fine grids of fixed effects.

Taxi-out time analysis. We use similar methods to estimate the effect of unexpected flights on taxi-out time. We illustrate our strategy in Appendix Figure A.1 Panel B. For a scheduled flight i that departs (leaves the gate) at time t, the realized take-off (in-air) time is distributed around a slightly later time due to the physical time needed to take off, as shown in the black dashed line. When there is n_{ot} unexpected flights on the runway, the distribution of realized take-off time will be shifted to a new distribution, as shown in the blue dashed line. The difference between the realized take-off time and realized outgate time is the taxi-out time. Therefore, we estimate the following equation for the taxi-out time:

$$\text{taxi-out}_{iot} = \beta_{1h} n_{ot} + \phi_{ob} + \phi_{ym} + \varepsilon_{iot} \tag{2}$$

To be consistent with the departure delay analysis, here we specify the same set of fixed effects as in Equation (1). Given that the shock n_{ot} arrives at the actual outgate time t, we use this as the reference time.[7]

We do not have to impose the strong assumption that scheduled airlines have no industrial knowledge of when an airport is busier in a day and, therefore cannot incorporate that information into their decisions. We only need to assume that (i) scheduled carriers' knowledge and foresight regarding the variation in n down to every single minute within a 15-minute block is imperfect, or (ii) neither carriers nor the airport tower can react perfectly in the immediate short-run given the frictions that carriers and air traffic towers face. For example, commercial airlines usually publish their schedules 9-12 months ahead of time on multiple Computer Reservation Systems (CRS), and it takes time and is costly to reschedule flights (see Rule 14 CFR § 255 for regulation details and Borenstein (1999) and

[7] All variables and controls in Equation (2) are constructed using the actual outgate time t, e.g., n_{ot} and ϕ_{ob}. We set up different reference times in Equations (1) and (2) based on our thought exercises in Appendix Figure A.1. Nevertheless, our estimated β_{1h} are almost identical if we instead estimate Equation (1) using actual outgate time t as the reference time, or if we estimate Equation (2) with scheduled outgate time τ as the reference time. The only difference is that using t as reference time leads to a greater R-squared as the fixed effects capture more variation.

Forbes (2008) for discussions). Engineering and economic literature on dynamic schedule recovery suggest that what carriers can do on the fly (immediate re-optimization) is quite limited and very costly (Rupp et al., 2005; Evler et al., 2021). Also, other aviation regulations make it difficult for carriers to do short-run rescheduling, such as duty period regulation for crew members. Similarly for airports, the terminal tower and ground staff are not scheduled to work on a dynamic shift contract to counteract the fluctuating demand shocks, so the ability of an airport to respond rapidly to changes on the fly is limited.

Capacity constraint. Our baseline allows β_1 to vary by the time of a day h (every 2-hour block) which, in practice, is a semi-parametric approach to incorporate the heterogeneous marginal effects of unexpected flights by whether all airports tend to be busy or not at the time h. To allow for some sophistication and for each airport to have its own effect, we propose to directly allow β_1 to take a different slope when an airport approaches its own capacity constraint. Table 1 Panel A.2 reports that on average a scheduled flight i experiences 13 other scheduled flights r that have left the gate and are waiting to take off; the average quarterly maximum r_{oq}^{max} that a flight i experiences at airport o is 43.

We begin by examining plausible suggestive evidence for our speculation by comparing r versus r_{oq}^{max}, which approximates airport o's *quarterly capacity*. We compare the outcome variables (departure delays and taxi-out time) based on whether the number of scheduled flights on the runway that flight i experiences, r, is greater than or less than 75% of r_{oq}^{max}. Table 1 Panel B shows that, on average, flight i's departure delay is about 4 minutes longer, and its taxi-out time is 19 minutes longer, if it departs at a time that exceeds 75% of the departure airport's quarterly capacity; and the differences are statistically significant.

Alluded to by results in Table 1 Panel B, we add an interaction term $\mathbb{1}(r > \delta r_{oq}^{max})(r - \delta r_{oq}^{max})$ for each two-hour block to our baseline models and estimate:

$$\text{departure delay}_{io\tau} = \beta_{1h} n_{o\tau} + \beta_{2h} n_{o\tau} \mathbb{1}(r_{o\tau} > \delta r_{oq}^{max})(r_{o\tau} - \delta r_{oq}^{max}) + \phi_{ob} + \phi_{ym} + \varepsilon_{io\tau} \quad (3)$$

$$\text{taxi-out}_{iot} = \beta_{1h} n_{ot} + \beta_{2h} n_{ot} \mathbb{1}(r_{ot} > \delta r_{oq}^{max})(r_{ot} - \delta r_{oq}^{max}) + \phi_{ob} + \phi_{ym} + \varepsilon_{iot} \quad (4)$$

The parameters of interest are β_{1h} and β_{2h} at different times of the day h. Our specifications follow recent studies that incorporate increasing marginal cost due to capacity constraints (e.g., Ryan, 2012; Farronato and Fradkin, 2022). Similar to Farronato and Fradkin (2022), we set a threshold $\delta = 0.75$ and allow the marginal effect of an extra unscheduled flight to increase when the departing airport approaches its quarterly maximum. Our results are robust if we set an alternative δ such as 0.7, 0.8, or 0.85.[8]

4 Results

4.1 Estimation results

Baseline estimates. We report our baseline estimates for Equations (1) and (2) in Table 2 columns 1 and 3. We allow β_{1h} to vary every two hours from 8:00 am to 11:59 pm, and we place all flights from 12:00 am to 7:59 am into one group to deal with the power issue from a lack of variation in a less busy time. We cluster the standard errors at the departing airport level throughout all our regressions to conservatively allow for correlation across error terms.

We find sizable and positive $\hat{\beta}_{1h}$ for both departure delays (column 1) and taxi-out time (column 3). Table 2 column 1 shows that $\hat{\beta}_{1h}$ ranges from 0.2 to 0.9 depending on the time of the day h (excluding midnight and early morning till 7:59 am, for which we find very small and imprecise $\hat{\beta}_{1h}$). Our estimates suggest that an extra unexpected flight from an unscheduled flight will increase departure delay for scheduled flights from 0.2 to 0.9 minutes for most of the business hours of a day, which is quite sizable. Also, $\hat{\beta}_{1h}$ tends to be greater for busier hours of a day, such as 10:00-11:59 am and 6:00-9:59 pm; and smaller for less busy hours of a day such as 2:00-4:59 pm.

