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On-Time Performance Policy in the Chinese Aviation Market

- An innovation or disruption?

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Abstract

Congestion and delay have become a critical challenge to the aviation industry, particularly in markets with sustained traffic growth. Despite significant investments in aviation infrastructures, congestion and delay in China has placed mounting pressure on the industry and its regulator to sustain good on-time performance. In 2017, CAAC introduced a new policy that in the case of poor on-time performances, reduces the allowable capacity of congested airports and forces airlines to cancel flight services. This study measures the policy's effects on congestion and delays, and quantifies the change in welfare. Empirical findings suggest that the new policy reduced flight delays considerably, bringing substantial welfare gains to the passengers even under conservative estimates. However, the new policy is inconsistent with international industry practices of slot allocation and airline service operations, and may cause operational disruptions to the aviation industry. We recommend continuation of such a policy with more detailed analysis, so that regulatory innovation can be encouraged and meanwhile extensively studied. We further argue a revised policy may be implemented in growth markets, which balances welfare gains and operation disruptions.

Keywords: Chinese aviation market; congestion and delay; on time performance; value of time

1. Introduction

Congestion and delay have become a critical challenge to the aviation industry, particularly in markets with sustained traffic growth. Taking the United States (US) as an example, in 2019 nearly one in five flights arrived over 15 minutes late (US BTS 2020). Ball et al. (2010) noted that scheduled flights increased by approximately 22% between 2002 and 2007, but the number of late-arriving flights more than doubled. They further estimated that the total cost of all US air transportation delays in 2007 reached US$32.9 billion. In its 2008 report, The Department of Transport (DOT) identified congestion as the second most important management challenge (US DOT 2008). However, no significant improvements have been observed since then. The data of US Bureau of Transportation statistics (US BTS, 2020) indicated that in 2012, 14.69% of the flights in the US domestic market were delayed. In 2020, this ratio increased to 20.8%. Airport congestion is a major cause for the increased delay problem in the US. Weather-related delay accounts for less than half of the total delay in the US, while other causes, such as the late arriving aircraft, air traffic control, significantly contributed to the increasing delay, and are related to airport congestion.

The challenge in the Chinese aviation market is arguably even more severe, where traffic volume has sustained double-digital growth for decades. In 2010, 268 million passengers were served and there were 175 civil airports nationwide. By 2019, the number of passengers was more than doubled to 660 million while the number of airports only increased marginally to 238. Much of the growth in traffic volume and flight frequency has been concentrated to metropolitan areas (Zhang 2010; Wang et al. 2014). Three major airline groups were formed in the early 2000s, namely, Air China, China Eastern and China Southern with hub development as their core strategy (Fu et al. 2015b; Yan et al. 2019). Unlike low cost carriers (LCCs) in North America and Europe that focus more on secondary airports, LCCs in the Chinese markets favor densely travelled routes out of major airports that are running short of capacities (Fu et al. 2015a). Despite substantial investments in aviation infrastructures, such fast growth and concentrated traffic distribution have placed mounting pressure on the Chinese aviation industry and its regulator (the Civil Aviation Administration of China, or CAAC) to maintain good on-time performance (OTP). A report by Economists indicated that in 2017, the top seven airports with the longest delays in the world are all in China.[1]

Addressing congestion and delay is a very challenging task, which generally involves two approaches. The first one is to increase the capacity of key infrastructures such as airport and air traffic control systems. However, the associated investments are often large and lumpy, and the planning process is routinely complicated and lengthy (Oum and Zhang 1990; De Neufville and Odoni 2003). This is not helped by the fact that there is significant uncertainty and volatility in aviation demand (Xiao et al. 2013, 2017). Furthermore, various airport-airline vertical arrangements have been formed, which may also influence the investment decisions on airport capacities (Fu and Zhang 2010; Zhang et al. 2010; Fu et al. 2011; Yang et al. 2015; Xiao et al.

[1] "Why China leads the world in flight delays", Daily chart Oct 30, 2017. https://www.economist.com/graphic-detail/2017/10/30/why-china-leads-the-world-in-flight-delays

2016). Therefore, capacity expansion is almost always costly, complicated and lengthy, difficult to cope with the fast traffic growth, such as those observed in the Chinese aviation market.[2]

The other approach is to improve the allocative efficiency of airport/infrastructure capacity, so that social welfare can be improved with given capacity. This approach often involves the optimization of airport pricing and/or slot allocation, which has been studied by a very well developed literature (see, for example, Daniel 1995, 2001; Brueckner 2002, 2009; Zhang and Zhang 2003; Pels and Verhoef 2004; Morrison and Winston 2007; Bruechkner and van Dender 2008; Basso 2008; Basso and Zhang 2010; Yuen and Zhang 2011; Zhang and Czerny 2012; Czerny and Zhang 2014a, 2014b, 2015; Czerny et al. 2017). However, the price elasticity of airport services tends to be quite low (Fu et al. 2006; Oum and Fu 2007), meaning congestion prices may need to be substantially increased to effectively control congestion. On the slot allocation side, although a large number of studies have proposed alternative methods of slot allocation and auction (see, for example Verhoef 2010; European Commission 2011; GAO 2012; Zografos et al. 2012; Zografos and Madas 2017; Ribeiro et al. 2018; Sheng et al. 2015, 2019), there has been virtually no change in primary (first time/initial) slot allocation rules in the past decades (Berardino 2010).[3] Although a number of studies have investigated the effects of slot trading in secondary markets (Fukui 2010, 2012; Valdes and Gillen 2018), there has been no evidence of effective congestion reduction.

The challenges in adopting either of the approaches probably explain why congestion and delay have been getting worse in many countries, especially in markets with relatively high traffic growth such as China. In 2017, the average flight arrival delay in China's largest hub airports were 42.4 minutes at Guangzhou Baiyun Airport, 46.1 minutes at Shanghai Hongqiao Airport, 47.9 minutes at Shanghai Pudong Airport, and 48 minutes at Beijing Capital Airport.[4] Such significant delays led to poor passenger satisfaction and frequent airline operation disruptions. This had become such a pressing issue that CAAC introduced a heavy-handed regulation on September 15, 2017, which came into effect on October 29, 2017 (the start of the Winter Schedule Season). This policy introduced strict rules on capacity increases for slot-coordinated airports, and in some cases reduced the allowable capacities for airports that had an on-time (departure) performance below 85% in the previous season. Airlines are also forced to cancel their flights that had repeatedly poor OTP. Such a policy has not been implemented elsewhere in the aviation industry, as it violates the internationally accepted airport slot rule of "grandfathered right". Under this well-established rule, if an airline has been using an airport slot in the previous (scheduling) period the carrier is automatically entitled to use this slot, which essentially guarantees the right for the continuation of the flight services, regardless of the OTP.

