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Schedule creep – In search of an uncongested baseline block time by examining scheduled flight block times worldwide 1986–2016

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ABSTRACT

Based on a stratified random sampling of airlines' schedules for 200 heavily travelled directional nonstop airport pairs, this paper examines systematically how scheduled block times in non-stop flights have changed from 1986 to 2016. Three econometric analyses, by way of a 10th percentile quantile regression, 15th percentile quantile regression and ordinary least-squares regression, show that after accounting for the effects of air traffic growth, airport-specific congestion, flight delays, number of seat per flight, aircraft type, flight heading, airport slot policy, other airport-specific anomalies, airline-specific policies and changes in crude oil price, scheduled block times have been growing at a pace between 0.21 and 0.33 min per year depending on the regression model, or a total of between 6.2 and 9.8 min per flight from 1986 to 2016. Over-flying crowded parts of Europe contributes to an increase of 4.1 min of block time in 2016 compared with 1986, while over-flying crowded parts of China contributes to a corresponding increase of 8.9 min of block time. Slot-based practices at one end of an airport pair reduce the scheduled block times between 1.3 and 2.0 min, and this reduction can vary slightly over time in depending on the regression model. Regional influences add to the changes in scheduled block times. Those airport pairs within north-eastern U.S. have scheduled block times between 3.6 and 4.0 min longer than their counterparts in the rest of North America, which in turn grow at 0.10 min per year in the 10th percentile regression. Airline-specific policies also add to further changes to the scheduled block times, with some starting with longer times in 1986 and reducing theirs over the years while others starting with shorter times in 1986 and increasing theirs over the years. Hub-specific adjustments to scheduled block times by individual airlines are also observed. Airlines with increasing frequency share at the departure and arrival airports, or in the non-stop airport pair itself, are shown to reduce the scheduled block times of that route. The overall increase from the projected baseline block times in 1986 to the actual scheduled block times in 2016 is 19.2 min per flight from the sampled nonstop city-pairs, consistent with a previous study on buffers in flight schedules within the U.S. Overall, un-adjusted scheduled block times are not a reliable benchmark for determining true flight delays, but using a percentile statistics from past flight records to determine a minimum feasible block time is a reasonable estimate even if aircraft types are not explicitly accounted for.

1. Introduction

With airlines deploying ever more advanced aircraft, anecdotal evidence suggests, ironically, that over the years, the amount of time between the scheduled departure and arrival times, i.e., the 'scheduled block times' (also referred to as 'scheduled transit time'),

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for a number of non-stop airport pairs has actually increased. A block time is the time elapsed from the time an aeroplane leaves its departure gate to the time when it parks at its arrival gate, i.e., 'gate to gate'. A scheduled block time is one that an airline uses to plan its scheduled operations, i.e., one that can be deduced from published schedules. Examining 50 U.S. domestic non-stop routes in 1996 and 2010, McCartney (2010) noted an increase in block times between 10 min to an hour in 90% of these routes, but any change due to differences in aircraft types is not accounted for. Focusing only on flights between Los Angeles International (LAX) and San Francisco International (SFO) Airports, Martin (2015) found that the block time for a formerly 90-min flights in 1996 became 91 to 110 min in 2015. These increases in airlines' scheduled block times over the years have been referred to as schedule creep (Kostiuk et al., 1999), and are the subject of investigation in this paper.

Airlines face conflicting pressures when they decide on their scheduled block times. On the one hand, scheduled block times set a minimum on which costs for flight crew are incurred. In the events flights arrive before their scheduled arrival times, flight crew typically are paid based on their block times; when flights are delayed, however, they are paid on their actual block times (McCartney, 2010). In the absence of any pressure on on-time performance, airlines are therefore motivated as a cost reduction measure to minimize block times needed for a particular flight, and to pay their crew (and fuel) for additional time incurred as and when it is needed. Following this principle, it is not surprising that a study conducted by the U.S. Department of Transportation (DoT) at major hub airports in 1986–87 counted more than half of the flights operated by major airlines to have arrived more than 15 min past their scheduled arrival times (Shumsky, 1993). Around the same period, more than half of the delays in the U.S. was determined to be caused by severe weather (Weiner, 1990).