For taxi-out time, Table 2 column 3 shows, that we find $\hat{\beta}_{1h}$ ranges from 0.1 to 0.4, i.e., an extra unexpected flight from an unscheduled flight will increase taxi-out time for a scheduled flight from 0.1 to 0.4 minutes on average. Similar to column 1, we also find that $\hat{\beta}_{1h}$ tends to take a greater value during busier times of the day and is smaller in less busy times.

Our results are robust if we start at 6:00 am and have an extra group from 6:00–7:59 am. The coefficients for the 6:00-7:59 am very small and insignificant. Also, our results are robust if we allow β_{1h} to vary at a longer time block (e.g., every 3 hours) or a shorter block (e.g., every hour). We will capture slightly less heterogeneity if β_{1h} varies every 3 or 4 hours, and we will have less precise results if we let β_{1h} vary every hour.

Incorporating capacity constraint. We proceed to estimate equations (3) and (4) which allow the slope to vary as the airport approaches its quarterly capacity. Table 2 columns 2 and 4 report the results. We find that the coefficients $\hat{\beta}_{1h}$ in columns 2 and 4 are very

[8] Our goal is to capture an increasing slope. So we set an arbitrary threshold as in Farronato and Fradkin (2022) rather than estimating βs and δ jointly as in Ryan (2012). Our result is robust if we further add a quadratic term $\mathbb{1}(r > \delta r_{oq}^{max})(r - \delta r_{oq}^{max})^2$.

similar to columns 1 and 3. This suggests that our baseline captures the marginal effect at most times of the day at an airport when the origin airport is less constrained.

We find $\hat{\beta}_{2h}$ are mostly positive and very sizable. These estimates suggest a greater marginal effect of unexpected flights at some times of the day. During occasional times h of the day, our estimates are less precise due to a lack of observations.

To interpret the magnitude of $\hat{\beta}_{2h}$, we produce the implied marginal effects under a few sets of scenarios in Appendix Table A.1. We consider the cases when the number of scheduled flights that a scheduled flight i experiences exceeds 75% of quarterly capacity r_{oq}^{max} by 1, 2, 5, and 10 flights. These are reasonable and modest numbers to consider based on the variation of these two variables (see Table 1 Panel A.2).

When the number of scheduled flight surpasses the departing airport's 75% quarterly capacity by 1, i.e., when $(r - 0.75 \cdot r_{oq}^{max}) = 1$, the marginal effect of n on departure delay ranges from 0.5 to 2.2 minutes (2 to 10 times the delays during less constrained hours); this number ranges from 0.9 to 2.6 minutes for taxi-out time (4 to 16 times the delays during less constrained hours), both excluding midnight and the early morning. These are very sizable numbers and apply to a decent share of scheduled flights. In our data, 0.5% of scheduled flights depart at a time when r exceeds the airport's 75% quarterly capacity.

The marginal effect is even greater when $(r - 0.75 \cdot r_{oq}^{max})$ takes on a greater value. When 5 extra scheduled flights exceed 75% of quarterly capacity r_{oq}^{max}, an unexpected flight will increase departure delays by 1.3–10.3 minutes (5 to 17 times the delays during less constrained times) and taxi-out time by 3.6–12.3 minutes (19 to 76 times the delays during less constrained time). When this extra number hits 10, the marginal effect on departure delays shoots up to 2.3-20.4 minutes (11 to 91 times the delays during less constrained times) and taxi-out time to 7.0-24.3 minutes (38 to 153 times the delays during less constrained times).

Lastly, the slope increase is much stronger for taxi-out time than departure delays especially during busier hours, which suggests the congestion arising from unexpected flights increases taxi-out time much more than departure delay as the airport approaches its capacity. Also, our findings add supporting evidence to the theories and empirical works that find airport capacity expansion or technological upgrade may lead to improvement in air travel performance (e.g., Zhang and Zhang, 2003, 2006; Morrison and Winston, 2008; Chu and Zhou, 2022).

Robustness. Our results are robust to the consideration of the slot-administrated airports, the number of terminals, the adoption of runway technologies, richer fixed effects, a host of other considerations, and alternative parametric specifications (see Appendix Section A.2).

4.2 Implications

Our empirical results suggest that there are gains for scheduled flights if unscheduled flights can move a few minutes before or after their departure time marginally. To assess the magnitude of such gains, we first consider the scenario when we allow all unscheduled flights to move up to +/- 1, 2, 3..., and till up to +/- 20 minutes. We simulate these scenarios by carrying out 1,460 simulations for all days in the sample for all airports.

We present these base simulation results in Figure 3 Panel A in the solid black line. Even just marginally having all unscheduled flights move up to +/- one minute will lead to total daily time savings for scheduled flights by 20 minutes at the origin airport, hence the title of the paper. If unscheduled flights can move up to +/- 5 minutes, the gains for scheduled flights amount to 63 minutes per day per airport. The gains are much more pronounced for congested days and locations. For example, the 90th and 95th percentile of the above time savings are 2 and 2.5 hours, respectively (see Figure 3 Panel B). These numbers are quite sizable given the minimal amount that unscheduled flights may move.

The gains are greater if unscheduled flights can move up to a wider range of minutes. Figure 3 Panel A shows that the average time savings go up to 100 minutes, 128 minutes, and 146 minutes per airport per day, if unscheduled flights can move up to +/- 10, 15, and 20 minutes, respectively. In Appendix Section A.3, we explain the source of the gains.