As discussed in more details in the following sections, this policy violates some of the essential rules adopted by the aviation industry, yet at least in the short term brings significant delay reduction and welfare gains. An assessment of such a policy thus offers valuable insights for the

[2] A significant share of the airspace in China has been controlled by and reserved for the use of the air force. With fast-growing civil aviation traffic, more airspace capacity has been made available for civil aviation use.

[3] For example, although the benefits of slot auction have been well studied in the literature for more than three decades, no country actually implemented such a policy. The only exception is the trial of small scale slot auction at the Guangzhou Baiyun Airport in 2015, which led to mixed outcomes and has since then not been implemented again.

[4] As explained in the following section, the flight arrival delay here is defined as the time difference between actual arrival time and the scheduled arrival time.

aviation industry. This study aims to provide a first investigation on this type of policy, and explores new ways of regulation based on actual performances.

The rest of this paper is organized as follows: Section 2 provides a background introduction of the regulatory policy under investigation, and an overview of its impacts in the Chinese aviation market. Section 3 outlines the economic assessment of this policy, with a focus on the associated value of travel time saved. The last section discusses and concludes the study.

2. Overview of the New Regulation

CAAC introduced a new policy on September 15, 2017, which came into effect at the start of the Winter Schedule Season on October 29, 2017.[5] Among others, the key regulations introduced include the following requirements:

I. In the Winter Schedule Season, declared capacities of the 21 major slot coordinated airports will remain unchanged. From this season, all slots throughout the day (i.e. 24 hours) will be coordinated/controlled. The total traffic volume at key airports will be controlled.

II. The declared airport capacity needs to be carefully analyzed with four alternative methods, and can only be increased if both of the following two conditions are satisfied:
   a. In the past year there was no serious safety incident that was caused by the airport or air traffic control (ATC); and
   b. In the past year, the OTP of flight departure was above 80% for at least 9 months.

III. The declared airport capacity shall be reduced if in the past year, the OTP of flight departure was below 70% in at least 9 months.

IV. The flight schedule and slot plan need to be restructured based on actual OTP. Specifically,
   a. In 2017 Winter Season and 2018 Summer Season, the slots for flight departure at Beijing Capital Airport and Shanghai Pudong Airport would be capped at 75% of the declared capacity;
   b. For airports with a single runway, if the departure OTP goes below 80%, then departure slots will be reduced to 80% of the declared capacity in the following season;
   c. For single-runway airports, if the departure OTP reaches above 85%, the departure slots can be increased to 80% of the declared capacity if it is currently below 80%;
   d. For two-runway and multi-runway airports, if the departure OTP goes below 80%, departure slots will be reduced to 75% of the declared capacity in the following season;
   e. For two-runway and multi-runway airports, if the departure OTP reaches above 85%, departure slots will be increased to 75% of the declared capacity in the following season if it is currently below 75%.

   The flight reduction measures follows the following priority sequence: to revoke slots that have been "abused"; airlines voluntarily return slots in exchange for priority when capacity is increased in the future; to cancel the slots for departing flights with the lowest OTP.

V. To tightly control charter flights and seasonal flights on international routes, no new airlines can be allowed to enter routes between the largest three hubs (Beijing, Guangzhou,

[5] The policy was released in Chinese, with an unofficial translation by us as "The notification of CAAC's policy measures: total traffic volume control, adjustment of flight structures, and improvement of OTP. Doc file (2017)115".

Shanghai Pudong). Regional flight services[6] cannot be increased at the four airports in Beijing, Shanghai and Guangzhou.

VI. Tight control on national total traffic volume growth, tight control over corporate jet flight services, especially during peak hours at hub airports.

The categories of affected Chinese airports are summarized in Table 1. One notable feature of such regulation is that the regulation is "outcome-based". That is, the actual measures taken (i.e. slot/flight change, airport declared capacity change) are dependent on OTP outcomes. Airports with good (poor) OTP are allowed to increase (required to reduce) their allowable capacity. Flights with poor OTP will be removed. It should be noted that it is very different from the "performance-based regulation" that has been utilized in sectors such as electricity and telecommunication (Sappington et al. 2001; Makholm et al. 2012; Sappington and Weisman 2016). The latter got its name in that firms under regulation has incentive to improve its performance (e.g., price cap regulation), which is in contrast to cost-based regulation (e.g., rate of return regulation). Firms under the performance-based regulation has clear incentive and target to improve their operations. In comparison, the policy introduced by CAAC is outcome-based in the sense that (a) it penalizes airlines and airports (i.e. forcing them to reduce operations and allowable capacities) based on their historical OTP, and (b) the service/capacity reduction will continue until target service levels are reached. Note under this scheme, an operator (airport or airline) may be punished/rewarded for an outcome beyond its own control - congestion and delay inevitably involve significant externalities, thus an airline's low OTP could have been caused by some other airlines' operation or the poor management/operation of airports. This leads to a "fairness" issue in policy design. The policy is quite strict as the allowable capacity is capped only at 75% or 80% of the declared capacity. This might suggest that the airport declared capacity could be "overestimated" when considering the practical handling ability, such that maintaining traffic volume at the declared capacity alone could not effectively remedy the serious delay problem.

<Table 1 about here>

Another major problem with the regulation is that it violates some of the fundamental principles of slot allocation, namely the "use-it-or-lose-it" rule and the "grandfathered right", both widely adopted in Europe and many other countries[7]. First, airlines were given right to use one slot based on its historical acquisition. An airline has a right to a slot if it has made use of the corresponding slot in the preceding equivalent season. Such right can be lost only as a consequence of the use-it-or-lose-it rule: a slot can be allocated to another airline if its usage in the preceding season has been lower than 80%. Then, the freed and newly available slots are grouped into a pool. Normally, half of this pool is allocated to new entrants (the "new entrant rule"). The remaining slots are then allocated in a non-discriminatory manner. Significant sunk costs are involved when airlines initiate/operate a flight service. If airlines may be forced to cancel their flight operations due to the poor performance caused by itself or competing airlines, substantial uncertainty, and thus costs, will be introduced to airlines' operation.

[6] In China, the regional flight service is mainly defined by the aircraft type deployed. The routes served by turboprop aircraft with less than 70 seats are regarded as regional flight service.

[7] Although the US airports do not formally adopt such rules, airlines are favored to inherit or acquire slots if they has previously operated such slots.

On the other hand, there are some good rationales in the mechanism proposed by CAAC: for whatever reason, the flights with the lowest OTP in a season will be removed. As such flights are likely to be offered during the period with the worst congestion or capacity shortage, or by airlines with the least capacity of operating flight services, intuitively this regulation may address the congestion problem with relatively small flight reduction. The expenses, in terms of flights cancelled, are not guaranteed to be the minimum. The mechanism is nevertheless transparent and easy to implement.

