Competition and Quality: Evidence from High-Speed Railways and Airlines[†]

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Abstract

The entry of High-Speed Railways (HSR) represents a disruptive competition to airlines, particularly for short- to medium-distance journeys. Utilizing a unique dataset that contains the details of all flights departing from Beijing to 113 domestic destinations in China since January 2009, we employ a difference-in-differences approach to examine the effects of HSR entry on the quality of service provided by airlines as proxied by their on-time performance and to identify the channels through which competition leads to quality improvement. We document two main findings. First, the competition from the entry of HSR leads to significant reductions in the mean and variance of travel delays on the affected airline routes. Second, the reductions in departure delays and taxi-in time at the destination airports are identified as the main sources of the improvement in the airlines' on-time performance. We provide indirect evidence that the airlines' improvement in operational efficiency is the most likely source of the delay reductions.

Keywords: Competition; Quality; Transportation; Airlines; High-speed Rail; On-time Performance

JEL Codes: L1, L91, O18, R4

1 Introduction

There has been a long-standing interest in the effects of competition, which is widely recognized as the drivers of improved product quality, operational efficiency, innovation, and economic growth (Nickell, 1996; Holmes and Schmitz Jr, 2010; Amiti and Khandelwal, 2013; Buccirossi et al., 2013). Theoretically, however, the effect of competition on quality is ambiguous (Dranove and Satterthwaite, 2000), thus the relationship between competition and quality is largely an empirical question. Establishing a causal impact of competition on quality or productivity presents substantial challenges due to the difficulty of identifying a clean source of exogenous variation in competition; it is even more challenging to isolate the mechanisms through which competition impacts quality or productivity (Holmes and Schmitz Jr, 2010). In this paper, we exploit the entry of Beijing-Shanghai high-speed rails (HSR) as an exogenous increase in competition for commercial airlines to investigate whether competition spurs quality improvement, and if so, how?

The entry of High-Speed Railways (HSR) represents a disruptive competition to airlines in the past decade, particularly for short- to medium-distance journeys (Adler et al., 2010; Yang and Zhang, 2012; Fu et al., 2012; Behrens and Pels, 2012; Albalate et al., 2015). Besides its exceptional punctuality, HSR offers improved traveling experiences, stable prices, energy efficiency, and environmental sustainability compared to other modes of intercity transportation.[1] China is a perfect testing ground to analyze the competition between HSR and airlines for several reasons. First, China has the largest and most extensively used HSR network in the world; second, the airline industry in China is rapidly growing both in the number of scheduled flights and passengers, yet it suffers from serious and

[1] The Green New Deal, proposed on February 7, 2019, advocates converting domestic air travel to intercity HSR travel in the US. It calls for a "10-year national mobilization." See `https://apps.npr.org/documents/document.html?id=5729033-Green-New-Deal-FINAL`.

chronic flight delays, which makes HSR a particularly attractive alternative mode of intercity transportation once introduced; third, the data on flights' on-time performance (OTP) is available, and OTP is well accepted as the key quality indicator for airlines; last but not least, the staggered entries of HSR lines in China offer unique opportunities to address the potential issues of non-random placement of HSRs, and thus offer a clean identification of the causal effects of competition on quality improvement.

More specifically, we argue that the exact date of entry of the Beijing–Shanghai HSR on June 30, 2011 is likely exogenous, and use it to construct treatment and control flights. The Beijing–Shanghai HSR line was the first and only Beijing-outbound HSR line linking Beijing to other cities during our main study period between January 1, 2009 and December 25, 2012. The second Beijing-outbound HSR line, named Beijing–Guangzhou line, launched on December 26, 2012, 18 months after the Beijing–Shanghai HSR line. Thus, our sample period covers both long pre- and post-HSR time windows, and yet ensures that the estimated treatment effect is free of the possible contamination from other Beijing-outbound HSR entries. To address the concern that cities on the Beijing-Shanghai HSR are selected, we then restrict our control flights to a subset of destinations on the Beijing-Guangzhou line. The Beijing-Shanghai line and the Beijing-Guangzhou line were planned and built in the same year but the former began operating 18 months earlier only because of its shorter construction timeline.[2]

In this study, we use a proprietary and comprehensive dataset containing 865,967 non-stop Beijing-outbound flights scheduled by 41 airlines to 113 destinations in China between January 1, 2009 and December 25, 2012. The richness of this flight data enables us to study the impact of HSR competition on the airlines' quality improvement measured by OTP and

[2]See Table A1 in the Appendix for the gradual expansion of China's HSR system. Source: `https://www.travelchinaguide.com/china-trains/high-speed/rail-network.htm`

to pinpoint the sources of the quality improvement. We use a difference-in-differences (DID) strategy that exploits the variation in competition caused by HSR entry across cities. The treatment group includes flights from Beijing Capital International Airport (BCIA) to cities along the Beijing-Shanghai HSR, and the control group is flights departing from Beijing for non-HSR destinations. Following Mayer and Sinai (2003) and Prince and Simon (2015), we employ six different OTP measures as outcome variables, namely, the arrival (and departure, respectively) delay in minutes, i.e., the difference between the actual arrival (and departure, respectively) time and scheduled arrival (and departure, respectively) time, which measures the intensive margin of the flight delay; an indicator for whether a flight arrives (and departs, respectively) 15 minutes later than the scheduled arrival (and departure, respectively) time, which measures the extensive margin of the flight delay; the actual travel time; and the excessive travel time.

When we compare the OTP of the Beijing-outbound flights to the 11 destination cities on the Beijing-Shanghai HSR (the treatment group) with Beijing-outbound flights to 102 non-HSR destinations (the control group) from January 1, 2009 to December 25, 2012, we find that, at the intensive margin, the HSR entry leads to an average decrease of 2.54 minutes in arrival delay minutes.[3] This represents an economically significant effect, accounting for about 14.67% of the average arrival delay of 17.32 minutes for the treatment flights before the HSR entry. At the extensive margin, we find that the HSR entry leads to a reduction of 2.5 (3.4, respectively) percentage points in arrival (departure, respectively) delays of 15 minutes or longer. Again, these are large effects given that, on average, before the HSR entry, 26% and 68% of flights had delays of at least 15 minutes relative to the scheduled

[3] We also find that the HSR entry causes the air time of the treatment flights to increase by 1.74 minutes on average relative to the control flights, which suggests that the control routes are less congested than the treatment routes and refutes the alternative hypothesis that airlines may reallocate flights from the treatment routes to the control routes.

arrival and departure times, respectively. We also find that the entry of HSR significantly reduces the variance of flight arrival delay minutes. These results are quantitatively similar when we restrict our control group to Beijing-outbound flights routed to the nine cities on the Beijing-Guangzhou HSR that opened on December 26, 2012.

We would like to emphasize that the magnitude of our estimated effect that the HRS entry reduced the arrival delays of the impacted flights by 2.54 minutes (about 14.67% reduction) is *significant*. To put it in proper context, it is useful to compare our estimated effects with those in the existing literature, which exclusively focused on the impact of competition on OTP *within* the airline industry. Mazzeo (2003) finds that arrival delays on competitive flight routes are about 1.35 minutes shorter than monopoly routes. Prince and Simon (2015) find that incumbents' OTP actually worsens (by 1.1 to 1.6 minutes) in response to entry, or even threat of entry, by the low-cost carrier Southwest Airlines. In general, the literature finds it difficult for airlines to reduce arrival delays. Forbes et al. (2019) study whether the US airlines engage in schedule padding to boost OTP and find that in the period of 2006 to 2016, airlines reduced the arrival delay minutes by only 0.42 to 4.18 minutes relative to the 1990 levels. Of course, our study differs somewhat in context from the existing literature, which focuses on the effect of within-airline-industry competition; we study the airlines' OTP improvements driven by competition from HSR. To the best of our knowledge, the competition effect of HSR on the airlines' OTP has not been previously studied; and indeed, our findings suggest that the response of airlines to the competition from traditionally a non-competing mode of transportation, i.e., railways, differs starkly from that when they face more competition from within the airline industry, which is the focus of Prince and Simon (2015).

Similar to their counterparts in the United States and Europe, Chinese airlines can potentially mitigate the delays, especially the extreme delays, by optimizing routes, rescheduling flights, and building redundancies. To identify the source of improvement in quality, we further investigate the impact of competition on each breakdown of flight schedule.[4] We find that HSR entry leads to an average reduction in *departure delay* by 5.28 minutes (about 15.20% of the pre-HSR entry average departure delay of 34.73 minutes), which accounts for the largest decline among all contributors to the post-HSR reduction in arrival delay minutes. The reductions in departure delay minutes may result from the airlines' improvement in operational efficiency (such as the check-in and boarding process, and gate-preparation at departure). In addition, HSR entry leads to a reduction of the *taxi-in time* of 1.39 minutes on average at the destination airports that are impacted by the HSR. The reductions in taxi-in time may result from the airport's air traffic control tower giving preferential treatments to the treated flights in, e.g., runway priorities. The destination airports have the incentives to give preferential treatment to the treated flights when they come under competitive pressure because the flights to Beijing are likely the most important flights for the destination city.

We consider and rule out eight alternative explanations for our findings. First, to examine whether a reduction in the number of passengers on the treatment flights, which leads to faster check-ins, could drive our findings, we test a subsample of flights during China's holiday periods when we ensure that all airports and airlines operate at full capacity. Second, to address the alternative explanation that airlines may reschedule the treated flights to off-peak time slots, we identify the less congested time slots and test the probability of schedule reshuffling. Third, to address the possible contamination from the flights allocation from the treatment to the control routes, we test the impact of the HSR entry on *air time* and find that

[4] As illustrated in the flowchart in Figure 2, the *departure delay* is calculated as the time spent before leaving the gate (the actual departure time minus the scheduled departure time) and the *actual duration* consists of the *taxi-out time* (time spent on the departure runway), *airtime*, and *taxi-in time* (time spent on the arrival runway).

the HSR entry does not cause congestion in the air corridor for the control flights. Fourth, to address the concern that the reduction in arrival delays might result from a deliberately prolonged scheduled duration, rather than a genuine improvement in OTP, we test the impact of the HSR entry on *scheduled duration* and rule out this alternative explanation. Fifth, to address the concern that the treatment effects might be driven by the increased air traffic controls on the control routes, we use an alternative control group consisting of flights that share the same air corridor with the treatment flights and find consistent results. Sixth, to address the possibility that our results are driven by some flights with more serious delays being either eliminated or re-assigned with new flight numbers, we focus on a subsample of flights that existed both before and after the HSR entry. We also consider and rule out other alternative explanations, such as the possibility that the control flights experience more delays due to delays of the incoming flights after the HSR entry, and the possibility that the outliers may drive our findings. Finally, we conduct placebo tests using a fictitious treatment group or a fictitious treatment date; both placebo tests confirm that the competition effects we estimated are not caused by other spurious factors.

The richness of our flight data also allows us to better understand the heterogeneity in the service quality response to the competition from the HSR entry. We find that non-hub airlines and flights on short-to-medium routes (air distance within 1,200 km) are more responsive to HSR entry than their respective counterparts. We also extend our analysis to cover the sample period up to September 2015, by when ten additional HSR lines were introduced.[5] We find that our results are robust to the extension to the longer sample period. Finally, we conduct a back-of-the-envelope calculation to obtain a lower-bound of

[5]Table A1 in the Appendix summarizes the opening dates of all these HSR lines. Many cities were connected to Beijing following the completion of some of these new HSR lines. For instance, the Beijing–Guangzhou HSR line was launched on December 26, 2012, and the Shanghai–Kunming HSR line was launched on September 14, 2014.

the monetary value of the time saving for air travelers on the routes affected by the HSR entry.