Our base simulation implicitly assume that as long as the adjustment is minimal, the unscheduled flights are sufficiently elastic to move and the marginal cost is little. Alternatively, to be very conservative, we can account for these factors. In an alternative simulation, we allow an unscheduled flight to move up to +/- certain minutes to maximize the time savings for scheduled flights within that movable range and at the same time net out the total minutes the unscheduled flight can move.[9]

As shown in Figure 3 Panel A dash black line, we find sizable savings for scheduled flights under this very conservative assumption too. For example, if unscheduled flights can move

[9] This is under a conservative assumption that the marginal cost to move a minute is the same for unscheduled and scheduled flights. While the demand elasticity with respect to price may be much higher for some unscheduled flights (e.g., some private charter), the elasticity of moving a marginal minute may be much lower given that (i) there are many more passengers on scheduled flights and (ii) scheduled carriers need to make their flights arrive on time for both DOT on-time regulation and their own connectability.

up to +/- 5 minutes, the gains for scheduled flights amount to 36 minutes per day per airport, 57% of the base simulation. Similarly to the base simulation, the gains may easily tripple or quadrupple in congested days.

Our simulated gains serve as a lower bound, as we only calculate the gains for scheduled flights i that are *immediately* affected by the unscheduled flights. The gains may be greater if we consider additional spillover from temporal propagation within an airport across carriers Lam and Zhou (2021) and spatial propagation within a carrier over destinations (Brueckner et al., 2022). Our results serve as a reference for policymakers to consider how much they need to compensate for unscheduled flights to move. Our results also imply that there are sizable gains if there is a market between unscheduled carriers and scheduled carriers to trade.[10]

The benefit that we found is not restricted to moving unscheduled flights. Our study uses unscheduled flights as a source of identification to estimate the effect of flight departure time adjustment and potential gain. Although the magnitude of effects for moving scheduled flights (i.e., moving a United flight at ATL) is not as easily identified unless in a randomized trial or at least in an airport-wide quasi-experiment setting, marginally moving a scheduled flight can generate time savings in the same nature as that of an unscheduled flight. Unscheduled flights only account for 10% of total flights departing from the US Top 40 airports, and the remaining 90% come from scheduled flights. Therefore, there can be even greater welfare and efficiency gains if a market can be created across scheduled carriers to allow them to trade a few marginal minutes (e.g., let United and Delta trade). Also, our findings are not restricted to the public policy of air traffic congestion. Broader gains may be achieved in other markets that experience congestion. For example, Starbucks recently started to experiment with the gains from having an option to "pay to skip the line".[11] More research will be needed to study both (i) the willingness-to-pay as well as (ii) the effect of the marginal user on other users in other markets.

Lastly, our simulation scenario stops at +/- 20 minutes as we consider the cases in which unscheduled flights are likely elastic enough to move. As we increase beyond that range, it is possible only a smaller subset of unscheduled flights are willing or feasible to move. If we further extrapolate the gains beyond +/- 20 minutes, there may be diminishing marginal

[10]This is subject to caveat. For example, there may be a free rider problem due to multiple carriers. This may be less of a concern for hub carriers at a hub as they have a clear clustering pattern and may be interested in negotiating with other carriers so that their flights can depart sooner. For another example, this may create a moral hazard problem in which some unscheduled flights game the system.

[11]https://www.insider.com/starbucks-app-lets-you-skip-the-line-2016-6.

returns of time savings for scheduled flights. As we do not directly estimate the demand elasticity and willingness-to-pay to move, we leave that to future research.

5 Conclusion

We document and estimate the effect of an unexpected flight on regularly scheduled commercial passenger flights by exploiting the quasi-randomness of the departure of unscheduled flights. We find a sizable increase in departure delay and taxi-out time from an unexpected flight. Our findings imply sizable gains from incentivizing unscheduled flights to move a few marginal minutes. A similar conclusion can be reached if a market can be created to allow carriers to trade, both between unscheduled and scheduled carriers such as Delta Airlines, or between scheduled carriers such as between Delta Airlines and United Airlines; or if incentives are created by airports or air traffic authorities. Our results also speak in general to the general body of literature that estimates the congestion effect of an unexpected marginal user on other users such as commuter traffic.

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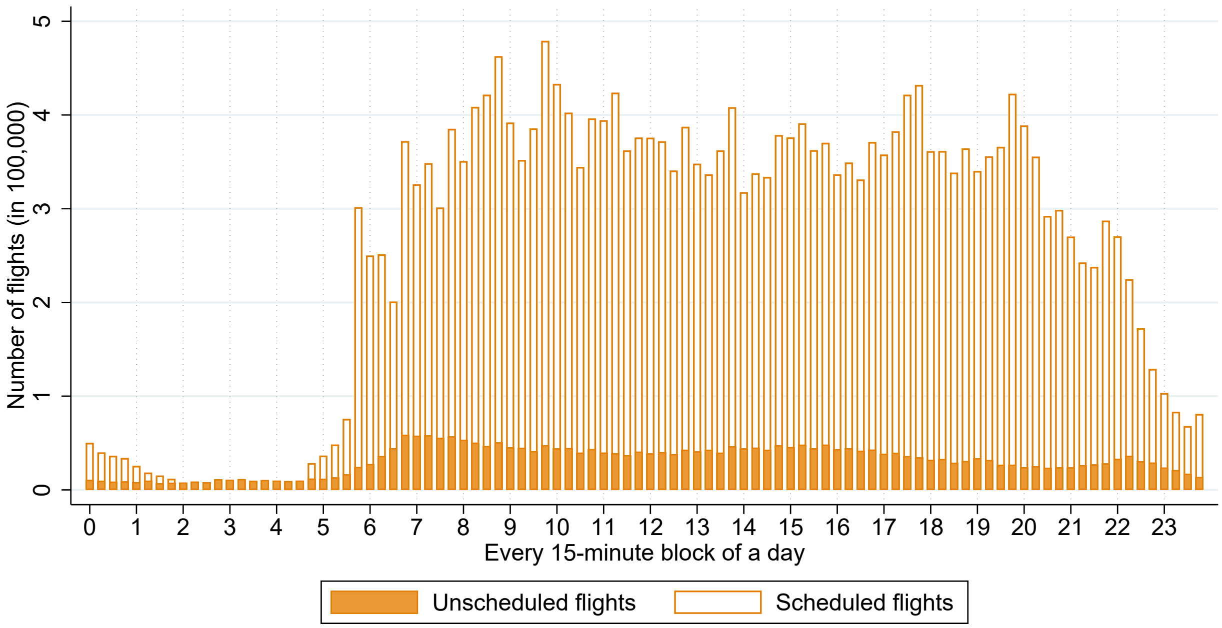
Figures