On the other hand, airlines do not want to see too many flights suffering from significant delays in their arrivals, as this would increase the chances of their passengers missing their onward connections and hence increase the airlines' costs in accommodating the affected passengers. In the three decades between 1986 and 2016, air traffic has grown 1.5 times in the U.S. alone, 2.9 times in the core area in Europe (Belgium, France, Germany, Netherlands and Switzerland), and 8.8 times in East Asia (China, Japan and Korea) according to the World Bank (2018). There were few new, large airports coming into operation around the world during this period. As a result, congestion at airports and nearby airspace likely contributed to an increase in scheduled block times as airlines tried to keep missed flight connections as a result of flight delays within a tolerable level. Prior to this study, no one has been certain how much increase in scheduled block times could be attributed to the increasingly crowded skies and airports. Airlines and policy analysts likewise may not know how much congestion-related costs have been inadvertently internalized.

Meanwhile, several other forces could act in concert to influence airlines' scheduled block times. Aircraft type, specifically the economic cruise speed for the specific aircraft type, has a direct effect on the actual flight time and therefore potentially influences scheduled block times. Large, twin-aisle aircraft like the Boeing 747 have all but disappeared from dedicated scheduled domestic flights within continental U.S., apart for several positioning routes between hubs or intercontinental gateways. These larger aircraft types tend to operate at higher speeds than the now common single-aisle aircraft types, potentially contributing to longer scheduled block times.

Prices in fuel cost could also influence actual flight times and therefore potentially scheduled block times, because slower cruising speeds could reduce aircraft fuel consumption. From 1997 to 2008, the price of U.S. crude oil rose from US$18.64 per barrel to US $91.48 per barrel in nominal terms (McMahon, 2017). Fuel expenses for American Airlines, for instance, increased from being 35% of total costs on wages, salaries and benefits to 135% in the same period (AMR Corporation, 1998, 2009). In response, some airlines reportedly flew their aircraft slightly slower to save fuel, resulting in an increase of two minutes per flight in actual flight time, depending on the airline (Morris, 2017). This opens the possibility that changes in fuel prices can also influence scheduled block times as a means to manage an airline's operating cost.

While airlines bear the ultimate responsibility of establishing their own scheduled block times for a specific route, their definition of the scheduled arrival times forms the basis on which flight delays are often calculated. The U.S. DoT considers a flight to be on time if it arrives no later than 15 min of its scheduled arrival time (Shumsky, 1993). This 15-min benchmark is also used in many other countries in the world in determining on-time performance of scheduled flights, such as the U.K. (CAA, 1990), Germany (DFS, 2017) and Hong Kong (Lee, 2017). This same benchmark has been adopted by a number of studies in calculating flight delays and their costs, including Suzuki (2000), Hansen et al. (2001), Forbes (2008), Prince and Simon (2009), and Mellat-Parast et al. (2015). As a rare exception, a flight is considered on time if it arrives later than 30 min from its scheduled arrival time in Brazil (Bendinelli et al., 2016).

Under the On-Time Disclosure Rule (OTDR) promulgated by the U.S. Department of Transportation in 1987, airlines accounting for at least one percent of U.S. domestic passenger revenue are required to report their on-time performance, which in turn is published monthly since 1995. With the increased prevalence of publicized aircraft-to-ground data communication since the late 1990s, numerous private organizations have been tracking on-time statistics linked to unique airline flight numbers. Flight-specific on-time statistics have been reported on airfare booking websites worldwide, potentially influencing passengers' future travel decisions. As a result, individual airlines can and have been observed to adjust their scheduled block times to engineer better on-time performance to potentially make their schedule offers more attractive (Prince and Simon, 2009). Prior studies have linked higher percentages of flights arriving on time (i.e., within 15 min of scheduled arrival time) to fewer customer complaints, which in turn leads to higher operating profits for airlines (Dresner and Xu, 1995; Steven et al., 2012).

Under European Union Regulation 261/2004, compensation owed by airlines to passengers on a delayed flight is also calculated based on the difference between actual and scheduled arrival times, along with flight distance. It is therefore in the interest of airlines as profit-maximizing entities to increase scheduled block times to improve their so-called on-time arrival performance if they operate in the European Union.