3. The Policy Effect on Airport Delay

In this section, we quantify the effect of the policy adopted by CAAC ("CAAC policy" hereafter) to alleviate the airport congestion. The actual flight-specific OTP data were provided by VariFlight for all flights in the Chinese domestic market before and after the implementation of the policy. The whole dataset spins from January 2015 to December 2017, and we focus on the Winter Season Schedule starting from October 2017. Both descriptive statistics and formal econometric analysis are used to evaluate the CAAC policy effect. In addition, the heterogenous effects across different categorized airports are also accounted for in our analysis.

First, we compute the average delay and buffer time for the airports and airlines. In this study, departure (arrival) delay is defined as the difference between the actual departure (arrival) time and the scheduled departure (arrival) time. It should be noted that this definition is different from many "official" measures published by the industry organizations and regulators, which regard a flight to be "on time" if the difference between the scheduled and actual time is within 15 minutes. This study adopted the current measure because the main objective is to analyze the operations of airlines and airports, instead of benchmarking travelers' experience. The buffer time is defined as the difference between the scheduled flight time and the unimpeded flight time (see Ball et al. 2010; Kafle and Zou 2014). On one route, all the flights' actual flying time are ranked from the shortest to the longest, and the 10th percentile in the actual flight time distribution is regarded as the unimpeded flight time, which is used to calculate the schedule buffer (Ball et al. 2010). A longer buffer helps improve one flight's nominal OTP. However, it reduces aircraft usage and increases staffing and operational costs. CAAC policy was effective during October to December of 2017 in our sample period. To minimize any confounding seasonality effect on flight delay, the same period in 2016 is chosen for comparison. We summarized the changes in averages of flight departure delay, the total number of departure flights and the buffer time in Table 2.[8] Airports are grouped into hub, major slot-coordinated, minor-slot coordinated and non-slot-coordinated airports. In addition, in Table 3, we select Beijing Capital Airport (PEK) as an example to demonstrate the change in each airline's average flight departure delay and buffer time before and after the implementation of CAAC policy.

< Table 2 about here> & <Table 3 about here>

Overall, the following patterns can be identified. First, compared with the same period in 2016, the CAAC policy clearly reduced the average delay for departure flights. Consistent results can be

[8] The changes in arrival delay and the number of arrival flights were also calculated. The results are quite similar to those based on departing flights data and are thus not separately reported.

found for flight arrival delays, which are not reported to save space. Second, flight delays decreased more significantly at those larger airports, particularly at the four hub airports. Third, non-slot-coordinated airports also benefited in terms of flight delay reduction, although they were not directly targeted by the policy. These positive "spillovers" are likely owing to network effects and (reduced) propagation effects. Fourth, at hub airports such as Beijing capital airport (see Table 2 and 3), the significant decline in flight delay was accompanied by a moderate increase (if any) in the schedule buffer time. Significant delay increases were only observed for relatively small airlines and for carriers with limited operations. Such increases may be due to the CAAC's slot allocation policy, which penalizes those airlines that had a poor OTP in the previous season. Last, after the implementation of the policy, average buffer time for departing flights did not change significantly at the slot-coordinated airports, while the buffer time for arriving flights dropped dramatically when compared with the same period in 2016.

Although the above summary statistics appear to suggest that the CAAC policy had reduced the airport congestion and delays, it is necessary to compare what could have happened if that policy had not been introduced (i.e., a counterfactual outcome). This calls for a more rigorous econometric analysis. As the policy did not directly influence the small airports that were not subject to slot coordination, a difference-in-differences (DID) analysis is carried out to evaluate the policy's effects with those non-slot-coordinated airports as control group. The regression model is given in the following equation,

$$y_{ijt} = \alpha_0 + \alpha_1 \times policy_{it} + \alpha_2 \times policy_{it} \times Slot\_Major_i + \alpha_3 \times policy_{it} \times Hub_i + \xi_i + \rho_j + \tau_t + \varepsilon_{ijt} \tag{1}$$

where subscript i stands for the airport, j stands for flight, and t stands for the day. y_{ijt} is the outcome variable, namely the flight delay (i.e., departure or arrival) or airport's number of flights. $policy_{it}$ is a dummy variable which equals to one after the policy implementation and when the airport is targeted by the policy. $Slot\_Major_i$ and Hub_i are the dummy variables to indicate the major slot-coordinated and hub airports, respectively. In this DID regression, the airport, flight and day-specific fix effects are also controlled for, reflected by the variables ξ_i, ρ_j and τ_t. ε_{ijt} is a pure stochastic term. With this specification, the parameter α_1 captures the policy effect on those minor slot-coordinated airports, the sum of parameters α_1 and α_2 is the policy effect on major slot-coordinated airports, and the sum of parameters α_1 and α_3 is the policy effect on the hub airports.

Before formally implementing the DID regression, we plot the daily average flight delays and the number of flight frequency for the airports targeted by the CAAC policy (i.e., the treatment airports) and those unaffected airports (i.e., control airports). The daily flight delays of the different kinds of airports have common time trend before Winter Scheduling Season of 2017. This suggests the "common trend" assumption to implement the DID is satisfied. However, from the plots, it is impossible to clearly identify the policy effect on the slot-coordinated airports. Therefore, one has to rely on DID regression for a more rigorous analysis.

<Figure 1 about here>

The policy effect estimations by DID regression are summarized in Table 4. It is suggested that, post the policy, on average, the departure (arrival) delays at hub airports decreased by 11.2 minutes

(10 minutes); the departure (arrival) delays at major slot-coordinated airports decreased by 4.7 minutes (6.2 minutes). Minor slot-coordinated airports also experienced a significant decline in flight departure and arrival delays of 3.5 and 5.3 minutes, respectively. As the CAAC policy might also reduce the delay in the control airports, namely the non-slot-coordinated airports (reported in Table 2), our estimated delay reduction for the policy-targeted airports could be conservative, serving as a lower-bound of the true policy effect.

< Table 4 about here>

4. Cost Saving and Welfare Analysis

This section aims to quantify the passenger's surplus change due to the CAAC policy. The passengers' surplus change may come from various sources: (i). the reduction in delay and buffer time; (ii). the change in flight frequency; (iii). the change in airline price. Section 3 has estimated the delay time savings thanks to the CAAC policy. It is intuitive that flight delay reduction saves passenger time cost. To convert the saved time into monetary term, one needs to know the value of time saved related to flight delay. In this section, an econometric approach is developed to estimate Chinese passenger's value of time saved related to flight delay. Moreover, passengers also value higher flight frequency, which makes it easier to depart at preferable time (i.e., lower schedule delay) (Wang et al. 2014). As shown in Section 3, the CAAC policy also reduces the flight frequencies at those slot-coordinated airports, thus negatively affecting passengers' surplus. Lastly, less flight delay also saves airline's operating cost thanks to an increasing aircraft and crew utilization. Such operation cost reduction could then lead to airfare cut, benefiting passengers. Therefore, to quantify passengers' surplus change, we should account for the cost savings through delay reduction, changes in the flight frequency and airline prices.