This study adds to the literature that examines the causal effects of competition. Most related is the literature on the effect of competition on quality or productivity, where authors examine the relationship between competition and firms' productivity growth (Nickell, 1996), retail pricing and stocking (Busso and Galiani, 2019; Matsa, 2011), labor productivity (Schmitz Jr, 2005), and management(Bloom et al., 2015). The papers tend to find a positive effect of competition on quality or productivity. In contrast, Propper et al. (2004, 2008) study the effect of competition on measured quality in the healthcare sector in the UK, using the interaction between the changes in the competition policies by the UK government in 1991 and 1997, as well as the local health care market structure, as the source of variation in competition. They find that competition lowered the overall care quality as measured by patients' mortality, though it also reduced the waiting time. The literature also examined the effect of competition on other outcomes. Aghion et al. (2005) and Hashmi (2013) document an inverted-U relationship between import competition and innovation, whereas Cornaggia et al. (2015) reveal a negative impact of bank competition on innovation. There is also a literature on the effect of airline competition where the source of variation in competition is typically from the entry of a new airline. This literature finds that competition *within* the airline industry improves the OTP of flights (Mazzeo, 2003; Rupp et al., 2006; Prince and Simon, 2009; Greenfield, 2014; Goolsbee and Syverson, 2008), except when the increase in competition was due to the entry of low-cost carriers (Prince and Simon, 2015). Our study complements this literature, with an arguably more exogenous source of variation in competition; moreover, to the best of our knowledge, ours is the first study that provides causal empirical evidence for how airline OTP is affected by a plausibly exogenous competition shock from a *different* sub-sector in the transportation industry, namely the entry of HSR.

This study also contributes to the growing literature on the economic impacts of transport infrastructure projects. Much of the literature explores the effects of urban transportation improvements in roads and railways on urban growth, urban form, congestion, and trade cost (Baum-Snow, 2007; Duranton and Turner, 2011, 2012; Baum-Snow et al., 2017; Donaldson, 2018). In addition, the literature has shown that HSR has a positive influence on intercity mobility (Chen, 2012; Tierney, 2012), market integration (Zheng and Kahn, 2013), population density, and employment (Lin, 2017; Levinson, 2012). However, some studies argue that HSR primarily benefits large cities, as opposed to small counties (Zheng and Kahn, 2013; Qin, 2017). Moreover, recent studies that examined the impacts of HSR on the airline industry focus on the market share and price response (Behrens and Pels, 2012; Yang and Zhang, 2012; Fu et al., 2012). This study contributes to this strand of literature by examining the causal impacts of China's HSR on the *non-price* characteristics of the airline industry, which provides useful policy implications for other countries that may be contemplating building an HSR network.

The remainder of the paper is structured as follows. In Section 2, we provide a brief background on the HSR networks and the airline industry in China. In Section 3, we describe our dataset and present summary statistics. In Section 4, we present our empirical strategies and the main results. In Section 5, we discuss various alternative explanations and present falsification tests. In Section 6, we provide a back-of-the-envelope calculation for a lower bound estimate of the time value from the OTP improvement. Finally, in Section 7, we conclude.

2 Background on the HSR and Flight Delays in China

After 20 years of development and expansion, China's high-speed railways, which are designed for speeds of 250 to 350 kilometers per hour (kph), have become the largest and most extensively used HSR network in the world. China's HSR network plan, which is often dubbed "the Eight Vertical and Eight Horizontal plan," is based on eight major HSR lines from the north to the south (the eight "verticals"), and another eight major HSR lines from the east to the west (the eight "horizontals"). Beijing is regarded as the most crucial starting point of the vertical lines.

The Beijing–Shanghai HSR line is the first medium- and long-haul Beijing-outbound HSR track that links Beijing to 26 other domestic destinations (see Table A1 in the Appendix).[6] 11 of the 26 cities are linked with Beijing by non-stop commercial flights.[7] The Beijing-Shanghai HSR operates 45 trips in each direction on a daily basis. Prior to the opening of Beijing-Shanghai HSR, the travel time by train from Beijing to Shanghai was 14 hours 35 minutes for the 1,318 km journey. Given that a direct flight between the two cities takes about 2 hours and 15 minutes of air time, even with the longer travel time from the city to the airport than to the train station and the longer boarding time for flights than for trains, train travel was clearly a much more time-consuming option prior to the HSR entry. However, the introduction of the Beijing–Shanghai HSR line on June 30, 2011 changed the situation completely by reducing the travel time by rail substantially to 4 hours and 48 minutes; moreover, the HSR is almost always punctual by the minute.[8] In this sense, we

[6] Spanning a distance of 117 km, the Beijing–Tianjin HSR line is the first Beijing-outbound HSR. However, owing to the short distance, there are no flights between Beijing and Tianjin.

[7] These 11 cities are Changzhou, Hangzhou, Hefei, Jinan, Nanjing, Ningbo, Qingdao, Shanghai, Wenzhou, Wuxi, and Xuzhou, which are denoted by the red train signs in Figure 1.

[8] The maximum speed for Beijing-Shanghai HSR was raised from 300 kph to 350kph on September 21, 2017, cutting the travel time from Beijing to Shanghai further down to 4 hours and 18 minutes. However, this is outside of our study period. See `http://www.gov.cn/ldhd/2011-06/30/content_1896883.htm`

interpret the entry of HSR as a serious competition to the airline industry, particularly for short-to-medium distance journeys.

The Chinese airline industry has experienced tremendous growth in the past decades, with air passenger traffic growing from 18.2 billion in 1987 to 837.8 billion in 2016.[9] Despite this huge growth, China's airline market is still in its nascent stage with inefficient operations and management. According to the 2018 world airport punctuality report, none of China's airports is ranked in the top 20 in terms of OTP.[10]

In this study, we focus on the flights departing BCIA. BCIA has been the world's second busiest airport in terms of passenger traffic since 2010, but it ranked only 44th out of China's 76 international airports in punctuality as of 2017. Specifically, of the 286,602 flights departing BCIA in 2017, only 53.7% departed on time, and average departure delay was around 48.5 minutes.[11] The chronic and often unpredictable delays in BCIA are among the major complaints from travelers through BCIA.

3 Data and Summary Statistics

The flight data used in this analysis were obtained from a leading data company that focuses on commercial aviation. The dataset in the baseline analysis contains 865,967 non-stop flights, scheduled by 41 airlines, departing from Beijing to 113 domestic destinations between January 1, 2009 and December 25, 2012.[12] Figure 1 presents the 113 destinations (denoted by the red, green and black train signs, as well as the blue airport signs) that have non-stop flights from Beijing. Focusing on the sample period between January 1, 2009 and

[9]Source: `http://www.caac.gov.cn/XXGK/XXGK/TJSJ/201702/t20170224_42760.html`.

[10]Source: `https://www.oag.com/hubfs/Free_Reports/Punctuality_League/2018/PunctualityReport2018.pdf`.

[11]The number is calculated using the data collected from Feichangzhun. Source: `https://data.variflight.com/analytics/OTPRankingbyAirport`.

[12]Cities without direct flights from Beijing are excluded from the analysis.

December 25, 2012 ensures that the Beijing–Shanghai HSR line, which opened on June 30, 2011, is the only Beijing-outbound HSR in the analysis; it also guarantees a sufficiently long pre- and post-HSR time window. To ensure that the results can be generalized to the entire population, we also repeat the main analysis using an expanded sample from January 2009 to September 2015.

[Figure 1 About Here]

For each flight in our sample period, we have the flight number, flight date, scheduled departure and arrival times, actual gate departure and gate arrival time stamps, time spent traveling from the gate to the runway (*taxi-out time*), time spent traveling to the gate after landing (*taxi-in time*), and time spent in the air *(air time*). The data also provide accurate real-time flight status, including temporary adjustments to scheduled departure time and scheduled arrival time. We illustrate the various components of flight duration in Figure 2. Following Prince and Simon (2015), we define a *route* as a directional Beijing–destination pair for any carrier that provides non-stop services. To avoid confusion, we refer to the takeoff/landing of a flight number on a given day as a *departure.* For instance, for flight CA1515, the destination city (e.g., Shanghai) refers to a route, CA (China Air) stands for an airline company, and CA1515 represents a flight; and CA1515 on any particular day will be called the departure of CA1515 on that day.

[Figure 2 About Here]

Following the existing literature, we construct two OTP measures for both the arrival and departure delays (Mayer and Sinai, 2003; Goolsbee and Syverson, 2008; Prince and Simon, 2009, 2015). Specifically, *Arrival Delay in minutes* (ADM) represents the difference between the scheduled and the actual arrival times. *Arrival Delay 15 minutes* (ADD15) is a dummy variable equal to 1 if a flight arrives at the gate at least 15 minutes late, and 0 otherwise.

We use the same approach to construct *Departure Delay in minutes* (DDM) and *Departure Delay 15 minutes* (DDD15).

To address the possibility that airlines could manipulate the OTP by artificially inflating the scheduled duration (Mayer and Sinai, 2003; Prince and Simon, 2015), we construct two alternative measures of OTP: *Actual Travel Time (ATT)* and *Excessive Travel Time (ETT)*. ATT is the time difference between the scheduled departure time and the actual arrival time, which measures the actual travel time because any passenger needs to be at the gate before the scheduled departure and will not leave the gate at the destination until the actual arrival time. ETT is the difference between ATT and the minimum feasible travel time. The minimum feasible travel time refers to the minimum travel time of the same flight observed each month, which serves as a benchmark for determining the travel time when a flight is free of any external influences such as air congestion, weather shocks, and air corridor military controls. Therefore, ETT controls for any unobserved or observed time-varying external influences and is immune to airline scheduling manipulations. In Figure A1 in the Appendix, we plot the distributions of ATT for Beijing-outbound flights and HSR trains to the 11 destination cities along the Beijing-Shanghai HSR; it shows that the ATT for flights (black lines) exhibits large variations.[13]

Table 1 shows the summary statistics of the OTP measures and other variables at the individual departure level. In the post-HSR period, the mean values of *ADM*, *DDM*, *ATT*, and ETT increase for both the treatment and control flights, reflecting the rapid growth of China's passenger travel industry, but it is interesting to note that the increases in the treatment group are smaller. More specifically, China has the world's fastest-growing pas-

[13] According to the latest World Bank report, the punctuality rate of HSR service in China is over 98 percent for departures and over 95 percent for arrivals. Source: `https://openknowledge.worldbank.org/handle/10986/31801`. Therefore, we consider the travel time invariant for HSR travel, which is denoted by the red vertical line in Appendix Figure A1.

senger aviation market based on the total passenger numbers. According to World Bank, the number of passengers climbed by more than 90% from 229,062,099 to 436,183,969 during our sample period (between 2009 and 2015);[14] and the total number of departures also increased steadily from about 3 million in 2011 to 4.28 million in 2015.[15] Indeed, this provides the rationale for using the Difference-in-Differences (DID) approach to estimate the causal effect of HSR entry on the OTP of the treated flights. The summary statistics at the aggregated airline-route-month level are reported in Table A2 in the Appendix.

[Table 1 About Here]

4 Empirical Strategies and Main Results

In this section, we first present evidence that the HSR entry poses real competition to the airline industry on the impacted routes. We then describe our empirical strategies, the main empirical results, and various robustness checks.

4.1 HSR Entry as a Competition Shock: Evidence from Supply-Side Response

We have argued that HSR is a disruptive transportation technology that poses competition to air travel, particularly for short-to-medium distance journeys. In this subsection, we provide direct evidence that the HSR entry indeed is a competition shock to the airline industry by examining the supply-side response of the airlines. Specifically, we examine the impact of the Beijing-Shanghai HSR entry on the number of departures on a given route

[14]Source: The World Bank, "Air transport, passengers carried - China", see `https://data.worldbank.org/indicator/IS.AIR.PSGR?name_desc=false&locations=CN`.