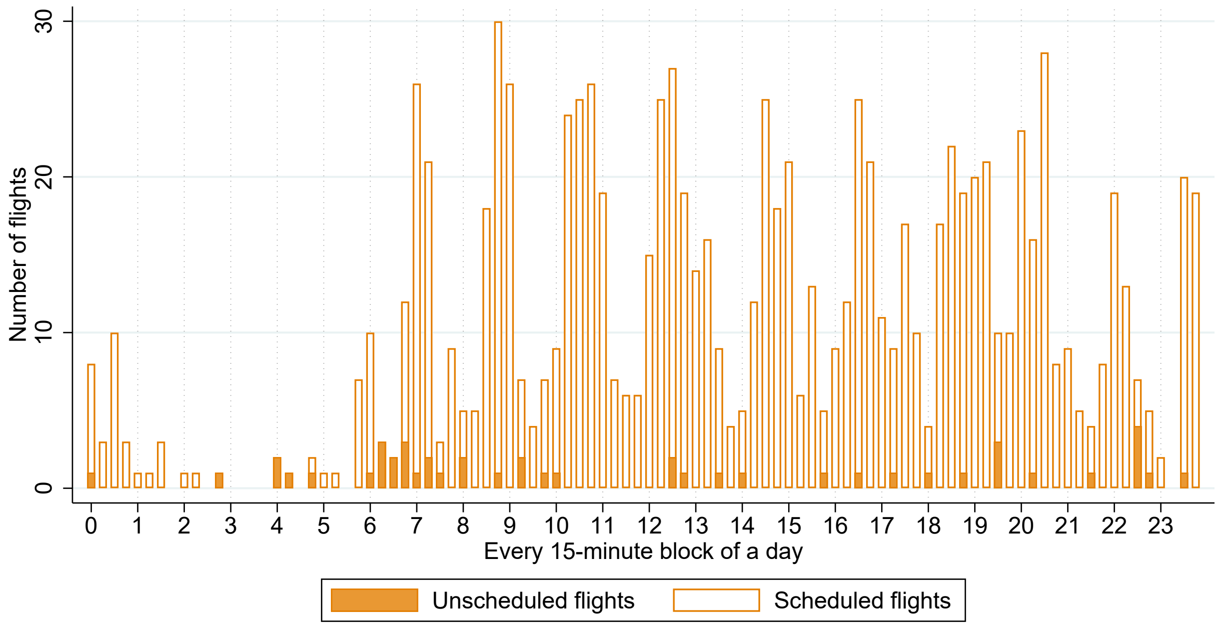
Figure 1: **Unscheduled and Scheduled Flights by Time in a Day, 2014–2017**



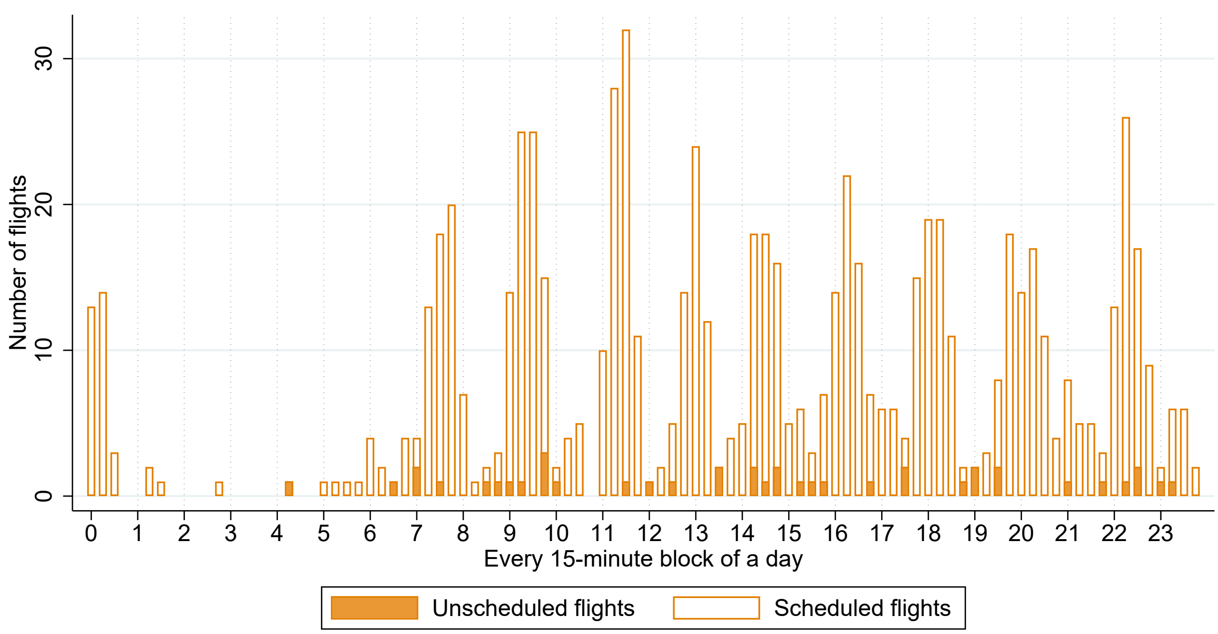
Notes: This figure plots the total unscheduled and scheduled flights at 15-minute intervals in the day in our sample.