First, to obtain passenger's value of time saved related to flight delay reduction, a passenger utility function is specified and estimated with a reduced-form regression approach, in the spirit of Berry and Jia (2010), Fu et al. (2014) and Choi et al. (2019). It is assumed that a representative passenger first chooses between non-air-travel or air-travel. If the passenger decides to travel by air, he/she then chooses one airline product j in market r to maximizes utility.

The utility of non-air-travel is,

$$u_{i0r} = \varepsilon_{i0r} \tag{2}$$

The utility of airline travel is,

$$\begin{aligned} u_{ijr} = {} & \lambda_0 + \lambda_1 Price_{jr} + \lambda_2 frequency_{jr} + \lambda_3 buffertime_{jr} + \lambda_4 arrivaldelay_{jr} + \\ & \lambda_5 distance_r + \lambda_6 LCC_{jr} + \lambda_7 HSR_r + \lambda_8 Numberofconnecton_{jr} + \lambda_9 GDPCapita_r + \\ & \lambda_{10} AirlineDummy_{jr} + \lambda_{11} Tour_{jr} + \xi_{jr} + \nu_{ir}(\sigma) + \sigma\varepsilon_{ijr} \end{aligned} \tag{3}$$

The variables are defined as follows,

- $Price_{jr}$: the airfare for airline product j in market r;
- $frequency_{jr}$: the weekly flight frequency for airline product j in market r;

- $buffertime_{jr}$: the buffer time for airline product j in market r;
- $arrivaldelay_{jr}$: the arrival delay of airline product j in market r;
- $distance_r$: the flying distance in market r;
- LCC_{jr}: the dummy for LCC product;
- HSR_r : the dummy for HSR presence in market r;
- $Numberofconnecton_{jr}$: the number of routes out of the origin airport for the airline that provides the airline product j in market r;
- $AirlineShare_{jr}$: the share of passengers in the endpoint airports for the airline that provides the airline product j in market r;
- $GDPCapita_r$: the average GDP per capital in the market r;
- $AirlineDummy_{jr}$: the vector of dummies for each airline;
- $Tour_{jr}$: the dummy for a tourist route.

ξ_{jr} is the product characteristic unobservable to the researcher but known by the passengers and airlines.

The value of time saved for flight delay reduction can be calculated via the "utility compensating variation method", which is $-\lambda_4/\lambda_1$. Similarly, the value of flight frequency can be calculated as $-\lambda_2/\lambda_1$, and the value of buffer time is calculated as λ_3/λ_1. Flight arrival delay is used in passenger's utility function, instead of departure delay. This is because the passengers incur time cost if arriving late at the destinations.

The error structure $v_{ir}(\lambda) + \lambda\varepsilon_{ijr}$ is assumed to follow the extreme type I distribution to generate the classic nested logit purchase probability. The market share of the airline product j in market r can be expressed as following Eq. (4),

$$s_{jr} = \left(\frac{e^{\frac{(\boldsymbol{X_{hj}\lambda}+\xi_{jr})}{\sigma}}}{\sum_{h=1}^{J} e^{\frac{\boldsymbol{X_{hr}\lambda}+\xi_{hr}}{\sigma}}}\right)\left(\frac{(\sum_{h=1}^{J} e^{\frac{\boldsymbol{X_{hr}\lambda}+\xi_{hr}}{\sigma}})^{\sigma}}{1+(\sum_{h=1}^{J} e^{\frac{\boldsymbol{X_{hr}\lambda}+\xi_{hr}}{\sigma}})^{\sigma}}\right) \tag{4}$$

Following Berry (1994), a linear regression model for the nested logit is derived as follows:

$$\begin{aligned} \ln \mathrm{s}_{jr} - \ln \mathrm{s}_{0r} = {} & \lambda_0 + \lambda_1 Price_{jr} + \lambda_2 frequency_{jr} + \lambda_3 buffertime_{jr} + \lambda_4 arrivaldelay_{jr} \\ & + \lambda_5 distance_r + \lambda_6 LCC_{jr} + \lambda_7 HSR_r + \lambda_8 Numberofconnecton_{jr} \\ & + \lambda_9 GDPCapita_r + \lambda_{10} AirlineDummy_{jr} + \lambda_{11} Tour_{jr} + \sigma \ln \overline{\mathrm{s}_{jr}} + \xi_{jr} \end{aligned} \tag{5}$$

where s_{jr} is the market share of the airline product, calculated by dividing the number of air passengers by the potential market size defined as the geometric mean of the endpoint cities' population, whereas s_{0r} is the market share of the non-travel population. Here, $\overline{s_{jr}}$ is the airline product share, conditional that the passenger chooses to fly. It is apparent that the unobservable product characteristic ξ_{jr} is likely to be correlated with the price and flight frequency variables, i.e., $Price_{jr}$ and $frequency_{jr}$. Therefore, instrument variables (IVs) need to be used to control for these endogeneities (Berry and Jia 2010; Wang et al. 2018). In addition, the buffer time is under the airlines' control, and can also be endogenous. The flight arrival delay, similar to the buffer time, can also be affected by airlines and is correlated to unobserved airline product characteristics. Therefore, we also use IVs to instrument the buffer time and arrival delay. Specifically, the IVs for the price includes route level HHI, the number of airlines competing on the route, HHI of origin and destination airports (Berry and Jia 2010). IVs for the frequency include the HHI at origin and destination airports, route level HHI, slot control, aircraft size (Yan and Winston 2014; Fu et al. 2014). The IVs for the buffer time and arrival delay are the average buffer time and arrival delay at the endpoint airports. The airport-level delay could be valid IVs for the flight level delays as the airport-level delay would affect flight level delay (i.e., the relevance condition), but would be independent to each individual flight level characteristics (i.e., the exclusion condition).

Our data for this utility function estimation spins from January 2015 to December 2017. Besides the flight delay and buffer time data obtained from VariFlight, the IATA PaxIS database was accessed to retrieve the passenger number, price, flying distance data and other flight specific characteristics. The population and GDP of the origin and destination cities were available from the city-level statistics yearbook. However, the IATA PaxIS data is accurate only at the quarterly level, thus we need to aggregate the flight delays into the quarterly averages as well. Each airline product is defined as an airline-route and quarter combination.

Our utility function parameter estimations are summarized in the following Table 5. Then the value of delay, buffer time and flight frequency are calculated as follows using the utility compensating variation methods,

- Average value of time saved for arrival delay: US$0.61 per minute, or US$36.73 per hour
- Average value of buffer time saved: US$0.34 per minute, or US$20.45 per hour
- Average value of one more daily flight: US$15.3 per flight for each passenger

< Table 5 about here>

These results suggest that a representative Chinese air passenger may be indifferent to a delay of 10 minutes if the ticket price is reduced by US$6.1, which is equivalent to US$36.7 per hour. These values are within a reasonable range considering the fact that airfares in China are not significantly lower than those in the US (Berry and Jia 2010; Wang et al. 2014; Wang et al. 2018). Also, a significant proportion of Chinese travelers are business travelers, who are expected to have high time cost and value of flight frequency. For example, US DOT recommended the following principles for determining the value of time saved: for air travel and high-speed rail travel, the values should be 60-90% of a traveler's earnings for leisure travel, and 80-120% for business travel, which correspond to US$36.1 and US$63.2 per hour, respectively.