[15]Source: Civil Aviation Administration of China (2015, p.5), see `http://www.caac.gov.cn/XXGK/XXGK/TJSJ/201605/P020160531575434538041.pdf`).

at the flight-month, the airline-route-month, and the route-month levels, by running the following regressions:

$$Y_{i,m} = \alpha + \beta \cdot Treatment_i * After_m + \mu_i + \gamma_m + \epsilon_{i,m}, \tag{1a}$$

$$Y_{j,d,m} = \alpha + \beta \cdot Treatment_{j,d} * After_m + \theta_j + \eta_d + \gamma_m + \epsilon_{j,d,m}, \tag{1b}$$

$$Y_{d,m} = \alpha + \beta \cdot Treatment_d * After_m + \eta_d + \gamma_m + \epsilon_{d,m}, \tag{1c}$$

where i, j, d, and m respectively index the flight, the airline, the route (or destination city), and year-month. $Y_{i,m}$, $Y_{j,d,m}$, and $Y_{d,m}$ represent the number of departures (in logs) by flight-month, by airline-route-month, and by route-month, respectively. $Treatment_i$, $Treatment_{j,d}$, and $Treatment_d$ are dummy variables that take value 1 if the flight i, the airline-route (j, d), and the route d, respectively, belong to the 11 HSR destination cities connected to Beijing by the Beijing-Shanghai HSR. $After_t$ is a dummy variable that takes the value 1 after June 30, 2011, and 0 otherwise. Flight fixed effect μ_i is included in Eq. (1a); airline fixed effects θ_j and route (or destination) fixed effects η_d are included in Eq. (1b); and the route (or destination) fixed effects η_d are included in Eq. (1c). Year-month fixed effects γ_m are included in all three equations. The standard errors are clustered at the flight-, airline-route-, and route-level in Eqs. (1a), (1b) and (1c), respectively.

Table 2 reports the results. It shows that the coefficients for the interaction terms are negative and statistically significant, suggesting that the number of departures on the treated routes decreases by 8.42% ($= 1 - exp(-0.088)$) to 17.63% ($= 1 - exp(-0.194)$) more than that on control routes in the post-HSR period. The results are consistent with both the anecdotal evidence and the findings in Fu et al. (2012).[16] We consider the *relative* reduction in flight supply as direct evidence that the HSR entry poses a serious competition shock to

[16]Source: `https://www.bloomberg.com/news/articles/2018-01-09/high-speed-rail-now-rivals-flying-on-key-global-routes`.

the airlines.[17]

[Table 2 About Here]

4.2 HSR Entry and Flight Delays: Baseline Results

Our basic specification to examine the causal effects of the Beijing-Shanghai HSR entry on the OTP of the treated flights is a DID regression at the individual-departure level:

$$Delay_{i,j,d,t} = \alpha + \beta \cdot Treatment_{i,j,d} * After_t + \mu_i + \delta_{hour} + \zeta_t + \epsilon_{i,j,d,t}, \tag{2}$$

where $Delay_{i,j,d,t}$ is one of the six OTP measures for flight i of airline company j departing from Beijing to destination d on date t. $Treatment_{i,j,d}$ is a dummy variable that takes value 1 if the destination city d of flight i is one of the 11 HSR destination cities connected to Beijing by the Beijing-Shanghai HSR. $After_t$ is a dummy variable that takes the value 1 after June 30, 2011, and 0 otherwise. β is the parameter of interest to be estimated, which captures the difference in the average post-HSR delays of a treated flight relative to the post-HSR delays of a control flight. μ_i refers to the flight fixed effect (flight number), capturing the unobserved factors that may affect delays at the departure level. The term δ_{hour} represents the hour fixed effects for the flight's scheduled departure time, which account for any hourly variations that may affect flight delays, such as the hourly congestion and weather conditions.[18] We also include the date fixed effects ζ_t to eliminate any seasonal effects and national trends. The standard errors are clustered at the route level to capture the potential heteroskedasticity of the error terms across the routes.[19]

[Table 3 About Here]

[17]However, as we will show in Figure A2 , the overall number of departures departing BCIA went up in this period because the Chinese air travel industry was rapidly expanding.

[18]Note that we do observe substantial changes in the scheduled departure time for the same flight because of the rapid growth of the commercial airline industry in China in this period. Thus we can include both flight fixed effects and departure hour fixed effects.

[19]The results, available upon request from the authors, are almost unchanged when we cluster the standard errors at the airline level, at the airline and route levels, or at the airline-route pair level.

Panel A of Table 3 presents the estimation results for Eq. (2). The estimated coefficients on *Treatment∗After* are consistently and significantly negative in all columns, which suggests that flights facing the new competition from the HSR entry improve their OTP in the post-HSR period relative to control flights. Specifically, at the intensive margin (Columns 1 and 3), on average the HSR entry reduces the arrival and departure delays for the treatment flights by 2.54 minutes and 5.28 minutes more than for the control flights. These represent economically significant effects relative to an average arrival delay of 17.32 minutes (about 14.67%) and average departure delay of 34.73 minutes (about 15.20%), respectively, for the treatment flights before the HSR entry. At the extensive margin (Columns 2 and 4), treated flights in the post-HSR entry period are less likely than the control flights to experience arrival (departure, respectively) delays longer than 15 minutes, by 2.5 (3.4, respectively) percentage points.[20] Again, these are large effects given that, on average, before the HSR entry, 26% and 68% of flights had delays of at least 15 minutes relative to the scheduled arrival and departure times, respectively. Using the alternative measures of OTP in Columns 5 and 6, we find very robust results indicating that the HSR entry reduces ATT and ETT by 4.73 and 3.92 minutes, respectively.

In Table A3 in the Appendix we report the estimation results when we include airline fixed effects interacted with the year-month fixed effects and route fixed effects interacted with the year fixed effects to address any omitted factors at the route and airline level. The results are consistent with our baseline results in Table 3.

[20]We also conduct robustness tests using ADD30 and DDD30 (delay over 30 minutes) and find consistent results.

4.3 Parallel Pre-Trends and Dynamic Effects of the HSR Entry

In this subsection, we verify the parallel pre-trend assumption that is necessary for the validity of the DID approach we used in estimating Eq. (2). We estimate the following equation to verify the parallel pre-trends between the treatment and control flights, and to capture the dynamics of the improvement of the OTP to the entry of the HSR:

$$Delay_{i,j,d,t} = \alpha + \sum_{s=-4}^{s=5} \beta_s \cdot Treatment_{i,j,d} * 1\{t \in Quarter_s\} + \mu_i + \delta_{hour} + \zeta_t + \epsilon_{i,j,d,t} \qquad (3)$$

where $1\{t \in Quarter_s\}$ is a binary indicator which takes value 1 if the date t is in quarter $s \in \{-4,-3,-2,...,0,...,3,4,5\}$ before/after June 30, 2011. The coefficient β_s measures the difference in the response of OTP compared with the first 12 months (benchmark period from January 1, 2009 to December 31, 2009) in our sample period between the treatment and control flights. More specifically, the coefficient β_0 measures the immediate response in OTP during the quarter of the HSR entry. The coefficients $\beta_1, \ldots, \beta_5$ measure the responses in the first to the fifth quarter following the entry of HSR, respectively. Similarly, coefficients $\beta_{-4}, \ldots, \beta_{-1}$ capture the difference in the OTP trends of OTP between the treatment and control flights in each of the four pre-treatment quarters. We plot the estimated coefficients of β_s for different measures of OTP in Figure 3. It shows that the treated flights start responding to the entry of the Beijing-Shanghai HSR immediately after the introduction, and the effects are persistent. Figure 3 also shows that the parallel pre-trend assumption holds, as the $\beta_{-4},...,\beta_{-1}$ coefficient estimates are statistically indistinguishable from 0, indicating that there is no systematic difference in pre-trends between the treatment and control flights in their OTP measures.

[Figure 3 About Here]

4.4 A Narrower Control Group

In our baseline analysis, we assumed that the placement of Beijing-Shanghai HSR is exogenous. Even though we provided evidence of parallel pre-trend between the control and treatment flights in Figure 3, one may still be concerned that the 11 destination cities affected by the Beijing-Shanghai HSR – the treatment group – are different from the 102 destination cities in the control group in factors such as the local economy, the industry composition, and geographic characteristics. Such differences *per se* are not an issue for the DID approach to work, provided that the parallel pre-trend assumption is satisfied. However, to ensure more comparable treatment and control groups, we create a narrower control group consisting of only the nine destination cities (indicated by the green train signs in Figure 1) along the Beijing–Guangzhou HSR line, which started operating on Dec. 26, 2012.[21]

Cities located along the Beijing–Shanghai and Beijing–Guangzhou HSR lines are definitely more comparable; in particular, both lines were initiated in the same plan in 2004, and their constructions started at the same time in October 2008.[22] The Beijing-Guangzhou line took 18 months longer than the Beijing-Shanghai line to complete only due to their different lengths: the Beijing-Guangzhou and Beijing-Shanghai HSR lines are respectively 2,298 km and 1,318 km in lengths. Indeed, as we report in Table A4 in the Appendix, the difference between the treatment and control destinations in the key economic variables, such as population, income, and GDP, etc. are economically small and statistically indistinguishable from zero.

Panel B of Table 3 reports the estimation results using the narrower control group. The estimated treatment effects β are statistically different from zero in all columns and the

[21]These nine cities are: Zhengzhou, Taiyuan, Luoyang, Wuhan, Yichang, Changsha, Xian, Guangzhou, and Shenzhen.

[22]Source: `https://www.travelchinaguide.com/china-trains/high-speed/rail-network.htm`

OTP improves by 2.2 to 3.6 minutes depending on the delay measures. The results are both qualitatively and quantitatively consistent with the baseline results reported in Panel A.

4.5 More HSR Entries After December 26, 2012

Between December 26, 2012 and September 2015, 10 additional HSR lines entered service in China. The number of destination cities connected to Beijing by HSR lines increased from 11 to 33 during this period (see Table A1 in the Appendix for more details). We examine the effects of all the HSR entries on the treated flights in this subsection. Extending the analysis to include more HSR entries can also help us to address the concern that the early HSR lines are selected to connect Beijing to the destination cities with the most severe flight delays: if so, we would expect that the estimated treatment effects will be smaller when we include later HSR entries in the analysis.

Panel C of Table 3 reports the results of regressing the different measures of OTP in the same specification as Eq. (2) in the enlarged sample. The estimated coefficients of the interaction term $\textit{Treatment} * \textit{After}$ are both qualitatively and quantitatively consistent with our estimates reported in Panel A of Table 3. This provides additional evidence against the concern that the baseline results reported in Panel A are driven by the Beijing-Shanghai HSR line being non-representative.

4.6 Effects on the Variance of the Delays

The HSR entry may also reduce the variance of the delay minutes of the treated flights, which can lead to substantial welfare gains if travelers are particularly wary of unpredictable long delays. To examine the effect of the HSR entry on the variance of flight delays, we first compute, for each flight, the weekly variance of the OTP measures, ADM, DDM, ATT and ETT; we then use them as the dependent variables in the DID analysis, similar to the regression specification of Eq. (2), except that we control for the year-week and flight fixed effects, instead of the hour and date fixed effects. We also cluster the standard errors at the route level. Table 4 reports that the interaction term $Treatment * After$ is negative and statistically significant, with the magnitude of the estimates indicating that the standard deviation of the delays of the treatment flights reduces by around 23 to 24 minutes after the HSR entry. This suggests that the HSR entry substantially reduces the unpredictable long delays of the treatment flights.

[Table 4 About Here]

4.7 Sources of On-time Performance Improvement

Tables 3 and 4 show that the airline industry reduces the mean and variance in flight delays in response to the competition from the HSR entry. In this section, we attempt to isolate the components in air travel, as depicted in Figure 2, that constitute the main contributing sources of potential OTP improvement. As illustrated in Figure 2, we decompose the *Actual Travel Time* (actual arrival time minus the scheduled departure time) into two parts: *actual duration* for flight and *departure delay*; and we can further decompose the *actual duration* into *taxi-out time*, *air time* and *taxi-in time*. Note that the different components are subject to the control of different parties: the *departure delay*, which measures the delay before leaving the gate, is mostly under the airlines' control (Prince and Simon, 2009); the *taxi-out time* and *taxi-in time* are, respectively, mostly under the control of the departing and destination airport authorities; and *air time* is difficult to improve upon without sacrificing safety or changing the plane models. Thus we expect that the major source of the OTP improvement will be the reduction in *departure delay*.