Figure 2: **Unscheduled and Scheduled Flights Examples at an Airport**

Panel A. Number of flights at Dallas-Fort Worth (DFW) in a day



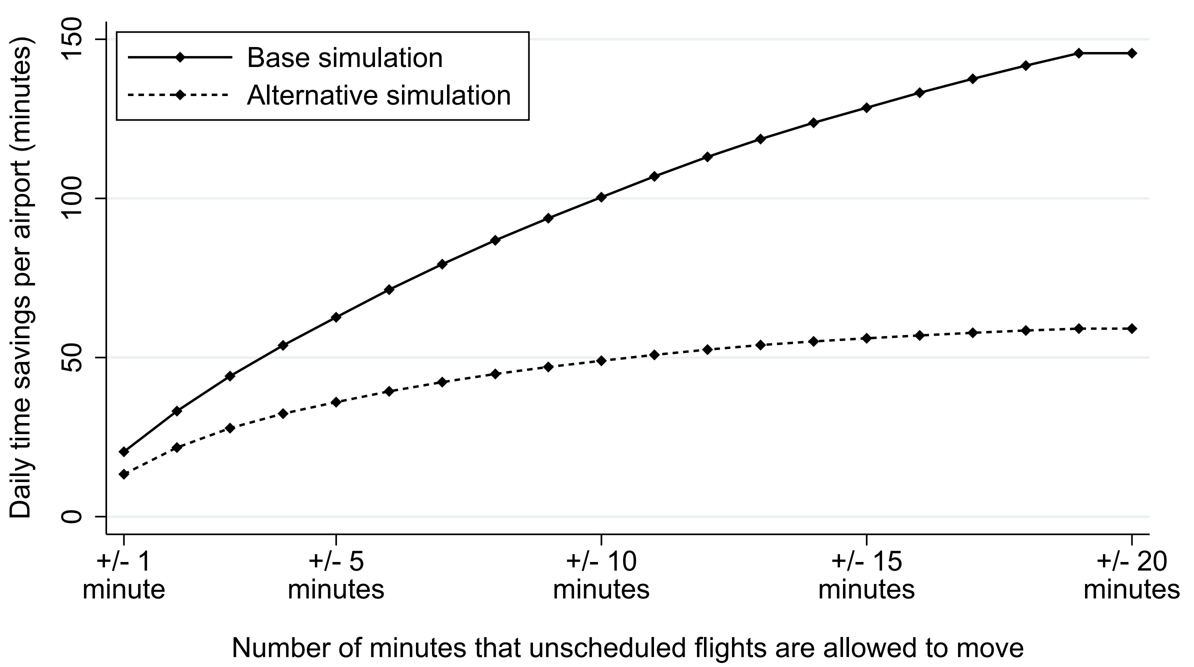
Panel B. Number of flights at Charlotte (CLT) in a day



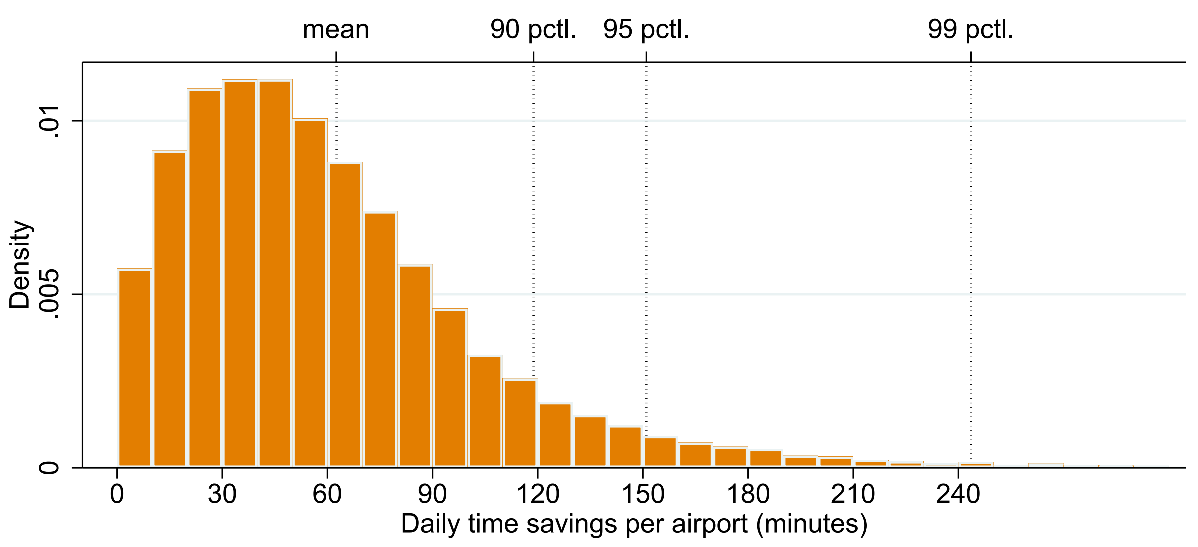
Notes: Panels A and B repeats Figure 1 on an arbitrary date, Friday, July 1st, 2016, at two airports, Dallas-Fort Worth International Airport (DFW) and Charlotte Douglas International Airport (CLT).

Figure 3: **Simulated Time Savings for Scheduled Flights from Marginally Moving Unscheduled Flights**

Panel A. Time savings if unscheduled flights allowed to move +/- n minutes



Panel B. Time savings distribution if unscheduled flights allowed to move +/- 5 minutes



Notes: Panel A plots the average daily time savings for scheduled flights at an airport when unscheduled flights can move their departure time by some marginal +/- minute(s). The base simulation plots the time savings for scheduled flights when an unscheduled flight can move up to +/- certain minutes to maximize the time savings for scheduled flights. The alternative simulation plots the time savings for scheduled flights under the assumption that an unscheduled flight can move up to +/- certain minutes to maximize the time savings for scheduled flights, and net out the absolute number of minutes it has to move. Panel B plots the distribution of time savings if unscheduled flights are allowed to move +/- 5 minutes as an example.

Tables

Table 1: **Summary Statistics for Scheduled Flights from Top 40 US Airports 2014–2017**

Panel A. Summary Statistics

Variables:	Mean	S.D.	1st pctl.	10th pctl.	25th pctl.	75th pctl.	90th pctl.	99th pctl.
A.1 Air travel performance for a scheduled flight								
Departure delay (minutes)	10.3	36.5	-13	-7	-5	9	38	171
Taxi-out (minutes)	18.0	10.1	6	10	12	21	28	55
A.2 Plausible congestion drivers for a scheduled flight								
Number of *unscheduled* flights taxiing out from the gate at a given minute (i.e., n)	0.5	0.9	0	0	0	1	2	4
Number of scheduled flights taxiing out from the gate at a given minute (i.e., r)	13.0	9.8	0	3	5	19	27	42
Quarterly maximum of r at airport o i.e., r_{oq}^{max}	43.3	20.0	10	15	29	55	71	88
Number of observations								24,416,468
Number of ϕ_{ob}								325,347
Number of ϕ_{ym}								48

Panel B. Main outcomes by capacity constraint

Variables: (in minutes)	When airport is more constrained defined as: $r > 0.75 \cdot r_{oq}^{max}$ (1)	When airport is less constrained defined as: $r \leq 0.75 \cdot r_{oq}^{max}$ (2)	P-value
Departure delay	14.0	10.3	0.000
Taxi-out	37.0	17.9	0.000

Notes: In Panel A, ϕ_{ob} are dummy variables of departing airports interacted by year, quarter, day-of-a-week, and (scheduled) 15-minute-block-of-a-day of departure. ϕ_{ym} are year by month dummy variables.