However, our airfare data used in the utility function estimation are at quarterly basis (i.e., quarterly average of airline-route specific data). As a result, it is impossible to separately identify the value of departing time within one day. If flights with convenient departure time also had fewer delays (e.g., morning flights 8-10AM), our estimation may be higher than the actual result because of the confounding effects of departure time and delays.

Next, we turn to examine the welfare change due to airfare and flight frequency variations. Wang et al. (2019) estimated a system of reduced-form equations consisted of the airline pricing, flight frequency and flight delay using the same dataset as ours. They found the airline price has elasticities of -0.203 to flight frequency and 0.062 to flight arriving delay, respectively. That said, a 1% increase in airline flight frequency would reduce airline price by 0.203%, while a 1% increase in flight arrival delay would raise airline price by 0.062%. An increase in flight frequency moves both airline demand and supply curve to the right hand side (i.e., both airline demand and supply increase), but the supply expands more significantly. As a result, the equilibrium airline price drops with an increasing flight frequency. Similarly, more flight delay would reduce both the airline demand and supply, but reducing the airline supply more significantly due to higher airline cost. This leads to an increase in airline price at equilibrium. With these estimated elasticities and the changes in airport's flight arriving delay and flight frequency estimated in Section 3, it is feasible to calculate the airline price changes for each airport due to the policy.

Based on year 2017 data and our DID estimation of the policy effect on airport delay and flight frequency, Table 6 summarizes the calculated annual changes in passenger's surplus due to the CAAC policy, which is categorized by the changes in delay time, flight frequency and airline price for each policy-affected airport. As analyzed in Section 3, since the buffer time did not change much before and after the CAAC's policy, it was not included in passenger surplus analysis. Overall, the CAAC policy is estimated to bring a total of US$1.44 billion savings in passenger delay time cost. The resultant flight frequency reduction (caused by the restrictive traffic control policy), however, caused passenger surplus loss by a total of US$ 488 million. The savings in the airline ticket cost were as much as US$ 396 million. Thus, the annual net gain in passenger surplus is about US$ 1.33 billion.

It is also noted that, our estimation suggests the value of time saved derived from reduced flight delay is approximately US$37 per hour, equivalent to approximate RMB 259 per hour. This is much higher than the average hourly salary in China. For example, in 2017, the minimum wage in Beijing was only RMB 20 per hour. Based on average salary level of 2017, if the value of travel time saved is assumed as RMB 40 per hour (i.e. twice of the minimum wage, or roughly the average salary level in major cities), the CAAC policy would bring approximately an (annual) benefit of RMB 1.5 billion (about US$ 0.242 billion). And the corresponding net gain, including the effects of frequency and airline price changes, is recalculated as approximately RMB 0.97

billion (about US$ 0.15 billion). We believe such an estimation is very conservative in that air services are only consumed by a small percentage of Chinese population with relatively high income, and business travelers account for a significant proportion of the total trips. As a result, using population average salary as a proxy is likely to underestimate the passenger surplus gain associated with delay time reduction. Still, the associated passenger surplus gain is quite significant.

< Table 6 about here>

For the airlines, the policy affects them through the changes in delay, frequency and airline price as well. Table 7 summarizes such changes in airlines ticket revenues, number of flight and the total delay time. Although the delay reduction also helps airlines save operational cost, forced flights cut by regulation cause significant operational disruptions on particular routes and even spread to larger airline networks. Such operational and implicit opportunity cost (e.g. lost sales) are difficult to quantify, but could be very substantial. The CAAC policy conflicts with the fundamental airport slot allocation rules, forcing airlines to remove flights in a sudden and disruptive manner. Such imposed flight reductions are more significant at the hub and major slot-coordinated airports, likely to cause more serious disruptions and economic loss.

< Table 7 about here>

5. Discussion and Conclusion

Our study examines the economic effects of a policy first implemented by the Chinese aviation regulator CAAC in 2017, which aims to improve the OTP in the domestic market. This policy is outcome-based in the sense that (a) it penalizes airlines and airports by forcing them to reduce flights and allowable capacity, respectively, based on their historical OTP, and (b) the service/capacity reduction will continue until target service levels are reached. Almost by definition, such "outcome-based regulation" will achieve the target measures (i.e. OTP indicators used by CAAC). It nevertheless violates the internationally well accepted practices and rules of airport slot allocation, notably the use-it-or-lose-it rule and grandfathered right. The policy may also be unfair, and introduces disruptions and uncertainties into the aviation market. Airlines and airports with poor OTP are forced to reduce services and capacity, even though flight delays may be (partially) beyond their control (e.g., determined by the overall aircraft movement pattern in a market/airport). Congested airports usually have limited capacity, where it is difficult and costly for airlines to obtain slots. Forced service reduction is expected to be costly and disruptive, and may trigger wider impacts through airline network effects. As a result, the proposed policy is controversial, which probably explains why it has not been adopted by policymakers elsewhere so far.

Our empirical analysis suggests that the OTP regulation recently imposed by CAAC is indeed very effective in achieving its target indictors. Flight delay in the Chinese domestic markets, especially at those hub and major slot-coordinated airports, have been reduced significantly. More importantly, welfare analysis further confirms that the policy brought significant gains in passenger surplus, mainly through savings associated with delay time reduction and lower airfares.

Our study thus presents an example of regulatory dilemma: a policy may be effective and welfare-enhancing, yet unfair and disruptive. This gives rise to many additional questions. For example, should such a policy be adopted? Are there definite and clear criteria with which such types of policy can be judged and evaluated? Our study does not provide a definite and immediate answer to these questions *per se*. Nevertheless, considering the fact that there have been few good alternatives, and even promising solutions may take a very long time to get a trial (recall the case of slot auction), we believe the CAAC's policy should be continued. This ensures the welfare gains can be maintained. In addition, the declared capacity of major airports could be formally reduced to a lower and sustainable level. This would provide airlines with a reasonable long-term expectation of the slot availability, facilitating their network and schedule planning. More importantly, in-depth analysis can be carried out when more comprehensive data becomes available. Where possible, policy innovation and trials should be encouraged. Instead of restricting imperfect ideas to debates and theoretical analysis, regulators should be allowed, or even encouraged, to test promising policies. Better understanding can be achieved with newly available data, which prompt more novel solutions.