In Column 1 of Table 5, we find that *departure delay* decreases by 5.28 minutes in response to the HSR entry. The coefficient is negative and statistically significant at the 1% level. In Column 2 of Table 5, we find that indeed, the HSR entry does not seem to have a statistically significant impact on the *actual duration.* In Columns 3-5 we examine the three sub-components of *actual duration*, namely, *taxi-out time*, *air time*, and *taxi-in time*. We find that the HSR entry had a statistically significant negative effect on *taxi-in time* and a positive effect on *air time*. Since the *taxi-in time* is likely to be substantially controlled by the airport authorities (Prince and Simon, 2009), the result that the HSR entry reduces *taxi-in time* at a significant magnitude (1.39 minutes on average) at the destination airports suggests that the destination airports strive to optimize the usage of the runway resources in the post-HSR period for the treated flights. The significantly positive coefficient on *Treatment* After* for *Air time* (1.74 minutes) could be explained by the increasing number of flights from other cities (e.g., Chengdu, Chongqing, etc.) to cities along the Beijing-Shanghai HSR line. The popularity of the cities along the Beijing-Shanghai HSR line may congest the air corridor along the Beijing-Shanghai HSR line, which could result in increased air time. Moreover, the estimated coefficient on *Treatment*After* for *Taxi-out* time is statistically insignificant. It could be explained by the fact that BCIA has little maneuvering room to give preferential treatment to the treated flights because all of the treated flights depart from Beijing and it is difficult to give priority to all of them; in contrast, the destination airport can better prioritize the incoming flights from Beijing because there are only few flights to and from Beijing, and likely the Beijing flights are the most high-profile flights for the destination airport.

[Table 5 About Here]

Mechanisms. The mechanisms for how the treated flights achieve the reduction in departure delay minutes may include the following: first, the airlines may accelerate the check-in and boarding process of the treated flights to reduce departure delays, and be more effective in getting the gates ready for the incoming flights to reduce the taxi-in time at BCIA; second, BCIA's air-traffic control could prioritize flights on the treated routes if there were extensive delays at the airport. Although we are unable to provide direct evidence to support the first mechanism due to the lack of airlines' operational data, we can formally test the second mechanism. Specifically, if BCIA's air traffic control tower giving preferential treatments to the treated flights in, e.g., runway priorities, is the reason for the reduction in departure delay minutes, we would expect the treated flights would exhibit a *larger* advantage in shorter departure delays relative to the control flights during the airport's busy slots. To test this, we include a triple interaction term *Treatment*After*BusySlot* in the regression specification (2), where *BusySlot* is a dummy variable that takes value of 1 if the flight departs in any of the busy slots defined in Figure A3 (in shaded bar), and 0 otherwise. Panel A of Table 6 analyzes the full sample; and Panel B uses a sub-sample that excludes flights that depart in time slots between 2 am and 3 am because those flights are almost always delayed for some other reasons (such as mechanical failures). We find that the coefficients on the triple interaction term are statistically insignificant, and if anything, positive. This suggests that the second mechanism is unlikely the main driving force for our findings, and thus indirectly, it lends some support to the idea that the airlines' operational efficiency improvement is the source of the estimated reductions in departure delays.

[Table 6 About Here]

4.8 Heterogeneity Effects

In this subsection, we explore the heterogeneity in the effects of HSR entry on hub versus non-hub airlines, and on short-to-medium-haul versus long-haul flights.

Hub airlines at BCIA may enjoy more market power than their non-hub peers, as a result, hub and non-hub airlines may respond differently to the competition from the HSR entry. According to the Civil Aviation Administration, China Air, China Southern Airlines, China Eastern Airlines, Hainan Airlines, and Beijing Capital Airlines are the hub airlines of BCIA.

Panel A of Table 7 presents the estimated heterogeneity of the hub and non-hub flights. *Hub* is a dummy that takes value 1 if the flight belongs to one of the five hub airlines, and 0 otherwise. We use the sample period from January 2009 to September 2015 in this estimation. The estimated coefficients on $Treatment{*}After{*}Hub$ are significantly positive for all measures of OTP, indicating that non-hub airlines are more responsive to the competition from the HSR entry.

[Table 7 About Here]

Since the introduction of HSR imposes the most fierce competition for air routes within 1,200 km (Fu et al., 2012; Yang and Zhang, 2012), we use 1,200 km as a cutoff to categorize flights into short-to-medium-haul and long-haul routes.[23] Panel B of Table 7 presents the results. *STM* is a dummy equal to 1 if the distance between Beijing and the destination city is below 1,200 km, and 0 otherwise. The estimated coefficients of $Treatment * After * STM$ are significantly negative for all four measures of OTP, implying that short-to-medium-haul flights are more responsive to competition from HSR lines. Instead of using *STM* dummy,

[23] According to Sachs (2010), the HSR trains is the most efficient for journeys that last between three to four hours. Thus, the HSR trains impose the most fierce competition for journey distance within 1,200 km, given the average HSR speed of 300 kph. Thus, the launch of the Beijing–Shanghai HSR line serves as the most substantial competition to the airline routes between Beijing and the 11 destination cities along the Beijing–Shanghai HSR line given the line's total track length of 1,300 km and total travel time of four to five hours.

we also create indicators of different distance categories. In Figure A4 in the Appendix we plot the coefficients of OTP response for the treatment flights for the entire distribution of travel distances, ranging from 500 km to over 1,500 km, along with their corresponding 95 percent confidence intervals. The coefficient estimates plotted in Figure A4 show that, on average, the OTP improvement of treated flights upon the HSR entry is the largest for short-haul flights.

5 Alternative Explanations and Falsification Tests

In this section, we consider several alternative explanations for our main findings reported in Section 4, and also offer two falsification tests to further strengthen the causality of our findings.

5.1 Alternative Explanations

Fewer Air Travelers on the Treated Flights. One concern for our finding is simply that the treatment flights have fewer passengers per flight after the HSR entry; fewer passengers per flight on the treatment flights can lead to faster check-in and boarding process, resulting in a reduction in departure delays and better OTP. To address this alternative explanation, we use a subsample of flights around the three most important Chinese *holidays*, specifically, the Spring Festival, the Mid-Autumn Festival, and the National Day. Due to the large scale migrant population movements around these holidays, all modes of transportation, including airplanes, HSR, and intercity buses operate at full capacity; thus for flights around these holidays, whether they are on the treated routes or the control routes, the concern of fewer passengers per flight on the treated flights is no longer relevant.

Specifically, we restrict ourselves to a subset of the observations seven days before and after the Spring Festival, three days before and after the Mid-Autumn day, and three days before and after the National Day. The numbers of travelers taking flights during holiday periods are comparable before and after the HSR entry. Panel A of Table 8 shows significantly negative treatment effects in this holiday subsample analysis, which indicates that the decrease in the departure delay is due to the entry of the HSR, rather than to a reduction in the number of air travelers. To further address the concern that reduced demand on the treated flights after the HSR entry might explain their better on-time performance, we perform the holiday analysis using two additional samples. Table A5 in the Appendix presents the results based on the full sample from January 2009 to September 2015 (Panel A), and on a subsample consisting only of flights to destination cities on the Beijing-Shanghai HSR and on the Beijing-Guangzhou HSR (Panel B). The results are consistent with the estimates in Panel A of Table 8.

We would like to further argue that the *relative* demand reduction on the treated routes should *not by itself* differentially affect the OTP of the treated and control flights. It is first of all useful to recall, as mentioned in footnote 17, the overall number of flights departing BCIA has been growing up due to the expansion of the Chinese air travel industry. Second, at the airline level, after the airlines reduced the number of departures on the treated routes in response to the entry of Beijing-Shanghai HSR (as we show in Subsection 4.1), they would optimally choose to reassign the idle aircrews to both the treated and control routes in order to minimize their overall operational efficiency. Third, similarly at the airport level, BCIA should allocate ground service equipment and staff optimally to minimize the overall congestion on the runways.

Flight Cancellation. Another alternative explanation is that, upon the HSR entry, the airlines might have permanently culled some flights with poor OTP; thus, our findings could result from a mechanical compositional change of the surviving flights, rather than genuine quality improvement. To address this concern, we re-estimate Eq.(2) using only the subsample of flights that operated continuously both before and after the HSR entry. We report the results in Panel B of Table 8, and find that our findings are quantitatively and qualitatively robust to this subsample analysis.[24]

Delays of the Previous Flights. Another alternative explanation for our finding is that the control flights in the post-HSR period experience more delays due to the delays of incoming flights (so called "snowball" delays). We already controlled for flight and hour fixed effects in Eq. (2), but to further address this concern, we focus on a subsample of the flights that depart from BCIA in the early morning (6 am to 9 am). It is well known that flights departing in the early mornings are less likely to be delayed due to the delays of the incoming flights. The results in Panel C of Table 8 show that the estimates of the interaction term are significantly negative in all columns in this subsample analysis, with similar magnitudes.

[Table 8 About Here]

Rescheduling to Less Congested Time Slots. Another alternative explanation is that, facing the competition from the HSR entry, airlines may also improve the OTP of the treated flights by rescheduling the treated flights to time slots that are less impacted by air traffic congestion.

In Figure A2 in the Appendix, we plot the average number of scheduled flight departures between January 2009 and December 2012 in 30-minute intervals throughout the day before

[24] Our dataset contains 102,931 canceled *departures* in our study period, and in our analysis, we have excluded all the cancelled departures. We find that there is no evidence that the airlines are more likely to cancel departures of treated flights following the introduction of the HSR. See Table A6 in the Appendix for details.

and after the introduction of the Beijing–Shanghai HSR line on June 30, 2011. It indicates that the number of flight departures increases in all time slots throughout the day after the HSR entry, which is consistent with the fact that China's commercial aviation industry was in the process of rapid expansion in this period.

To identify the peak and off-peak time slots, we divide the day into 24 slots. In Figure A3 in the Appendix we plot the traffic volume and average departure delay minutes in each of the 24 time slots *before* the introduction of the Beijing–Shanghai HSR line. It shows that the departure flights scheduled for the 1 am, 6 am, 7 am, 9 am, 10 am, 10 pm and 11 pm slots have better OTP before the HSR entry. We call these time slots *Better Slots* in terms of OTP of departures.

We then estimate Eq. (2) using a binary variable $Better\ Slot_{i,j,d,t}$ as the dependent variable. $Better\ Slot_{i,j,d,t}$ takes value 1 if the flight was scheduled to depart in one of the better time slots described above, and 0 otherwise. In addition, we also calculate the aggregate fraction of flights in the better time slots at the airline-route-month level and use it as a new dependent variable. Results in Table 9 show that the estimated coefficients on $Treatment * After$ are neither positive nor statistically significant for both the individual departure level analysis and the aggregate airline-route-month level analysis.

[Table 9 About Here]

Corridor and Airport Congestion. Another concern is that, in response to the HSR entry, airlines may allocate flights from treatment routes, i.e., routes that are now subject to the HSR competition, to control routes. This may cause air corridor congestion in the control routes and decrease the OTP for the control flights. However, this alternative hypothesis is inconsistent with our finding reported in Column 5 of Table 5, where we use the *air time* as the dependent variable. We find that the HSR entry causes the *air time* of the treatment flights to increase by 1.74 minutes on average relative to the control flights. This suggests that air corridor congestion in the control routes is unlikely the source for our main finding as reported in Table 3.

In addition, we directly examine whether the HSR entry affects the allocation of the departure hours of the control and treatment flights across different hours of the day. Figure A5 in the Appendix plots the distribution of flight departures per hour at BCIA before and after the HSR entry. We observe a similar number of treatment and control flights departing throughout the day in the post-HSR period, especially during peak hours (1 am, 6 am, 7 am, 9 am, 10 am and 10–11 pm). This suggests that our main findings in Table 3 are unlikely due to the differential impact on the congestion delays in BCIA of the treatment and control flights upon the HSR entry.