Table 2: **Effect of Unscheduled Flights on Scheduled Flights**

Dependent variable (in minutes):	Departure delay		Taxi-out	
	(1)	(2)	(3)	(4)
$n \times \mathbb{1}(8\text{–}9\text{ am})$	0.226***	0.215***	0.258***	0.215***
	(0.064)	(0.064)	(0.044)	(0.051)
$n \times \mathbb{1}(10\text{–}11\text{ am})$	0.557***	0.536***	0.368***	0.305***
	(0.068)	(0.065)	(0.042)	(0.042)
$n \times \mathbb{1}(12\text{–}1\text{ pm})$	0.466***	0.449***	0.285***	0.258***
	(0.084)	(0.082)	(0.033)	(0.033)
$n \times \mathbb{1}(2\text{–}3\text{ pm})$	0.233***	0.223***	0.181***	0.166***
	(0.079)	(0.080)	(0.030)	(0.030)
$n \times \mathbb{1}(4\text{–}5\text{ pm})$	0.291**	0.280***	0.219***	0.185***
	(0.114)	(0.102)	(0.041)	(0.046)
$n \times \mathbb{1}(6\text{–}7\text{ pm})$	0.615***	0.585***	0.212***	0.162***
	(0.116)	(0.116)	(0.048)	(0.043)
$n \times \mathbb{1}(8\text{–}9\text{ pm})$	0.901***	0.879***	0.221***	0.175***
	(0.135)	(0.136)	(0.042)	(0.047)
$n \times \mathbb{1}(10\text{–}11\text{ pm})$	0.577***	0.578***	0.137***	0.108**
	(0.108)	(0.110)	(0.039)	(0.041)
$n \times \mathbb{1}(12\text{–}7\text{ am})$	-0.022	-0.020	0.114***	0.108***
	(0.028)	(0.027)	(0.022)	(0.021)
$n \times \mathbb{1}(\text{scheduled flights} > \delta\cdot\text{quarterly max})$		0.538**		1.957***
$\times(\text{scheduled flights} - \delta\cdot\text{quarterly max}) \times\mathbb{1}(8\text{–}9\text{ am})$		(0.228)		(0.332)
$n \times \mathbb{1}(\text{scheduled flights} > \delta\cdot\text{quarterly max})$		0.558**		1.542***
$\times(\text{scheduled flights} - \delta\cdot\text{quarterly max}) \times\mathbb{1}(10\text{–}11\text{ am})$		(0.237)		(0.138)
$n \times \mathbb{1}(\text{scheduled flights} > \delta\cdot\text{quarterly max})$		1.498***		2.227***
$\times(\text{scheduled flights} - \delta\cdot\text{quarterly max}) \times\mathbb{1}(12\text{–}1\text{ pm})$		(0.491)		(0.284)
$n \times \mathbb{1}(\text{scheduled flights} > \delta\cdot\text{quarterly max})$		2.016**		2.417***
$\times(\text{scheduled flights} - \delta\cdot\text{quarterly max}) \times\mathbb{1}(2\text{–}3\text{ pm})$		(0.762)		(0.445)
$n \times \mathbb{1}(\text{scheduled flights} > \delta\cdot\text{quarterly max})$		0.203		0.678*
$\times(\text{scheduled flights} - \delta\cdot\text{quarterly max}) \times\mathbb{1}(4\text{–}5\text{ pm})$		(0.426)		(0.349)
$n \times \mathbb{1}(\text{scheduled flights} > \delta\cdot\text{quarterly max})$		1.251***		1.659***
$\times(\text{scheduled flights} - \delta\cdot\text{quarterly max}) \times\mathbb{1}(6\text{–}7\text{ pm})$		(0.226)		(0.417)
$n \times \mathbb{1}(\text{scheduled flights} > \delta\cdot\text{quarterly max})$		0.959**		2.082***
$\times(\text{scheduled flights} - \delta\cdot\text{quarterly max}) \times\mathbb{1}(8\text{–}9\text{ pm})$		(0.414)		(0.490)
$n \times \mathbb{1}(\text{scheduled flights} > \delta\cdot\text{quarterly max})$		0.598		1.643***
$\times(\text{scheduled flights} - \delta\cdot\text{quarterly max}) \times\mathbb{1}(10\text{–}11\text{ pm})$		(1.497)		(0.410)
$n \times \mathbb{1}(\text{scheduled flights} > \delta\cdot\text{quarterly max})$		-0.432**		1.565***
$\times(\text{scheduled flights} - \delta\cdot\text{quarterly max}) \times\mathbb{1}(12\text{–}7\text{ am})$		(0.187)		(0.494)
Number of observation	24,416,468	24,416,468	24,416,468	24,416,468
R-squared	0.06	0.06	0.23	0.23

Notes: Robust standard errors clustered at departing airport level in parenthesis. *, **, and *** indicate statistical significance at 10, 5, and 1 percent levels respectively.

Appendix A. Additional Materials

A.1 OAG dataset and the list of airports

OAG constructs the US historical flight data by compiling data from the Department of Transportation (DOT) On-Time Performance dataset for domestic flights, FAA's Aviation System Performance Metrics (ASPM) dataset, and carrier-provided data. OAG is the data supplier to major flight statistics companies such as *flightaware.com* and *flightstats.com*. Past studies on air travel performance usually use DOT's On-Time Performance (e.g., Mayer and Sinai, 2003; Forbes et al., 2015; Brueckner et al., 2022; Chu and Zhou, 2022). Having all domestic and international flights is important for correctly estimating the shocks from unexpected flights on all flights and simulating the marginal effects.