While anecdotal evidence has pointed to increasing scheduled block times over the years, evidence has concentrated in the U.S., and only in specific periods or in certain routes. In the few years after the OTDR began, Shumsky (1993) found that the scheduled block times of several hundred randomly selected non-stop U.S. domestic routes had increased significantly. There was, however, no continued effort to continue Shumsky's analysis. Anecdotal figures reported in McCartney (2010) and Martin (2015) showed that schedule creep has likely continued to the present at least in the U.S., although neither accounted for changes in aircraft type or changes in the share of airlines operating the same routes throughout these intervening decade(s). Most major airports outside of the U.S. follow slot-based demand management practices, placing limits on the number of flights airlines can operate at these airports in specific time intervals (Fan and Odoni, 2002). In contrast, most airports within the U.S. do not place such limits. As a consequence, patterns of schedule creep outside of the U.S. could differ from that within the U.S.

In this paper, the longer-term evidence of schedule creep is systematically analysed on an international context, including flights both within and outside of the U.S. and taking into the account the effects of increased air traffic, aircraft type, airline-specific policy and regional influences. By estimating the long-term creep in scheduled block times, it is possible to work backwards to deduce what the block times ought to have been just prior to OTDR – an approximate minimum feasible time. A baseline block time is crucial for policy analysts to estimate the extent to which flights are actually delayed, and ultimately how much return can be expected from investments in aviation infrastructure. A baseline block time also better informs airlines their internalized cost of congestion.

Specifically, scheduled block times from a sample of 100 heavily travelled routes yielding 200 directional, one-way airport pairs around the world from 1986 to 2016 are analysed in this paper, with the twin goals of estimating any systematic, long-term schedule creep and a baseline of reference block times. These routes are taken from a stratified random sampling procedure to ensure sufficient representation from slot-controlled and non-slot-controlled airports, and from routes representing different flight distances. The econometric analyses employ quantile regressions of airline-aircraft-specific block times for each airport pair over the years, in addition to ordinary least-squares. Details of the methodology are described in Section 2, and results of the analysis in Section 3.

2. Methodology

Schedule data is first obtained from *Official Airline Guide* (OAG), an authoritative source of airline schedules worldwide for the past few decades, to determine the sampling frame. The goal is to sample flight schedules from 1986, a year before OTDR started, to 2016, the last full year the data was available when this study began. OAG provided a convenient listing of the top 1000 bi-directional non-stop airport pairs based on the number of seats provided in a year, and this listing is sampled every 5 years from 1996 to 2016. A route that is featured in this list over the years is likely to be one where airline operators would pay reasonable attention on determining its scheduled block times as a result of the impact on cost management and operational planning. Those bi-directional airport pairs that appear in every one of these 5-yearly lists are short-listed, resulting in 443 such airport pairs. The compilation of top airport pairs is not available in years before 1996, and any pre-1996 data has to be ordered for specific airport pairs selected based on the 1996–2016 compilation.

In a stratified random sampling procedure, OAG's top 1000 airport pairs are separated into 5 groups according to the great-circle distance between the airports: (i) less than 341 km, (ii) 341–632 km, (iii) 633–1573 km, (iv) 1574–3974 km, and (v) more than 3974 km – corresponding to the 10th, 33rd, 67th, and 90th percentile of distances. Within each of these distance bands, airport pairs are ordered in decreasing median available seats on subsonic flights from 1996 to 2016, and these airport pairs are further classified into three categories: those involving no slot-controlled airports as in Level 3 slot coordination in the nomenclature of the International Air Transport Association (IATA) or High Density Rule (HDR) in the U.S., those involving one such slot-controlled airports, and those where neither end-points of the city-pairs are slot-controlled.

Three particular cities – Bangkok, Seoul and Shanghai – are avoided in the sampling because each of these cities witnesses a new airport introduced in the intervening years but only some of the flights are transferred to the new airports over a period of time, complicating the estimate of a long-run creep in scheduled block times. Meanwhile, Denver, Guangzhou, Haikou, Hong Kong, Ishigaki (Japan), Kuala Lumpur and Munich have a clean switch-over from their old airport to the new ones, and thus the discontinuity can be more easily modelled.