Schedule Manipulation. Another alternative explanation is that our finding of the reduced arrival delay minutes may result from a deliberately prolonged scheduled duration, rather than a genuine improvement in the OTP, of the treated flights (Mayer and Sinai, 2003; Prince and Simon, 2015). However, this alternative explanation is inconsistent with Column 6 of Table 5, where we report the response of *scheduled duration* to the HSR entry of the treatment flights. We find that the estimated coefficient β for the interaction term is significantly negative, implying that the treatment flights do not deliberately extend the scheduled duration.[25]

Air Traffic Control. One may be concerned that our estimated treatment effects might be driven by the increased air traffic controls on the control routes. For instance, military

[25]As the dataset records the real-time flight status information, including temporary adjustments to scheduled departure time and scheduled arrival time, we also calculate the *scheduled duration* using the most updated scheduled departure/arrival time. When we use the recalculated *scheduled duration* as the outcome variable for the estimation, we still reject the hypothesis that a deliberately prolonged scheduled duration causes the reduction in arrival delays.

bases could shift their air traffic control to the control routes in the post-HSR period. This is *a prori* quite implausible, but to address it more formally, we use an alternative control group consisting of flights that share the *same air corridor* with the treated flights. Specifically, we find 13 non-HSR cities located geographically close to the 11 HSR cities along the Beijing-Shanghai line.[26] Due to the geographical proximity, the Beijing-outbound flights to the 13 non-HSR cities share the same air corridors with the Beijing-outbound flights as the 11 HSR cities. In this regard, using the flights from 13 non-HSR cities as a new control group largely mitigates the concern that our estimated treatment effects are driven by the preferential treatment received by the treatment routes from the air traffic control relative to the control routes. Table 10 reports the results, which indicate that the estimated coefficients for the interaction term *Treatment*After* are qualitatively similar to, though quantitatively somewhat smaller than, our baseline results reported in Table 3.

[Table 10 About Here]

Outliers. Finally, one may also be concerned that our findings may be driven by outliers, for instance, by some flights with extremely long delays. To examine whether the outliers drive the treatment effects, we also run a series of quantile regressions (Koenker and Hallock, 2001). The estimated coefficients of the interaction term *Treatment∗After* for the nine deciles and the four OTP measures are plotted in Figure A6 in the Appendix. We find that all four OTP measures show significant responses to the HSR entry in all deciles, and that the OTP improvements are more substantial in the upper decile than in the lower decile, suggesting that flights with the poorest OTP are more responsive to the entry of HSR. This also explains why the HSR entry reduced the variance of the delays as we reported in Section 4.

[26]The 13 cities are Dongying, Jining, Lianyungang, Nantong, Taizhou, Weifang, Yancheng, Linyi, Huai'an, Anqing, Yiwu, Tunxi, Zhoushan. See Figure A7 in the appendix for an illustration of the air corridors of the control and treatment flights.

5.2 Aggregate-Level Analysis

Our baseline results are conducted at the individual departure level. If some flights may be eliminated or re-assigned, the departure level analysis may be prone to measurement error. For example, Air China flight CA0000 from Beijing to Shanghai was changed to CA0123 in our sample period; the individual departure level analysis will not be able to recognize that CA0000 and CA0123 are in fact the same flight.[27] To deal with the complications from such unobserved changes, we aggregate our individual-departure level data into the *airline-route-month* level using the following specification:

$$Delay_{j,d,m} = \alpha + \beta \cdot Treatment_{j,d} * After_m + \theta_j + \eta_d + \gamma_m + \epsilon_{j,d,m} \quad (4)$$

where $Delay_{j,d,m}$ is the *average* delay for airline company j departing from Beijing to destination city d in year-month m. In the aggregate-level regressions, we control for airline fixed effects, route fixed effects, and year-month fixed effects. We estimate weighted least squares (WLS) models using the number of departures on each airline-route-month cell as the weight (Prince and Simon, 2009, 2015). The results are reported in Table A7 in the Appendix. The coefficients on the interaction terms $Treatment_{j,d} * After_m$ are negative and significant in all columns. The results are consistent with the baseline analysis and quantitatively similar to the results obtained at the individual departure level: the HSR entry leads to 3.4 minutes reduction in the average arrival delay minutes of treated flights relative to the control flights.

5.3 Falsification Tests

As a final verification that our findings are not spurious, we conduct two falsification tests. The first is a placebo test in which we create a *fictitious treatment group* that consists

[27] In Section 5, we will also report results where we only include flights that appeared in both the pre- and post-HSR entry periods. The results are robust.

of the nine destination cities linked to the Beijing–Guangzhou HSR line. As discussed above, although these nine cities entered the HSR network after December 26, 2012, none of them was linked to the Beijing–Shanghai HSR line between January 1, 2009 and December 25, 2012. This test addresses whether the difference in the original DID regressions reflects the effect of the HSR competition or the effect of just being chosen as an eventual HSR destination.

In the second placebo test, we examine whether the original DID effects simply reflect changes in the Chinese airline industry, or the effect of the broader planning and construction of the HSR network. To do this, we create a *fictitious treatment date*. Specifically, we set the introduction of the Beijing–Shanghai HSR line as occurring one year before when it actually occurred, i.e., on June 30, 2010 (instead of the actual date of June 30, 2011). This fictitious treatment date ensures that we still have long pre- and post-period data.

In Tables A8 in the Appendix, we report the regression results on the placebo treatment group and placebo treatment date in Panels A and B, respectively. In both placebo tests, we find that the estimated coefficients of the interaction terms are not statistically significant. These findings reinforce our interpretation that our results reported in Table 3 are driven by the treatment flights responding to the competition from the HSR entry, and not spurious.

6 The Back-of-the-Envelope Calculation

In this section, we use our estimates to conduct a back-of-the-envelope calculation of a lower bound of the value of the time savings resulting from the improved OTP of the treated flights for air travelers. Following Li et al. (2007) and Yang and Zhang (2012), we consider two types of air travelers, $i = 1$ denotes the business travelers, and $i = 2$ the leisure travelers. We calculate the hourly monetary cost of flight delay for type $i \in \{1, 2\}$, which we denote by V_i, as follows:

$$V_i = \alpha_i * \frac{Wage}{2000}, \tag{5}$$

where *Wage* denotes the average annual salary and α_i denotes conversion factors for type i travelers relative to the average person in the population. According to the data released by the National Bureau of Statistics of China, the average yearly salary in Beijing in 2012 was CNY 62,676.[28] The denominator, 2000, represents the average total hours worked in a year.[29] Following Li et al. (2007) and Yang and Zhang (2012), we set the conversion factor for business and leisure travelers to be $\alpha_1 = 9$ and $\alpha_2 = 3$, respectively. Thus, the hourly flight delay costs for business and leisure passengers are calculated according to Eq. (5) to be CNY 282 (USD$44.62) and CNY 94 (USD$14.87), respectively.[30] Note that, our estimated willingness to pay (WTP) for reductions in flight delay is less than that in Gayle and Yimga (2018), which report that travelers are willing to pay $1.56 per minute to avoid arrival delays; but they are close to the WTP in Prince and Simon (2015), which show that the WTP for a one-hour reduction in travel time is $36 and $15 for business and non-business travelers, respectively.

We next calculate the total monetary cost C for all the passengers on a flight due to an additional minute of delay:

$$C = \sum_{i=1}^{2} N \cdot \beta \cdot \theta_i \cdot \frac{V_i}{60}, \tag{6}$$

where N denotes the total seat count, β denotes the occupancy rate of the flight, and θ_i denotes the share of passenger type i. According to the Civil Aviation Administration, 46% of all airline passengers travel on business and 54% travel on leisure.[31] That is, $\theta_1 = 0.46$ and $\theta_2 = 0.54$. Suppose that each flight has 200 seats on average and an occupancy rate of

[28] Source: `http://www.stats.gov.cn/tjsj/sjjd/201305/t20130517_74300.html`.

[29] Suppose people work 8 hours per day, 5 days per week, and 52 weeks per year. After excluding 10 days of statutory public holiday, the total working hours are 8*5*52-8*10=2000.

[30] We convert the Chinese Yuan to US dollar at the exchange rate 1 CNY = 0.158240 USD.

[31] Source: `https://www.mot.gov.cn/tongjishuju/minhang/201510/P020200709615571511237.pdf`.

80%, then the cost C for all passengers on a flight due to an additional minute of delay is CNY 481.28 ($76.16).

Given that our estimated reduction in the arrival delay for all treated flights before September 2015 is 4.36 minutes (as shown in Column 1 of Table 3, Panel C), a simple estimate of the value of the time saving per flight from the reduced arrival delay in the post-HSR period is equivalent to CNY 2,098.38 (=4.36*481.28, USD$332.02). To obtain a lower bound estimate of the monetary value of the improvement in OTP by treated flights due to the competition from HSR entries, we use all flights along the HSR routes in the post-HSR period for calculation. In our data, 796,191 treated flights fly from Beijing to the 33 HSR destinations between June 30, 2011 and September 30, 2015. Thus on average, there are 187,370 (=796,191/4.25) treated Beijing-outbound flight departures per year. We assume that Beijing-inbound flight arrivals achieve similar improvements in OTP. Moreover, we assume a 5% annual discount rate. A lower bound of the discounted present value of the time saving for air travelers taking round-trip flights on the affected routes due to the HSR entries is thus given by:

$$\frac{187,370 * 2 * 2,098}{0.05} = CNY\ 15.724\ Billion \approx USD\$2.48\ Billion.$$

Notably, this is a lower-bound estimate of the benefits for air travelers on the treated routes because it does not take into account the decrease in airfare caused by the entry of the HSR, or the benefit gained by the travelers who switched from airline to HSR (see Yang and Zhang (2012)); in addition, to the extent that passengers are risk-averse to unpredictable flight delays, the reduction in the *variance* of the flight delays also improves passenger welfare.

It is worth emphasizing that, from a social planner's perspective, all costs and benefits of affected parties including both the direct and indirect effects of HSR should be accounted for. Therefore, our back-of-the-envelope calculation above provides a useful lower-bound estimate of a hitherto unaccounted socially valuable non-price response, namely quality response, by the airlines in response to the HSR entries.

7 Conclusion

High-speed railway, as one of the major disruptive technologies in transportation in the last twenty years, has posed fierce competition for passenger air travel, especially short-to-medium-distance travel. This paper uses the entry of Beijing-Shanghai HSR as an exogenous increase in competition to affected flights to the destination cities along the HSR line, and investigate whether competition spurs quality improvement, and if so, how.

We first document direct evidence that HSR entry poses a competition shock to airlines in affected routes by showing that the number of flight departures on the treated routes is reduced in the post-entry period relative to the control routes. We then find that the competition from the HSR entry significantly reduced the arrival delay minutes of the treated flights by an average of 2.54 minutes (about 14.51% reduction). At the extensive margin, the HSR entry causes 2.5 percentage points reduction in arrival delays of 15 minutes or longer. We also find that the entry of HSR significantly reduces the variance of flight arrival delay minutes. These results are quantitatively similar when we restrict our control group to Beijing-outbound flights to the nine cities on the Beijing-Guangzhou HSR that opened on December 26, 2012. In addition, by decomposing the actual travel time, we find that the decreases in the departure delay and taxi-in runway times are the major sources of the improvement in OTP.

We also evaluate and rule out an exhaustive list of alternative explanations for our findings. The alternative explanations we examined include cancellation of flights on the treated routes with poor OTP, rescheduling treatment flights to better time slots, delays of the incoming flights, among others. We also conduct two falsification tests, one based on a fictitious treatment group and another based on a fictitious treatment date, to rule out that our findings are driven by spurious effects. The results from heterogeneity analysis further reveal that non-hub airlines, i.e., those with less market power, and flights on short-to-medium distance routes, are more responsive to HSR entry in their OTP improvement. Finally, we provide a back-of-the-envelope estimate of the lower bound of the values from the time savings by air travelers due to the improvement of OTP, which amounts to more than 15.7 billion CNY. Our paper thus contributes to the literature on the causal impact of competition on quality, and on the economic benefits of HSR.