For the OTP policy implemented by CAAC, one possible way to reduce operation uncertainty and disruption is to limit this regulation to the allocation of newly added slots, without forcing an airline to reduce its (existing) flight services. That is, an airline will be rewarded for good OTP (i.e. with the allocation of newly added slots), but not punished for poor performance beyond its own control. Such a policy is consistent with existing rules and practices (i.e. the use-it-or-lose-it rule and grandfathered right), but nevertheless retains incentives for better operations. Like any other proposed solutions, it would be good to have more in-depth analysis of this initiative, and where possible and prudent, a trial of actual implementation.

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Table 1. Capacity regulated airports according to CAAC classification

Type	Airport
Hub airports	Beijing Capital, Guangzhou, Shanghai Pudong, Shanghai Hongqiao
Major slot-coordinated	Tianjin, Dalian, Hangzhou, Xiamen, Nanjing, Qingdao, Fuzhou, Shenzhen, Wuhan, Haikou, Changsha, Sanya, Chongqing, Kunming, Chengdu, Xi'an, Urumqi
Minor slot-coordinated	Taiyuan, Lanzhou, Nanning, Jinan, Shenyang, Guiyang, Harbin, Zhengzhou

Note:
1. Hub airports are also included in the list of major slot-coordinated airports.
2. Hub and major slot-coordinated airports are required to have slot control.
3. The minor slot-coordinated airports are those not included in the list of major slot-coordinated airports but have more than 10 million passenger throughputs.

Table 2. Comparison of airport on-time performance between 2016 and 2017
(start of Winter Scheduling Season to the end of each year)

(a). Flight average departing delay and total departing flight frequency

Airport type	Airport code	Airport Name	Avg departing delay (mins)			Total departing flight frequency		
			2017 Winter	2016 Winter	Change	2017 Winter	2016 Winter	Change
Non-slot coordinated airport			21.1	26.6	-0.21	910	810	0.123
Hub	CAN	GUANGZHOU BAIYUN	24.9	30.4	-0.18	36116	36512	-0.011
	PEK	BEIJING CAPITAL	28.7	36.6	-0.217	47351	49614	-0.046
	PVG	SHANGHAI PUDONG	24.7	43.1	-0.427	36136	37161	-0.028
	SHA	SHANGHAI HONGQIAO	19.7	40.4	-0.513	21280	22403	-0.05
Major slot-coordinated airport	CKG	CHONGQING JIANGBEI	19.3	22.2	-0.134	22946	22751	0.009
	CSX	CHANGSHA HUANGHUA	20.0	30.7	-0.349	13676	13678	0.001
	CTU	CHENGDU SHUANGLIU	27.1	34.9	-0.224	27145	27199	0.002
	DLC	DALIAN ZHOUSHUIZI	13.3	20.8	-0.362	9746	10282	0.055
	FOC	FUZHOU CHANGLE	27.1	24.1	0.126	7043	7956	0.130
	HAK	HAIKOU MEILAN	21.8	27.9	-0.22	13067	13642	0.044
	HGH	HANGZHOU XIAOSHAN	26.1	38.1	-0.316	19456	19794	0.017
	KMG	KUNMING CHANGSHUI	23.7	29	-0.182	28550	28435	-0.004
	NKG	NANJING LUKOU	25.1	39.8	-0.369	14240	15628	0.097
	SYX	SANYA PHOENIX	25.9	30.2	-0.144	10468	10426	0.004
	SZX	SHENZHEN BAO'AN	21.2	28.9	-0.267	25736	25755	-0.001
	TAO	QINGDAO LIUTING	18.3	27	-0.322	13228	13139	0.007
	TSN	TIANJIN BINHAI	28.1	40.3	-0.303	12958	10772	0.203
	URC	URUMQI DIWOPU	23.7	52.6	-0.549	12317	12269	0.004
	WUH	WUHAN TIANHE	22	26.3	-0.162	14592	14992	-0.027
	XIY	XI AN XIANYANG	19.3	24.2	-0.201	25145	24978	0.007
	XMN	XIAMEN GAOQI	32.3	33.2	-0.027	15099	15190	-0.006
Minor slot-coordinated airport	HRB	HARBIN TAIPING	25.3	29.4	-0.138	10886	10209	0.066
	KWE	GUIYANG LONGDONGBAO	20.3	30.4	-0.334	11966	11009	0.087

	LHW	LANZHOU ZHONGCHUAN	17.8	23.4	-0.239	7538	6973	0.081
	NNG	NANNING WUXU	34.1	32.0	0.064	8314	8213	0.012
	SHE	SHENYANG TAOXIAN	23.6	30.2	-0.22	10232	9785	0.046
	TNA	JINAN YAOQIANG	15.6	27.6	-0.434	9210	8011	0.150
	TYN	TAIYUAN WUSU	19.3	21.6	-0.107	8073	7057	0.144

(b). Departing flight average buffer time

Airport type	Airport code	Airport Name	Buffer time		Change
			2017 Winter	2016 Winter	
Non-slot coordinated airport			26.1	25.6	0.02
Hub	CAN	GUANGZHOU BAIYUN	40.8	41.6	-0.022
	PEK	BEIJING CAPITAL	43.3	41.9	0.032
	PVG	SHANGHAI PUDONG	49.8	48.6	0.024
	SHA	SHANGHAI HONGQIAO	42.8	44.6	-0.04
Major slot-coordinated airport	CKG	CHONGQING JIANGBEI	32.1	32.8	-0.023
	CSX	CHANGSHA HUANGHUA	28.2	27.6	0.022
	CTU	CHENGDU SHUANGLIU	35.2	34.2	0.028
	DLC	DALIAN ZHOUSHUIZI	28	28.4	-0.015
	FOC	FUZHOU CHANGLE	30.3	29.5	0.03
	HAK	HAIKOU MEILAN	28.8	27	0.067
	HGH	HANGZHOU XIAOSHAN	36.5	36.5	0
	KMG	KUNMING CHANGSHUI	31.1	31	0.003
	NKG	NANJING LUKOU	32.9	32.3	0.021
	SYX	SANYA PHOENIX	29.1	30.6	-0.048
	SZX	SHENZHEN BAO'AN	38	38.7	-0.019
	TAO	QINGDAO LIUTING	31.4	30.4	0.033
	TSN	TIANJIN BINHAI	31.8	29.3	0.085
	URC	URUMQI DIWOPU	33.9	27.7	0.223
	WUH	WUHAN TIANHE	28	27.2	0.027
	XIY	XI AN XIANYANG	33.6	32.9	0.021
	XMN	XIAMEN GAOQI	35.5	32.8	0.085
Minor slot-coordinated airport	HRB	HARBIN TAIPING	34.3	27.3	0.257
	KWE	GUIYANG LONGDONGBAO	25.3	23.9	0.057
	LHW	LANZHOU ZHONGCHUAN AIRPORT	25	26.2	-0.047
	NNG	NANNING WUXU	26.6	25.5	0.044
	SHE	SHENYANG TAOXIAN	35.4	29	0.223
	TNA	JINAN YAOQIANG	26.9	26.9	0.001

	TYN	TAIYUAN WUSU	25.2	26.2	-0.037

Note: Winter Scheduling Season was from Oct 30, 2016 for year 2016, and from Oct 29, 2017 for year 2017. Our sample period is from Oct 30, 2016 to Dec 31, 2016, and from Oct 29, 2017 to Dec 31, 2017.