Within each of these three slot-controlled regimes, airport pairs are arranged in declining median available seats to ensure a reasonable geographic distribution of the airport pairs selected. Every fifth airport pairs is then selected for econometric analyses. A maximum of ten airport pairs in each slot-controlled regime is selected in the middle three flight distance categories. A maximum of three and two airport pairs are chosen in the longest and shortest distance categories respectively because there are not sufficient number of airport pairs for the same number of airport pairs in each of these slot regimes to be sampled. This procedure yields a total of 98 bi-directional non-stop airport pairs. Two more airport pairs are included to allow for airport-specific comparisons: Dallas-Fort Worth – Newark (to complement flights to New York LaGuardia) and Houston Bush Intercontinental – New York LaGuardia (to complement flights to Newark). These add to a total of 100 airport pairs with an average flight distance of 1527 km, whose schedules are then abstracted from the OAG database once every 5 years from 1986 to 2016. Among these, four bi-directional airport pairs have no non-stop service in 1986: Dublin – Stansted, Newark – London Heathrow, Osaka Itami – Sendai, and Osaka Kansai – Sapporo Chitose. The sampled airport pairs offer 219 million available seats in 2016, and yield 200 directional airport pairs, as illustrated in Table 1.

In each of the 200 directional airport pairs, each airline-aircraft combination is treated as one observation, with an average block time derived by dividing the total block time by the number of scheduled flights in that combination. Because the sample included many international airports in different time zones, it is difficult to determine any particular peak time of operation. Meanwhile, the sample includes many un-congested airports, such as Durban – Johannesburg (South Africa), Helsinki – Oulu (Finland), and Ishigaki – Okinawa (Japan). In quantile regressions, where deviations from a specific percentile of observations are minimized, non-stop routes

Table 1
List of 200 directional non-stop city pairs selected from stratified random sampling in analysis.

Directional non-stop city pair sampled	KM	No. of slot airports	Sample airline-aircraft combination	Actual 2016 scheduled block time (min)	Difference from projected 1986 block time (min)
Adelaide to Sydney Kingsford-Smith	1164	1	QF73H	112.1	18.1
Amsterdam to Paris Charles de Gaulle	398	2	AF321	75.5	14.3
Atlanta Hartsfield to Chicago O'Hare	974	0	DL717	125.6	33.3
Atlanta Hartsfield to Memphis	531	0	DLM88	83.1	27.9
Atlanta Hartsfield to Minneapolis/St Paul	1458	0	DL757	160.1	30.8
Atlanta Hartsfield to Newark	1197	0	DL717	136.4	28.3
Atlanta Hartsfield to Philadelphia	974	0	UA739	126.5	31.7
Atlanta Hartsfield to Washington Dulles	856	0	DLM88	106.8	31.6
Atlanta Hartsfield to Washington Regan	879	1	DLM90	108.6	33.8
Auckland to Sydney Kingsford-Smith	2158	2	NZ763	215.0	31.1