We define the top 40 airports by accounting for the airports with the most scheduled domestic flights using the DOT On-Time Performance dataset when collecting flight information from OAG. This list correlates to the top airports measured by both international and domestic flights. The airports in our sample are the following, in alphabetical order: ATL, AUS, BNA, BOS, BWI, CLE, CLT, DAL, DCA, DEN, DFW, DTW, EWR, FLL, HNL, HOU, IAD, IAH, JFK, LAS, LAX, LGA, MCI, MCO, MDW, MIA, MSP, OAK, ORD, PDX, PHL, PHX, SAN, SEA, SFO, SJC, SLC, SMF, STL, and TPA.

A.2 Additional results and robustness

As explained in the main text, our results are robust to alternative specifications such as (i) including a quadratic interaction term, (ii) alternative choices of the threshold of δ such as 0.7, 0.8, and 0.85, and (iii) alternative choices of reference time. Here we describe additional results and robustness checks.

It is plausible that slot-administrated airports are subject to different capacities and regulations than other airports. We repeat our baseline for subsamples of slot-administrated airports versus other airports.[12] Appendix Table A.2 columns (1a), (1b), (2a), and (2b) report the results. We find $\hat{\beta}_{1h}$ is similar between these two types of airports. $\hat{\beta}_{1h}$ appears to be slightly greater for slot-administrated airports, but with no statistically significant difference. Some coefficients are less precisely estimated due to a lack of observation at selected times of the day. We also repeat the same exercise for equations (3)-(4). Again, we find similar results between these two types of airports. Given that the sample is smaller, some $\hat{\beta}_{2h}$ are less precise and some are subject to outliers.

One may concern that airport capacities can correlate both with the outcomes and the number of unscheduled flights at a time n. We investigate this possibility by splitting the

[12] We follow the FAA's definition and denote an airport is slot-administrated if it is either under slot control, or under schedule restriction. John F. Kennedy International Airport (JFK), LaGuardia Airport (LGA), and Ronald Reagan Washington National Airport (DCA) are under slot controls; and Chicago O'Hare International Airport (ORD), Los Angeles International Airport (LAX), Newark Liberty International Airport (EWR), and San Francisco International Airport (SFO) are under schedule restriction.

sample using the number of terminals which may correlate with airport size and capacities. In our sample, 54% of scheduled flights departed from an airport with 1–5 terminals, and 46% with 6–10 terminals. We re-estimate our baseline on these two sub-samples. Appendix Table A.2 columns (1c), (1d), (2c), and (2d) report the results. The coefficients are very similar and there is no statistical difference between the two groups. Furthermore, we directly control for runway technologies at an airport in a quarter, known as multiple-runway operation (MRO), which allows multiple departure operations such as parallel departures using data constructed in (Chu and Zhou, 2022). It happens that MRO was mostly adopted over 2014–2017, which overlap with our sample. Our results are robust to this consideration.

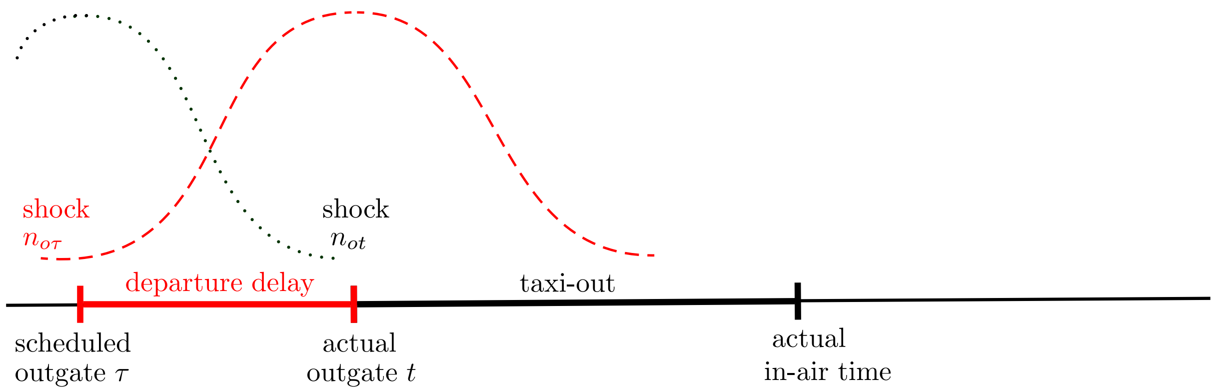
Our results are also robust to other considerations such as (i) the buffer time between a previous flight and the current flight (of the same aircraft); (ii) the minutes of prior delay of the previous flight (of the same aircraft); (iii) destination characteristics, such as whether the flight is an international flight, whether the destination is a top 40 US airport, and the flight distance; (iv) whether the flight is a direct non-stop flight or a leg within a multiple-stop ticket; and (v) the exclusion of less busy airports by restricting the sample to top 30 or top 35 airports. Our results are also almost identical if we specify richer fixed effects such as (i) adding route fixed effects or route-by-carrier fixed effects, (ii) interacting ϕ_{ob} with the departure terminal, and (iii) including aircraft model fixed effects.

A.3 Source of gains

The possible gains can be three folds in that, first, moving an unscheduled flight to a less busy time can benefit a greater number of scheduled flights i at the original busier time than it may congest flights at the less busy time, leading to a net time savings. Second, when an unscheduled flight moves from a busier time to a slightly less busy time, there is a possibility that it may (i) move to a time h with a smaller β_{1h}, or (ii) it may move to a minute when the capacity constraint, quantified by β_{2h}, no longer applies. Third, again by moving to a less busy time, the moved unscheduled flight will also stay on the runway for a shorter duration (i.e., experience a shorter taxi-out time), which further reduces the set of flights affected by this flight.