Table 3. Change of airline average departing flight delay and buffer time in Beijing Capital airport (PEK) for 2017 and 2016 Winter Scheduling Season

Airline_name	Airline Code	Origin Airport	Change in departing delay	Change in buffer time
LUCKY AIR	8L	PEK	-75%	72%
Grand China Air	CN	PEK	-44%	-2%
Zhejiang Loong Airlines	GJ	PEK	-68%	10%
Shandong Airlines	SC	PEK	-32%	15%
Juneyao Airlines	HO	PEK	-34%	1%
Air China*	**CA**	**PEK**	**-24%**	**0%**
Beijing Capital Airlines	JD	PEK	-39%	11%
Hainan Airlines	HU	PEK	-12%	4%
Sichuan Airlines	3U	PEK	-45%	-9%
Chongqing Airlines	OQ	PEK	-35%	-8%
Donghai Airlines	DZ	PEK	-46%	20%
China Eastern Airlines	MU	PEK	-17%	7%
Shenzhen Airlines	ZH	PEK	-33%	1%
Shanghai Airlines	FM	PEK	-21%	10%
China Southern Airlines	CZ	PEK	-20%	2%
Tibet Airlines	TV	PEK	-30%	5%
Xiamen Airlines	MF	PEK	-24%	11%

*Air China is the hub carrier of Beijing Capital Airport

Table 4 DID estimation on the CAAC policy effect on airport average delay

	Departing delay	Departing flight frequency	Arrival delay	Arrival flight frequency
Hub	-11.2 mins	-5.23%	-10.0 mins	-4.8%
Major slot-coordinated	-4.7 mins	-4.31%	-6.2 mins	-4.6%
Minor slot-coordinated	-3.5 mins	-3.28%	-5.3 mins	-2.4%

Note: As the CAAC policy aims to reduce the departing flight frequency by percentage to be below 75% or 80% of the airport design capacity, we use the log-linear DID regression to get the treatment effect on flight frequency percentage change.

Table 5. Passenger utility estimation results

Variable	**Coefficient**	**St. error**
fare	-0.098***	0.016
delay	-0.060***	0.025
buffer	-0.033**	0.014
frequency	0.015***	0.0008
distance	0.007***	0.0016
GDP	0.232***	0.083
LCC	-0.621**	0.286
HSR	-0.438***	0.039
origin_connection	-0.0553***	0.007
dest_connection	-0.0397***	0.002
tour	0.746***	0.049
σ	0.093**	0.039
slot_control	-0.707***	0.078

Note: To save space, the estimated coefficients for yearly, quarterly and the intercepts are not reported. The number in the parenthesis is the estimated standard deviation. *, ** and *** represent 1%, 5% and 10% significance levels, respectively.

Table 6. Annual consumer surplus change because of CAAC policy to improve on-time performance

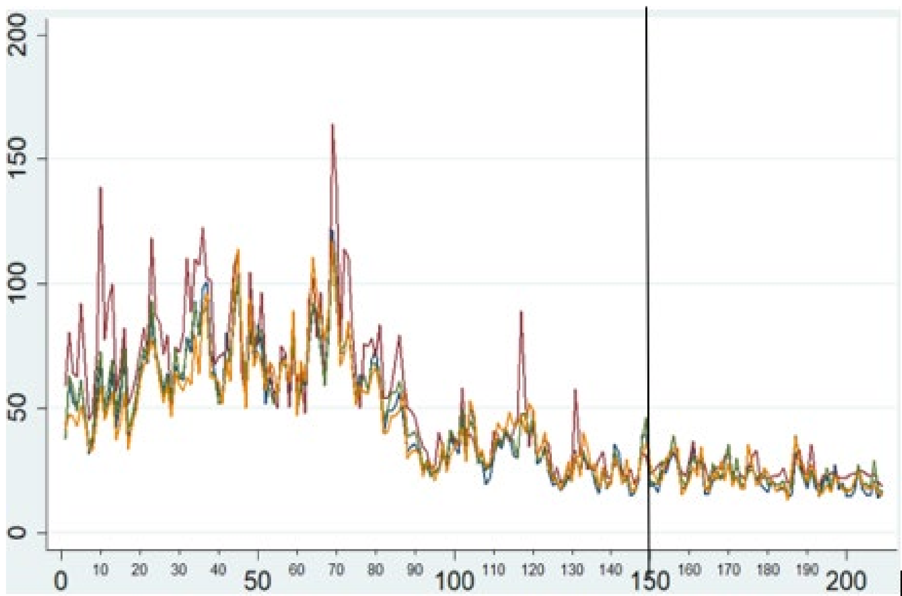
Airport type	**Code**	**Airport Name**	**Arriving passenger (million)**	**Average flight arrival delay change (minute)**	**Flight frequency per route change**	**Average fare change**	**Delay effect on consumer surplus** (million USD)	**Frequency effect on surplus change** (million USD)	**Ticket price effect on consumer surplus** (million USD)	**Total consumer surplus change** (million USD)
Hub	PEK	BEIJING CAPITAL	30.6	-10	-0.14	-2.05	186.6	-59.6	62.9	190
	CAN	GUANGZHOU BAIYUN	20.2	-10	-0.14	-2.08	123.2	-41.1	42.1	124
	SHA	SHANGHAI HONGQIAO	17.4	-10	-0.17	-1.81	106.1	-42.1	31.5	95
	PVG	SHANGHAI PUDONG	15.2	-10	-0.12	-2.56	92.7	-25.6	38.9	105
Major slot-coordinated	KMG	KUNMING CHANGSHUI	18.9	-6.2	-0.12	-0.66	71.4	-33.3	12.6	50
	CTU	CHENGDU SHUANGLIU	18.7	-6.2	-0.1	-0.87	70.7	-28.2	16.4	58
	SZX	SHENZHEN BAO'AN	18.3	-6.2	-0.11	-0.46	69.2	-29.8	8.5	47
	XIY	XI AN XIANYANG	18	-6.2	-0.11	-1.28	68	-27.8	23	63
	CKG	CHONGQING JIANGBEI	15.6	-6.2	-0.11	-0.77	58.9	-23.5	12.1	47
	HGH	HANGZHOU XIAOSHAN	13.9	-6.2	-0.11	-0.55	52.5	-21.4	7.6	38
	CGO	ZHENGZHOU XINZHENG	10.5	-6.2	-0.1	-0.75	39.7	-14.6	7.9	33
	XMN	XIAMEN GAOQI	9.7	-6.2	-0.1	-0.35	36.5	-14.1	3.4	25
	CSX	CHANGSHA HUANGHUA	9.6	-6.2	-0.08	-0.98	36.1	-11.6	9.4	33
	WUH	WUHAN TIANHE	9.5	-6.2	-0.09	-1.25	35.8	-12.2	11.9	35