Auckland to Wellington	480	1	NZ320	65.0	18.6
Beijing Capital to Guangzhou Baiyun	1880	2	CZ321	205.1	46.3
Berlin Tegel to Cologne-Bonn	463	0	4U319	69.9	9.9
Bogota to Cartagena	1379	2	QF73H	92.0	24.9
Boston Logan to Dallas-Ft Worth	639	1	AA319	261.2	39.8
Boston Logan to London Heathrow	296	1	AAE90	386.0	17.4
Boston Logan to Los Angeles Int'l	322	0	B6E90	393.4	38.5
Boston Logan to New York LaGuardia	4191	0	AA738	79.8	22.0
Boston Logan to Newark	2507	0	AA738	86.9	27.3
Boston Logan to Philadelphia	5238	1	BA744	93.4	27.5
Boston Logan to Washington Regan	1032	2	9W738	98.4	19.5
Brisbane to Melbourne Tullamarine	1070	0	DLM88	143.0	26.9
Bueons Aires Pistarini to Sao Paulo Guarulhos	1722	1	G3738	166.7	22.9
Cairo International to Jeddah	449	0	AA321	130.0	20.7
Cartagena to Bogota	538	2	FR73H	89.8	22.8
Catania to Rome Fiumicino	463	0	4U319	88.4	21.4
Chennai to Mumbai	1032	2	9W738	113.2	9.7
Chicago O'Hare to Atlanta Hartsfield	974	0	DL717	122.9	38.6
Chicago O'Hare to Las Vegas	2430	0	AA738	236.6	32.6
Chicago O'Hare to Orlando	1619	0	AA738	159.7	30.6
Chicago O'Hare to St Louis	415	0	AAM80	69.1	28.5
Cologne-Bonn to Berlin Tegel	435	1	AB73G	70.0	12.5
Cologne-Bonn to Munich	880	2	GA738	69.1	23.0
Dallas-Ft Worth to Boston Logan	1370	0	WN73H	217.7	26.0
Dallas-Ft Worth to Las Vegas	2203	0	YXE70	174.9	29.9
Dallas-Ft Worth to Los Angeles Int'l	1693	0	AA321	205.5	37.9
Dallas-Ft Worth to New York LaGuardia	1981	0	AA32B	200.7	29.3
Dallas-Ft Worth to Newark	1914	1	AA738	216.7	37.9
Dallas-Ft Worth to San Francisco Int'l	2231	1	AA738	229.6	28.5
Dallas-Ft Worth to Washington Regan	2507	0	AA738	172.8	29.6
Denpasar to Jakarta Soekarna-Hatta	2351	0	AA32B	115.0	18.3
Denver to Los Angeles Int’l	2233	0	CPE75 (Compass)	160.8	31.6
Denver to San Diego	1384	0	CPE75	140.8	15.2
Detroit Metropolitan to New York LaGuardia	982	2	JT739	112.6	36.6
Dubai International to Karachi	1926	2	9W73H	124.1	20.0
Dubai International to London Heathrow	1188	2	EK77W	462.2	29.6
Dubai International to Mumbai	476	2	SA320	190.1	33.6
Dublin to London Heathrow	805	1	DL717	83.2	21.4
Dublin to London Stansted	449	2	EI320	80.1	23.0
Durban to Johannesburg	470	2	FR73H	65.0	6.7
Edmonton Int'l to Toronto Pearson	2688	1	AC320	219.3	12.8
Frankfurt-am-Main to London Heathrow	653	2	BA319	109.6	26.4
Frankfurt-am-Main to Zurich	285	2	LH319	55.0	7.0
Geneva to Paris Charles de Gaulle	407	2	AF318	72.5	10.9
Glasgow to London Heathrow	554	1	BA320	87.8	18.3
Guangzhou Baiyun to Beijing Capital	481	2	CZ320	192.5	33.9
Guangzhou Baiyun to Haikou	1217	1	MS330	73.0	21.5
Haikou to Guangzhou Baiyun	481	2	CZ320	72.8	23.4
Hamburg to Munich	599	2	AB320	77.7	17.1
Hanoi to Saigon	1159	2	VJ320	125.0	14.7
Helsinki to Oulu	510	1	D873H	65.0	4.9
Hong Kong to Taipei Taoyuan	805	2	CX333	113.3	36.4
Honolulu to Kona	262	0	HA717	46.4	9.0
Honolulu to Los Angeles Int'l	4105	0	AA32B	332.1	35.3
Houston Bush to New York LaGuardia	2274	1	UA320	210.1	18.1
Houston Bush to Newark	2248	0	UA739	210.7	16.7
Ishigaki to Okinawa	402	0	NU734	55.7	6.0