Also, we should note that OTP is an observable and arguably the most important measure of quality of airline travels, particularly for short- to medium-distance journeys that last less than two hours. However, there could be other important dimensions of quality, such as in-flight food, beverage and service, that are unmeasured in our study (e.g. (Propper et al., 2008)). How are these unmeasured dimensions of quality impacted by competition? Also, how can we comprehensively evaluate the welfare effects of the HSR entry in an equilibrium framework, taking into account travelers' endogenous choices of travel modes? These are important and interesting avenues for future research.

The results in this paper have important implications for countries, including the United States, that are considering the development of HSR networks. Our finding suggests that HSRs can generate substantial reductions in both the mean and the variance of travel delays in airline routes that compete with the HSRs for passengers. Our empirical results not only contribute to the existing theoretical studies that explore the competition effects of HSR on airline OTP (Jiang et al., 2022), but also highlight the potential importance of accounting for the indirect competition effects of the HSR on airlines and airports when countries assess the costs and benefits of HSR networks.

References

Adler, N., E. Pels, and C. Nash (2010). High-speed Rail and Air Transport Competition: Game Engineering as Tool for Cost-benefit Analysis. *Transportation Research Part B: Methodological 44*(7), 812–833.

Aghion, P., N. Bloom, R. Blundell, R. Griffith, and P. Howitt (2005). Competition and Innovation: An Inverted-U Relationship. *The Quarterly Journal of Economics 120*(2), 701–728.

Albalate, D., G. Bel, and X. Fageda (2015). Competition and Cooperation between High-speed Rail and Air Transportation Services in Europe. *Journal of Transport Geography 42*, 166–174.

Amiti, M. and A. K. Khandelwal (2013). Import Competition and Quality Upgrading. *Review of Economics and Statistics 95*(2), 476–490.

Baum-Snow, N. (2007). Did Highways Cause Suburbanization? *The Quarterly Journal of Economics 122*(2), 775–805.

Baum-Snow, N., L. Brandt, J. V. Henderson, M. A. Turner, and Q. Zhang (2017). Roads, Railroads, and Decentralization of Chinese Cities. *Review of Economics and Statistics 99*(3), 435–448.

Behrens, C. and E. Pels (2012). Intermodal Competition in the London–Paris Passenger Market: High-Speed Rail and Air Transport. *Journal of Urban Economics 71*(3), 278–288.

Bloom, N., C. Propper, S. Seiler, and J. Van Reenen (2015). The Impact of Competition on Management Quality: Evidence from Public Hospitals. *The Review of Economic Studies 82*(2), 457–489.

Buccirossi, P., L. Ciari, T. Duso, G. Spagnolo, and C. Vitale (2013). Competition Policy and Productivity Growth: An Empirical Assessment. *Review of Economics and Statistics 95*(4), 1324–1336.

Busso, M. and S. Galiani (2019). The Causal Effect of Competition on Prices and Quality: Evidence from a Field Experiment. *American Economic Journal: Applied Economics 11*(1), 33–56.

Chen, C.-L. (2012). Reshaping Chinese Space-economy through High-speed Trains: Opportunities and Challenges. *Journal of Transport Geography 22*.

Cornaggia, J., Y. Mao, X. Tian, and B. Wolfe (2015). Does Banking Competition Affect Innovation? *Journal of Financial Economics 115*(1), 189–209.

Donaldson, D. (2018). Railroads of the Raj: Estimating the Impact of Transportation Infrastructure. *American Economic Review 108*(4-5), 899–934.

Dranove, D. and M. Satterthwaite (2000). The Industrial Organization of Health Care Markets. in *Handbook of Health Economics A. J. Culyer and J. Newhouse, eds.*, 1093–1139.

Duranton, G. and M. A. Turner (2011). The Fundamental Law of Road Congestion: Evidence from US Cities. *American Economic Review 101*(6), 2616–52.

Duranton, G. and M. A. Turner (2012). Urban Growth and Transportation. *Review of Economic Studies 79*(4), 1407–1440.

Forbes, S. J., M. Lederman, and Z. Yuan (2019). Do Airlines Pad Their Schedules? *Review of Industrial Organization 54*(1), 61–82.

Fu, X., A. Zhang, and Z. Lei (2012). Will China's Airline Industry Survive the Entry of High-speed Rail? *Research in Transportation Economics 35*(1), 13–25.

Gayle, P. G. and J. O. Yimga (2018). How much do Consumers Really Value Air Travel on-time Performance, and to What Extent are Airlines Motivated to Improve their On-time Performance? *Economics of Transportation 14*, 31–41.

Goolsbee, A. and C. Syverson (2008). How do Incumbents Respond to the Threat of Entry? Evidence from the Major Airlines. *Quarterly Journal of Economics 123*(4), 1611–1633.

Greenfield, D. (2014). Competition and Service Quality: New Evidence from the Airline Industry. *Economics of Transportation 3*(1), 80–89.

Hashmi, A. R. (2013). Competition and Innovation: The Inverted-U Relationship Revisited. *Review of Economics and Statistics 95*(5), 1653–1668.

Holmes, T. J. and J. A. Schmitz Jr (2010). Competition and Productivity: a Review of Evidence. *Annual Review of Economics 2*(1), 619–642.

Jiang, C., K. Wang, Q. Wang, and H. Yang (2022). The impact of high-speed rail competition on airline on-time performance. *Transportation Research Part B: Methodological 161*, 109–127.

Koenker, R. and K. F. Hallock (2001). Quantile Regression. *Journal of Economic Perspectives 15*(4), 143–156.

Levinson, D. M. (2012). Accessibility Impacts of High Speed Rail. *Journal of Transport Geography 22*, 288–291.

Li, X., G.-c. LIU, M.-c. YAN, and W. ZHANG (2007). The Economic Loss of Airlines and Passengers Caused by Flight Delays [J]. *Systems Engineering 12*, 005.

Lin, Y. (2017). Travel Costs and Urban Specialization Patterns: Evidence from China's High Speed Railway System. *Journal of Urban Economics 98*, 98–123.

Matsa, D. A. (2011). Competition and Product Quality in the Supermarket Industry. *The Quarterly Journal of Economics 126*(3), 1539–1591.

Mayer, C. and T. Sinai (2003). Network Effects, Congestion Externalities, and Air Traffic Delays: Or Why not all Delays are Evil. *American Economic Review 93*(4), 1194–1215.

Mazzeo, M. J. (2003). Competition and Service Quality in the US Airline Industry. *Review of Industrial Organization 22*(4), 275–296.

Nickell, S. J. (1996). Competition and Corporate Performance. *Journal of Political Economy 104*(4), 724–746.

Prince, J. T. and D. H. Simon (2009). Multimarket Contact and Service Quality: Evidence from On-time Performance in the US Airline Industry. *Academy of Management Journal 52*(2), 336–354.

Prince, J. T. and D. H. Simon (2015). Do Incumbents Improve Service Quality in Response to Entry? Evidence from Airlines' On-time Performance. *Management Science 61*(2), 372–390.

Propper, C., S. Burgess, and D. Gossage (2008). Competition and Quality: Evidence from the NHS Internal Market 1991–9. *The Economic Journal 118*(525), 138–170.

Propper, C., S. Burgess, and K. Green (2004). Does Competition between Hospitals Improve the Quality of Care?: Hospital Death Rates and the NHS Internal Market. *Journal of Public Economics 88*(7-8), 1247–1272.

Qin, Y. (2017). 'No County Left Behind?'The Distributional Impact of High-speed Rail Upgrades in China. *Journal of Economic Geography 17*(3), 489–520.

Rupp, N., D. Owens, L. Plumly, et al. (2006). Does Competition Influence Airline On-time Performance. *Advances in Airline Economics 1*, 251–272.

Sachs, G. (2010). China Transportation: Airlines-High Speed Rail Less of a Threat Than You May Think. *Report issued on Oct 28*, 2010.

Schmitz Jr, J. A. (2005). What Determines Productivity? Lessons from the Dramatic Recovery of the US and Canadian Iron ore Industries following their Early 1980s Crisis. *Journal of Political Economy 113*(3), 582–625.

Tierney, S. (2012). High-speed Rail, the Knowledge Economy and the Next Growth Wave. *Journal of Transport Geography 22*, 285–287.

Yang, H. and A. Zhang (2012). Effects of High-speed Rail and Air Transport Competition on Prices, Profits and Welfare. *Transportation Research Part B: Methodological 46*(10), 1322–1333.

Zheng, S. and M. E. Kahn (2013). China's Bullet Trains Facilitate Market Integration and Mitigate the Cost of Megacity Growth. *Proceedings of the National Academy of Sciences*, 201209247.

Table 1: Summary Statistics: Departure Level

	Treatment				Control			
	Before		After		Before		After	
	Mean	S.D	Mean	S.D	Mean	S.D	Mean	S.D
ADM	17.32	41.91	17.51	35.99	20.42	40.35	22.64	42.99
ADD15	0.26	0.44	0.28	0.45	0.35	0.48	0.37	0.48
DDM	34.73	44.53	36.5	38.26	32.41	41.48	39.37	46.83
DDD15	0.68	0.47	0.74	0.44	0.66	0.47	0.74	0.44
ATT	129.65	49.09	131.21	43.3	158.17	66.74	166.58	68.51
ETT	32.71	44.44	32.53	38.16	33.09	43.48	36.78	44.79
Actual Duration	94.97	20.1	94.81	19.51	125.68	50.35	127.45	50.33
Schedule Duration	112.11	18.61	113.14	19.49	136.98	46.12	143.57	47.09
Taxi-in Time	15.14	9.73	13.61	9.48	14.37	9.8	14.46	10.21
Taxi-out Time	18.49	13.24	18.11	11.49	19.35	16.2	18.97	15.38
Air Time	62.79	23.9	64.35	23.58	93.19	50.65	94.92	51.02
Observations	98,987		107,266		292,818		366,896	

Notes: This table presents the summary statistics of the treatment and control sample in the baseline analysis. The sample includes all Beijing-outbound flights between January 1, 2009 and December 25, 2012. The treatment sample consists of flights departing from Beijing to cities along the Beijing–Shanghai HSR line, and the control sample consists of flights departing from Beijing to other non-HSR cities. The definitions and constructions of the variables are introduced in detail in Section 3.