	HAK	HAIKOU MEILAN	9.1	-6.2	-0.07	-0.75	34.5	-10.1	6.9	31
	URC	URUMQI DIWOPU	9	-6.2	-0.12	-1.1	34.1	-15.4	9.9	28
	TAO	QINGDAO LIUTING	8.9	-6.2	-0.1	-0.83	33.7	-12.7	7.4	28
	TSN	TIANJIN BINHAI	8.6	-6.2	-0.06	-0.68	32.5	-7.6	5.8	30
	SYX	SANYA PHOENIX	7.7	-6.2	-0.08	-0.55	29.1	-9.1	4.2	24
	DLC	DALIAN ZHOUSHUIZI	7.1	-6.2	-0.08	-1.01	26.6	-8.3	7.1	25
	FOC	FUZHOU CHANGLE	5.2	-6.2	-0.06	-0.42	20.3	-4.8	2.2	17
Minor slot-coordinated	NKG	NANJING LUKOU	10.6	-5.3	-0.05	-0.98	34.2	-8.7	10.4	35
	KWE	GUIYANG LONGDONGBAO	7.9	-5.3	-0.04	-1.19	25.7	-5.3	9.5	29
	HRB	HARBIN TAIPING	7.9	-5.3	-0.03	-1.22	25.4	-4.2	9.6	30
	SHE	SHENYANG TAOXIAN	6.7	-5.3	-0.03	-1.01	21.8	-3.4	6.8	25
	TNA	JINAN YAOQIANG	6.4	-5.3	-0.03	-1.37	20.7	-3.4	8.8	26
	LHW	LANZHOU ZHONGCHUAN	6.1	-5.3	-0.03	-1.52	19.6	-3.3	9.2	25
	TYN	TAIYUAN WUSU	5.9	-5.3	-0.04	-1	19.1	-3.5	5.9	21
	NNG	NANNING WUXU	5.9	-4.3	-0.03	-0.7	15.3	-2.9	4.1	16
Total							1,440	-488	396	1,333

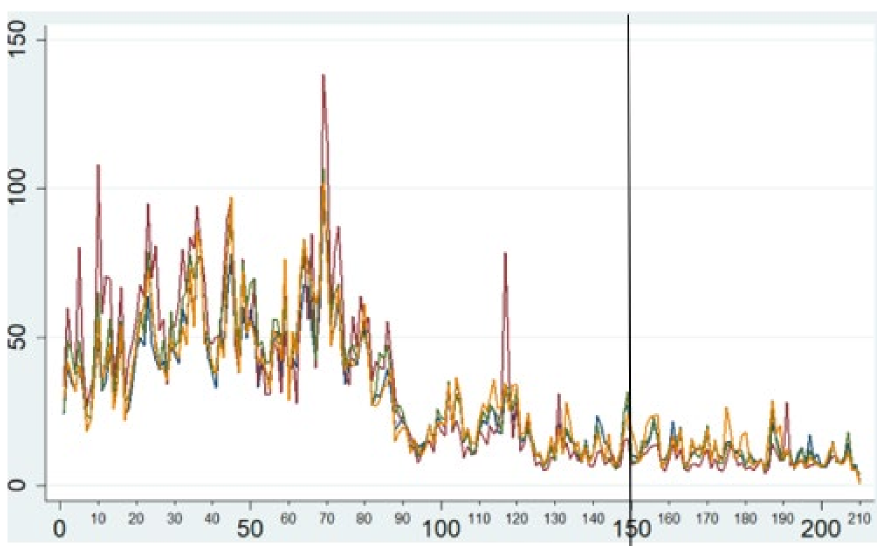
Table 7. CAAC policy effect on airlines operating at different airports

Airport type	Airport code	Airport name	Ticket revenue change (million USD)	Delay change (in thousand mins)	frequency change
Hub	PEK	BEIJING CAPITAL	-62.9	-2,810	-13,490
	CAN	GUANGZHOU BAIYUN	-42.1	-2,182	-10,478
	SHA	SHANGHAI HONGQIAO	-31.5	-1,283	-6,159
Major slot-coordinated	PVG	SHANGHAI PUDONG	-38.9	-2,197	-10,547
	KMG	KUNMING CHANGSHUI	-12.6	-1,066	-7,916
	CTU	CHENGDU SHUANGLIU	-16.4	-993	-7,369
	SZX	SHENZHEN BAO'AN	-8.5	-946	-7,021
	XIY	XI AN XIANYANG	-23.0	-967	-7,177
	CKG	CHONGQING JIANGBEI	-12.1	-857	-6,363
	HGH	HANGZHOU XIAOSHAN	-7.6	-752	-5,580
	CGO	ZHENGZHOU XINZHENG	-7.9	-565	-4,194
	XMN	XIAMEN GAOQI	-3.4	-554	-4,114
	CSX	CHANGSHA HUANGHUA	-9.4	-531	-3,941
	WUH	WUHAN TIANHE	-11.9	-547	-4,063
	HAK	HAIKOU MEILAN	-6.9	-470	-3,489
	URC	URUMQI DIWOPU	-9.9	-503	-3,737
	TAO	QINGDAO LIUTING	-7.4	-531	-3,945
	TSN	TIANJIN BINHAI	-5.8	-478	-3,549
	SYX	SANYA PHOENIX	-4.2	-358	-2,660
	DLC	DALIAN ZHOUSHUIZI	-7.1	-422	-3,134
	FOC	FUZHOU CHANGLE	-2.2	-284	-2,112
Minor slot-coordinated	NKG	NANJING LUKOU	-10.4	-504	-2,285
	KWE	GUIYANG LONGDONGBAO	-9.5	-380	-1,725
	HRB	HARBIN TAIPING	-9.6	-350	-1,588
	SHE	SHENYANG TAOXIAN	-6.8	-323	-1,463
	TNA	JINAN YAOQIANG	-8.8	-286	-1,299

	LHW	LANZHOU ZHONGCHUAN	-9.2	-264	-1,198
	TYN	TAIYUAN WUSU	-5.9	-257	-1,164
	NNG	NANNING WUXU	-4.1	-221	-1,238
Total			-391	-21,881	-132,998



(a). Airport average flight departing delay



(b). Airport average flight arriving delay

Figure 1. Airport daily average flight delay from June 1st 2017 to Dec 31st 2017 (total 214 days)

Note:

1. The "red line" represents the average for "hub airport," the "green line" represents the average for "major slot-coordinated airport," the "orange" represents the average for "minor slot-coordinated airports," and the "blue" represents the average for the "non-slot-coordinated airports."
2. The vertical line is the 150th day of the year 2017, which is Oct 29, 2017, the first day of the Winter Scheduling Season for 2017.