Figure A.1: **Illustration of Empirical Strategy**

Panel A. Identifying variation for the departure delay regression



Panel B. Identifying variation for the taxi-out regression

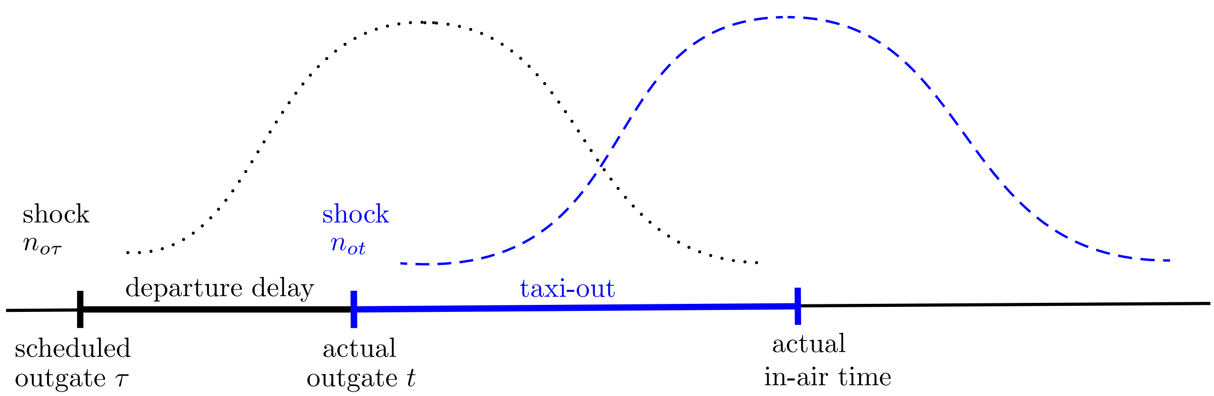


Table A.1: **Marginal effects based on Table 2 columns 2 and 4**

Marginal effect of n on:	Departure delay (minutes) (1a)	(1b)	(1c)	(1d)	Taxi-out (minutes) (2a)	(2b)	(2c)	(2d)
If the number of extra scheduled flights that is greater than r_{oq}^{max} equals	1	2	5	10	1	2	5	10
During time blocks:								
8–9 am	0.75	1.29	2.91	5.60	2.17	4.13	10.00	19.78
10–11 am	1.09	1.65	3.32	6.11	1.85	3.39	8.01	15.72
12–1 pm	1.95	3.44	7.94	15.43	2.48	4.71	11.39	22.52
2–3 pm	2.24	4.25	10.30	20.38	2.58	5.00	12.25	24.34
4–5 pm	0.48	0.69	1.29	2.30	0.86	1.54	3.57	6.96
6–7 pm	1.84	3.09	6.84	13.09	1.82	3.48	8.46	16.75
8–9 pm	1.84	2.80	5.67	10.47	2.26	4.34	10.58	20.99
10–11 pm	1.17	1.76	3.56	6.55	1.75	3.39	8.32	16.54
12–7 am	-0.45	-0.88	-2.18	-4.34	1.67	3.24	7.93	15.75

Notes: This table computes the marginal effect of outcomes with respect to n when $(r - 0.75 \cdot r_{oq}^{max})$ equals 1, 2, 5, and 10. For reference, the number of flights that experience $(r - 0.75 \cdot r_{oq}^{max})$ equal or greater than 1, 2, 5, 10 when the airport is capacity constrained (i.e., when $(r - 0.75 \cdot r_{oq}^{max}) > 0$) are 100%, 69%, 24%, and 5%.

Table A.2: **Robustness**

Dep. variable (in minutes):	Departure delay				Taxi-out			
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
	slot admin airport	non-slot admin airport	num. of terminals: 1–5	num. of terminals: 6–10	slot admin airport	non-slot admin airport	num. of terminals: 1–5	num. of terminals: 6–10
A. Estimate $\hat{\beta}_{1h}$ *for time blocks*:								
8–9 am	0.312	0.202***	0.268***	0.166*	0.141	0.286***	0.300***	0.199**
	(0.242)	(0.052)	(0.086)	(0.092)	(0.149)	(0.039)	(0.044)	(0.082)
10–11 am	0.653**	0.535***	0.549***	0.564***	0.603**	0.317***	0.361***	0.378***
	(0.266)	(0.065)	(0.101)	(0.084)	(0.187)	(0.032)	(0.064)	(0.047)
12–1 pm	0.626*	0.418***	0.463***	0.471***	0.375***	0.258***	0.278***	0.298***
	(0.258)	(0.071)	(0.127)	(0.062)	(0.064)	(0.038)	(0.043)	(0.056)
2–3 pm	0.313	0.211**	0.222**	0.245*	0.234**	0.165***	0.199***	0.153**
	(0.250)	(0.078)	(0.100)	(0.134)	(0.096)	(0.031)	(0.036)	(0.053)
4–5 pm	0.583*	0.217*	0.212	0.420***	0.353***	0.184***	0.224***	0.211***
	(0.271)	(0.112)	(0.156)	(0.135)	(0.072)	(0.046)	(0.061)	(0.046)
6–7 pm	0.656**	0.603***	0.703***	0.499**	0.254**	0.197***	0.194***	0.238***
	(0.254)	(0.133)	(0.121)	(0.217)	(0.098)	(0.058)	(0.066)	(0.070)
8–9 pm	1.068***	0.827***	0.914***	0.881***	0.249***	0.207***	0.202***	0.247**
	(0.271)	(0.145)	(0.188)	(0.199)	(0.024)	(0.058)	(0.051)	(0.070)
10–11 pm	0.591*	0.572***	0.821***	0.415***	0.102	0.154***	0.136*	0.140***
	(0.293)	(0.085)	(0.145)	(0.115)	(0.067)	(0.051)	(0.078)	(0.038)
12–7 am	0.051	-0.036	-0.032	-0.013	0.155***	0.108***	0.121***	0.108***
	(0.086)	(0.028)	(0.036)	(0.047)	(0.038)	(0.025)	(0.034)	(0.029)
Num. of obs.	6,511,568	17,904,900	13,248,609	11,167,859	6,511,568	17,904,900	13,248,609	11,167,859
R-squared	0.06	0.06	0.07	0.06	0.22	0.18	0.19	0.25

Notes: Robust standard errors clustered at departing airport level in parenthesis. *, **, and *** indicate statistical significance at 10, 5, and 1 percent levels respectively.