Table 2: Effect of Competition on the Number of Departures

Dep. Variables	ln(Number of Departures)		
	Flight-Month	Airline-Route-Month	Route-Month
	(1)	(2)	(3)
Treatment*After	-0.088***	-0.146***	-0.194**
	(0.015)	(0.042)	(0.091)
Observations	47,391	22,499	5,424
R-squared	0.512	0.865	0.959
Year-Month FE	Yes	Yes	Yes
Flight FE	Yes	No	No
Airline FE	No	Yes	No
Route FE	No	Yes	Yes

Notes: This table reports the results of estimating Equation (1). The sample period is between January 1, 2009 and December 25, 2012. Supply in Columns (1), (2), and (3) is the number of departures aggregated at the flight-month, airline-route-month, and route-month cells, respectively. The year-month fixed effects are included in all specifications. The flight fixed effects are included in Column (1), airline and route fixed effects are included in Column (2), and route fixed effects are included in Column (3). Standard errors clustered by flight, airline-route, and route in Columns (1), (2), and (3), respectively. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Table 3: Effect of Competition on the On-time performance Measures: Departure Level Results

Panel A. Flight-level Baseline Results						
Dep. Variables	ADM	ADD15	DDM	DDD15	ATT	ETT
Model	(1)	(2)	(3)	(4)	(5)	(6)
Treatment*After	-2.539***	-0.025***	-5.282***	-0.034***	-4.726***	-3.919***
	(0.230)	(0.002)	(0.224)	(0.002)	(0.236)	(0.240)
Observations	865,967	865,967	865,967	865,967	865,967	865,967
R-squared	0.266	0.196	0.254	0.209	0.636	0.208
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Flight FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B. Beijing–Shanghai HSR (Treatment) vs. Beijing–Guangzhou HSR (Control)						
Dep. Variables	ADM	ADD15	DDM	DDD15	ATT	ETT
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment*After	-2.241***	-0.035***	-2.991***	-0.030***	-3.587***	-2.345***
	(0.284)	(0.003)	(0.277)	(0.011)	(0.285)	(0.283)
Observations	400,158	400,158	400,158	400,158	400,158	400,158
R-squared	0.296	0.212	0.274	0.213	0.577	0.238
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Flight FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel C. All HSR Entries up to September 2015						
Dep. Variables	ADM	ADD15	DDM	DDD15	ATT	ETT
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment*After	-4.357***	-0.024***	-3.553***	-0.039***	-2.455***	-2.154***
	(0.274)	(0.001)	(0.116)	(0.001)	(0.130)	(0.128)
Observations	2,001,362	2,001,362	2,001,362	2,001,362	2,001,362	2,001,362
R-squared	0.231	0.196	0.246	0.220	0.564	0.197
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Flight FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Panel A reports the results of estimating Equation (2) and examine the impacts on the six measures of OTP. Panel B reports the results of estimating the HSR competition effects in the subsample. The treatment group includes flights departing from Beijing to the 11 destinations linked to the Beijing–Shanghai HSR line. The control group includes flights departing from Beijing to the 9 destinations that would later be linked to the Beijing–Guangzhou HSR line after December 26, 2012. The sample period is from January 1, 2009 to December 25, 2012 for Panels A and B. Panel C reports the results of estimating the HSR competition effects in an extended sample. The sample period is from January 2009 to September 2015. The number of treated routes increased from 11 to 33 in September 2015. The hour, date, and flight fixed effects are included in all specifications. Standard errors clustered at the route level are reported in parentheses. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Effect of Competition on the Variance of On-time Performance: Flight-Weekly Level Results

Dep. Variables	Var. of ADM	Var. of DDM	Var. of ATT	Var. of ETT
	(1)	(2)	(3)	(4)
Treatment*After	-475.113***	-487.390***	-509.221***	-507.734***
	(58.658)	(59.993)	(70.310)	(70.426)
Observations	150,019	150,019	150,019	150,019
R-squared	0.100	0.117	0.049	0.049
Year-Week FE	Yes	Yes	Yes	Yes
Flight FE	Yes	Yes	Yes	Yes

Notes: This table reports the results of variance analysis. The dependent variable is the weekly variance of OTP measures. The sample period is from January 1, 2009 to December 25, 2012. The year-week and flight fixed effects are included in all specifications. Standard errors clustered at the route level are reported in parentheses. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Sources of Quality Improvement from Competition: Departure Level Results

			Components of Actual Duration			
Dep. Variables	Departure Delay	Actual Duration	Taxi-out	Taxi-in	Air time	Scheduled Duration
Model	(1)	(2)	(3)	(4)	(5)	(6)
Treatment*After	-5.282***	0.391	0.117	-1.389***	1.740***	-2.039***
	(0.224)	(0.541)	(0.086)	(0.055)	(0.124)	(0.061)
Observations	865,967	865,967	865,387	865,387	865,387	865,967
R-squared	0.254	0.929	0.097	0.141	0.813	0.962
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Flight FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the results of estimating the effects of the HSR introduction on the *departure delay, actual duration,* and *scheduled duration*. *Actual Duration* is divided into *taxi-out time* (Column 3), *taxi-in time* (Column 4) and *air time* (Column 5). The sample period is from January 1, 2009 to December 25, 2012. The hour, date, and flight fixed effects are included in the individual regressions. Standard errors clustered at the route level are reported in parentheses. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Does the Airport Give Treatment Flights Priority? Departure Delay at Busy Slots

Sample	Panel A: Full Sample		Panel B: Subsample excluding 2am-3am	
Dep. Variables	DDM	DDD15	DDM	DDD15
	(1)	(2)	(3)	(4)
Treatment*After	-5.706**	-0.069**	-5.271**	-0.068**
	(2.594)	(0.030)	(2.630)	(0.030)
Treatment*After*BusySlot	0.466	0.049	0.288	0.048
	(2.507)	(0.033)	(2.570)	(0.033)
Observations	865,967	865,967	865,290	865,290
R-squared	0.258	0.198	0.257	0.198
Hour FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Flight FE	Yes	Yes	Yes	Yes

Notes: This table tests whether air-traffic control could prioritize flights on the treated routes i if there were extensive delays at the airport. *BusySlot* is a dummy variable that takes the value of 1 if flights depart in any of the busy slots defined in Figure A3 (in shaded bar), and 0 otherwise. Panel A analyzes the full sample and Panel B uses a sub-sample that excludes flights depart in time slots 2am and 3am because those were delayed flights from previous slots. The sample period is from January 1, 2009 to December 25, 2012. The hour, date, and flight fixed effects are included in all specifications. Standard errors clustered at the route level are reported in parentheses. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Heterogeneous Effects of the Competition on the On-Time Performance Measures: Departure Level Results

	Panel A. Hub Airlines Heterogeneity				Panel B. Distance Heterogeneity			
Dep. Variable	ADM	DDM	ATT	ETT	ADM	DDM	ATT	ETT
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment*After	-6.793***	-3.780***	-3.079***	-1.433***	-2.696**	1.054	-0.889	-0.556
	(0.415)	(0.176)	(0.196)	(0.193)	(1.331)	(0.989)	(0.967)	(0.843)
Treatment*After*Hub	3.698***	0.344*	0.947***	0.422*				
	(0.473)	(0.200)	(0.224)	(0.227)				
Treatment*After*STM					-1.252***	-3.781***	-2.825**	-2.737***
					(0.068)	(0.759)	(1.425)	(0.891)
Observations	2,001,362	2,001,362	2,001,362	2,001,362	2,001,362	2,001,362	2,001,362	2,001,362
R-squared	0.231	0.246	0.564	0.197	0.346	0.517	0.890	0.363
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Flight FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table examines the heterogeneity in the HSR competition effects on hub airlines and distance. Hub is a dummy variable that takes value 1 if the flights are operated by Air China, China South Airlines, China East Airlines, Hainan Airlines, or Beijing Capital Airlines, and 0 otherwise. STM is a dummy variable that takes value 1 if the distance between Beijing and a destination city is below 1200 km, and 0 otherwise. We examine the four measures of OTP: arrival delay in minutes (ADM), departure delay in minutes (DDM), actual travel time (ATT), and excessive travel time (ETT). The hour, date, and flight fixed effects are included in all specifications. The estimations are conducted at the individual level. Standard errors clustered at the route level are reported in parentheses. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Subsample Analysis

Panel A. Only Departures in the Holiday Periods

Dep. Variables	ADM	ADD15	DDM	DDD15	ATT	ETT
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment*After	-1.628**	-0.017**	-2.505***	-0.024**	-3.558***	-2.001**
	(0.798)	(0.008)	(0.781)	(0.011)	(0.838)	(0.826)
Observations	54,719	54,719	54,719	54,719	54,719	54,719
R-squared	0.266	0.204	0.239	0.220	0.700	0.202
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Flight FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B. Only Flights that Operated Both Before and After the HSR Entry

Dep. Variables	ADM	ADD15	DDM	DDD15	ATT	ETT
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment*After	-2.579***	-0.026***	-5.374***	-0.035***	-4.717***	-3.975***
	(0.230)	(0.003)	(0.229)	(0.003)	(0.234)	(0.362)
Observations	716,304	716,304	716,304	716,304	716,304	716,304
R-squared	0.262	0.193	0.253	0.206	0.637	0.237
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Flight FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel C. Only Morning Flights Between 6 am and 9 am

Dep. Variables	ADM	ADD15	DDM	DDD15	ATT	ETT
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment*After	-2.057***	-0.019***	-2.717***	-0.023***	-2.992***	-1.993***
	(0.419)	(0.004)	(0.401)	(0.005)	(0.425)	(0.417)
Observations	216,840	216,840	216,840	216,840	216,840	216,840
R-squared	0.318	0.246	0.330	0.257	0.692	0.268
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Flight FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Panel A reports the results of estimating Equation (2) on a subsample that includes observations seven days before/after the Spring Festival, three days before/after the Mid-Autumn Festival, and three days before/after the National Day. Panel B includes flights that existed both before and after the introduction of the Beijing–Shanghai HSR line. Panel C focuses on a subsample consisting only of flights departing in the early morning (6am to 9am). The sample period is from January 1, 2009 to December 25, 2012. The hour, date, and flight fixed effects are included in all specifications. Standard errors clustered at the route level are reported in parentheses. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Table 9: DID Tests on the Probability of Schedule Reshuffling

Sample	Departure Level	Aggregate Level
Dep. Variables	Better Time Slot Dummy	Monthly Better Time Slot Fraction
	(1)	(2)
Treatment*After	-0.021	-0.018
	(0.019)	(0.020)
Observations	865,967	22,499
R-squared	0.781	0.581
Date FE	Yes	No
Year-Month FE	No	Yes
Flight FE	Yes	No
Airline FE	No	Yes
Route FE	No	Yes

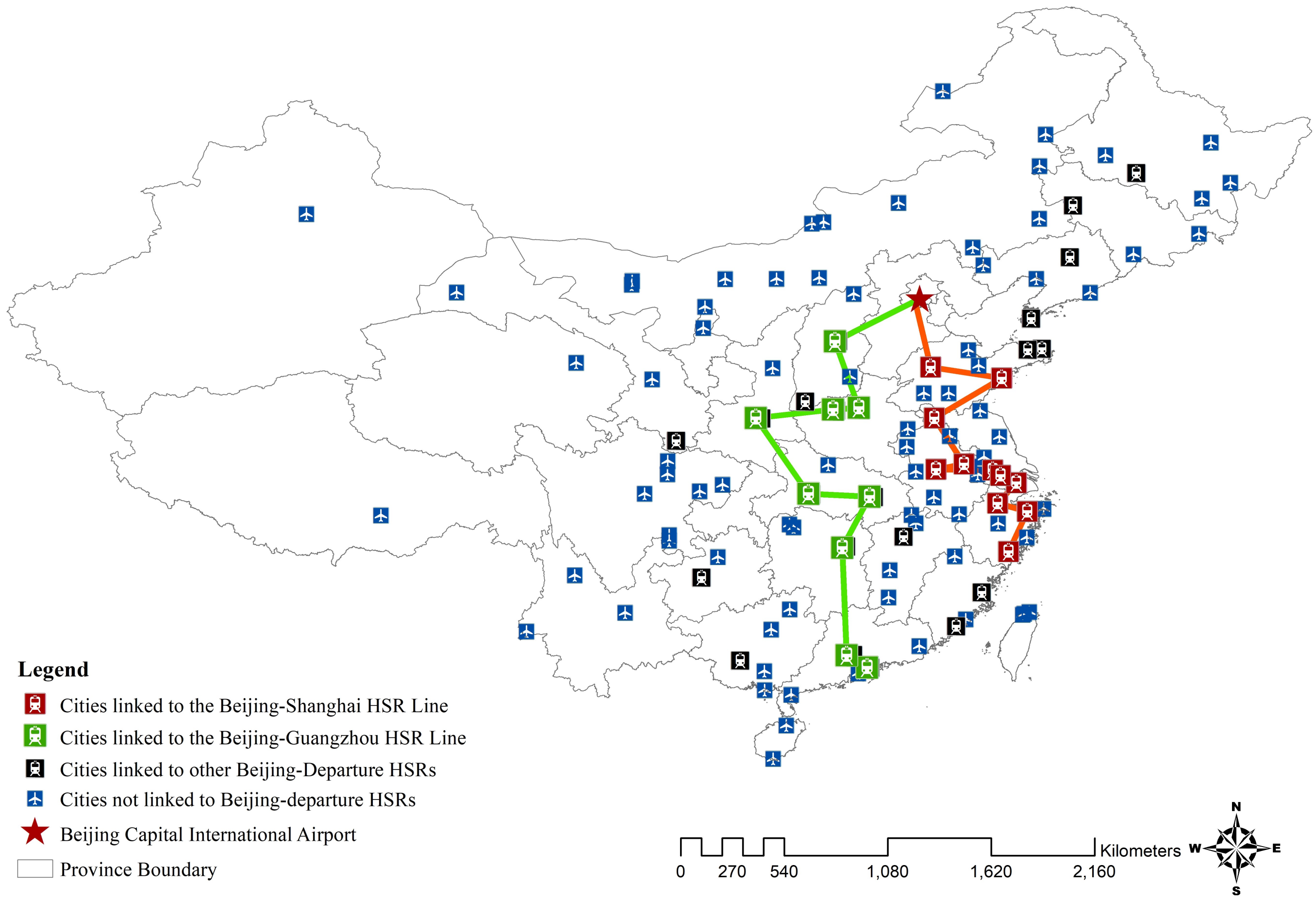
Notes: This table examines whether the affected airlines are more likely to allocate their flights to preferred time zones after the introduction of the HSR. The dependent variable in Column (1) is a dummy equal to 1 if the flight was scheduled in the better time slots and 0 otherwise. The dependent variable in Column (2) is the proportion of flights in the better time slots over the total flights in the airline-route-month cells. The date and flight fixed effects are included in Column (1) and the year-month, airline, and route fixed effects are included in Column (2). Standard errors clustered at the route level are reported in parentheses. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Table 10: Subsample Anaysis: Flights from Beijing to Cities that Share the Same Air Corridor as the Control

Dep. Variables	ADM	ADD15	DDM15	DDD15	ATT	ETT	Taxi-out	Taxi-in	Air time
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment*After	-1.135*	-0.017***	-2.904***	-0.017**	-2.954***	-3.204***	-0.214	-1.515***	1.253***
	(0.621)	(0.006)	(0.608)	(0.007)	(0.639)	(0.632)	(0.163)	(0.138)	(0.240)
Observations	232,129	232,129	232,129	232,129	232,129	232,129	232,129	232,129	232,129
R-squared	0.289	0.23	0.272	0.201	0.406	0.236	0.105	0.138	0.565
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Flight FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

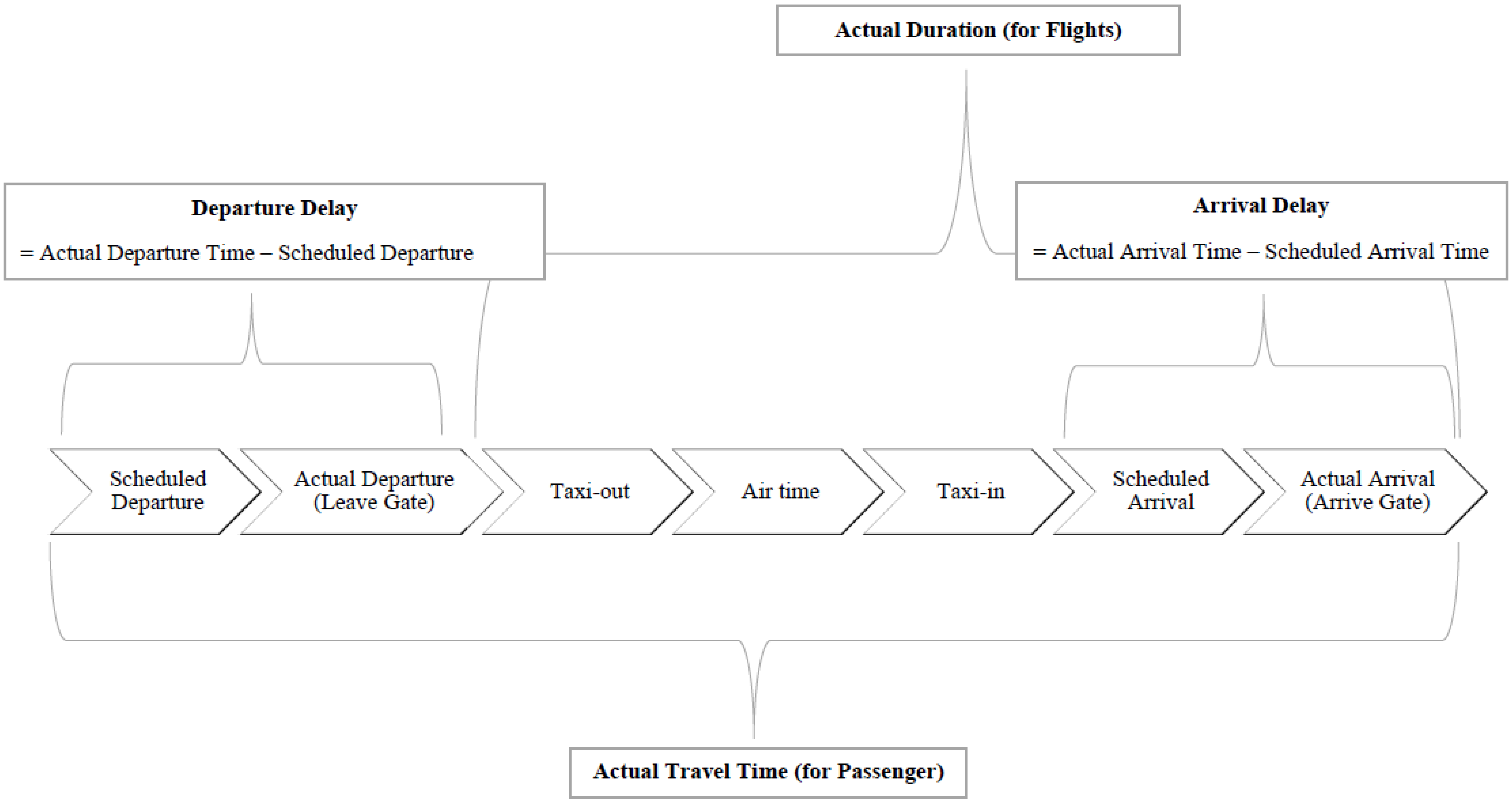
Notes: This table reports the results of estimating the effect of the HSR introduction on departure delays with the control group consisting only of 13 non-HSR cities located geographically close to the 11 HSR cities along the Beijing-Shanghai line. The hour, date, and flight fixed effects are included in all specifications. Standard errors clustered at the route level are reported in parentheses. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Figure 1: Geographic Distribution of Sample Cities in September 2015



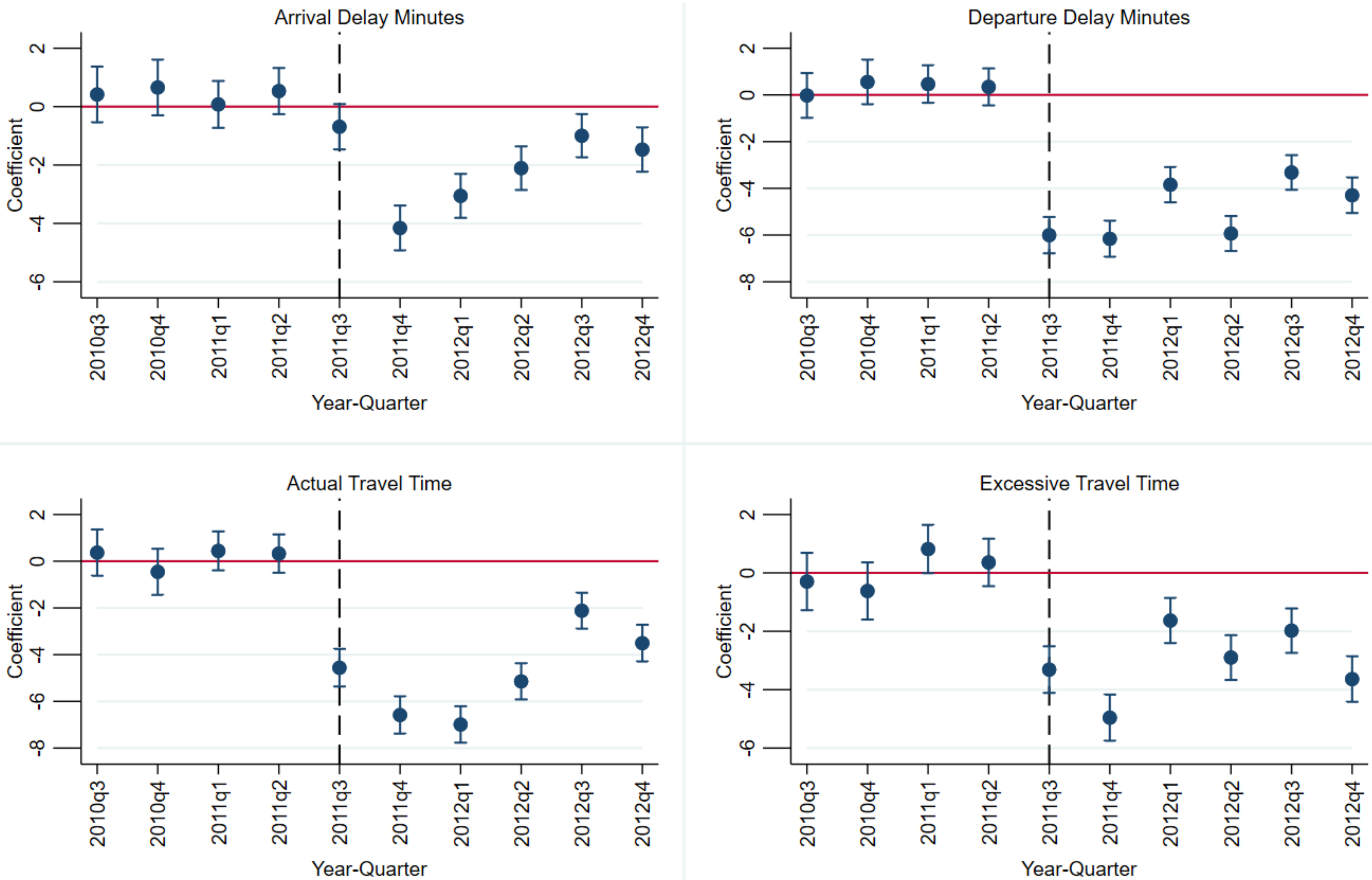
Notes: This figure presents the geographic distribution of the sample destinations in September 2015. The red train signs denote the 11 treated destinations linked to the Beijing–Shanghai HSR line introduced on June 30, 2011. The green train signs denote the nine destinations linked to the Beijing–Guangzhou HSR line introduced on December 26, 2012. The black train signs denote the 13 destinations linked to other Beijing–departure HSR lines, which were introduced after December 26, 2012. The blue airport signs denote the destinations with direct flights from Beijing but not linked to any Beijing-bound HSR lines during our sample period. All the destinations in this figure are linked by direct flights departing from Beijing.

Figure 2: Flowchart for Flight Delays



Notes: The flowchart illustrates the components of the flight departure and arrival delays. *Actual Travel Time* (ATT) captures the time difference between the *scheduled departure time* and *actual arrival time*. The *departure delay* is calculated as the time spent before leaving the gate (the difference between the *actual departure time* minus the *scheduled departure time*) and *arrival delay* (the difference between the *actual arrival time* minus the *scheduled arrival time*). The *actual duration* consists of the *taxi-out time* (time spent on the departure runway), *airtime*, and *taxi-in time* (time spent on the arrival runway).

Figure 3: Dynamic Changes of the Four OTP Measures



Notes: This figure plots the dynamic responses of the four OTP measures to the introduction of the Beijing–Shanghai HSR line. The benchmark period is from January 1, 2009 to December 31, 2009.The coefficients and 95% confidence intervals are obtained from estimating Equation (3).