(*continued on next page*)

Table 1 (*continued*)

Directional non-stop city pair sampled	KM	No. of slot airports	Sample airline-aircraft combination	Actual 2016 scheduled block time (min)	Difference from projected 1986 block time (min)
Jakarta Soekarna-Hatta to Denpasar	407	2	AF318	110.6	21.2
Jakarta Soekarna-Hatta to Kuala Lumpur Subang/KLIA	982	2	JT739	122.4	12.3
Jakarta Soekarna-Hatta to Singapore Changi	1127	2	MH738	112.8	24.0
Jeddah to Cairo International	1217	1	MS330	130.4	14.0
Johannesburg to Durban	476	2	SA320	65.0	9.3
Karachi to Dubai International	1188	2	EK77W	132.2	22.4
Kona to Honolulu	262	0	HA717	45.0	6.2
Kuala Lumpur Subang/KLIA to Jakarta Soekarna-Hatta	1127	2	MH738	121.0	19.7
Kuala Lumpur Subang/KLIA to Penang	323	1	AK320	56.7	14.1
Kuala Lumpur Subang/KLIA to Singapore Changi	296	2	AK320	65.4	26.0
Las Vegas to Chicago O'Hare	2430	0	AA738	219.7	34.6
Las Vegas to Dallas-Ft Worth	1693	0	AA738	165.5	28.5
Las Vegas to Reno	555	0	WN73W	78.2	15.2
Las Vegas to San Francisco Int'l	665	0	VX320	92.1	12.1
Las Vegas to San Jose Mineta	618	0	WN73W	82.8	14.3
London Heathrow to Boston Logan	5238	1	BA744	444.5	31.5
London Heathrow to Dubai International	5493	2	EK388	413.6	16.3
London Heathrow to Dublin	449	2	EI320	79.5	12.7
London Heathrow to Frankfurt-am-Main	653	2	BA319	102.8	25.9
London Heathrow to Glasgow	554	1	BA320	86.7	17.0
London Heathrow to Munich	940	2	BA319	113.5	20.7
London Heathrow to New York Kennedy	5536	2	BA744	467.2	51.4
London Heathrow to Newark	5560	1	UA763	494.8	44.9
London Heathrow to Rome Fiumicino	1442	2	BA321	151.4	13.3
London Heathrow to Zurich	785	2	LX320	104.9	15.2
London Stansted to Dublin	470	2	FR73H	84.6	23.3
Los Angeles Int'l to Boston Logan	4191	0	AA738	331.2	28.7
Los Angeles Int'l to Dallas-Ft Worth	1981	0	AA32B	186.8	33.0
Los Angeles Int'l to Denver	1384	0	CPE75	143.5	26.3
Los Angeles Int'l to Honolulu	4105	0	AA32B	366.1	34.5
Los Angeles Int'l to Mexico City	2498	1	AM7S8	225.6	28.5
Los Angeles Int'l to Newark	3938	0	UA752	322.7	27.3
Los Angeles Int'l to Oakland	542	0	WN73W	74.9	15.6
Los Angeles Int'l to Phoenix	594	0	AA321	90.2	31.0
Manila Aquino to Tokyo Narita	3048	2	JL763	261.3	22.6
Marseille Provence to Paris Orly	626	1	AF320	80.0	11.3
Melbourne Tullamarine to Brisbane	1379	2	QF73H	130.0	13.9
Memphis to Atlanta Hartsfield	531	0	DLM88	83.4	29.4
Mexico City to Los Angeles Int'l	2498	1	AM7S8	255.2	39.8
Miami to New York Kennedy	1756	1	AA757	178.2	44.0
Miami to New York LaGuardia	1767	1	AA738	175.9	22.0
Minneapolis/St Paul to Atlanta Hartsfield	1458	0	DLM90	152.4	27.5
Montreal Dorval to Toronto Pearson	505	1	AC320	85.6	26.6
Moscow Sheremetyevo to St. Petersburg Pulkovo	599	1	SU321	82.2	12.7
Mumbai to Chennai	1926	2	9W73H	117.6	19.7
Mumbai to Dubai International	653	1	AV320	195.9	27.1
Munich to Cologne-Bonn	435	1	AB73G	70.0	13.3
Munich to Hamburg	599	2	AB320	78.9	10.1
Munich to London Heathrow	940	2	BA319	127.4	21.4
New York Kennedy to London Heathrow	5536	2	BA744	419.2	25.7
New York Kennedy to Miami	1756	1	AA757	195.5	29.3
New York Kennedy to San Francisco Int'l	4150	1	B632S	393.7	32.0
New York LaGuardia to Boston Logan	296	1	AAE90	73.8	20.0
New York LaGuardia to Dallas-Ft Worth	2231	1	AA738	246.1	48.7
New York LaGuardia to Detroit Metropolitan	805	1	YXE75	127.7	35.1
New York LaGuardia to Houston Bush	2274	1	UA320	240.5	32.4
New York LaGuardia to Miami	1767	1	AA738	198.1	39.7
New York LaGuardia to Toronto Pearson	571	2	ACE90	102.3	23.6
New York LaGuardia to Washington Regan	343	2	S5E70	82.3	26.6
Newark to Atlanta Hartsfield	5493	2	EK388	149.7	28.1
Newark to Boston Logan	1197	0	DL717	69.9	15.1
Newark to Dallas-Ft Worth	322	0	B6E90	237.3	39.0
Newark to Houston Bush	2203	0	AA738	235.0	26.4
Newark to London Heathrow	5560	1	UA763	430.6	32.5
Newark to Los Angeles Int'l	3938	0	UA752	368.2	26.5
Newark to San Francisco Int'l	4117	0	UA757	372.4	17.3

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Table 1 (*continued*)

Directional non-stop city pair sampled	KM	No. of slot airports	Sample airline-aircraft combination	Actual 2016 scheduled block time (min)	Difference from projected 1986 block time (min)
Oakland to Los Angeles Int'l	542	0	WN73W	76.4	15.4
Okinawa to Ishigaki	402	0	EH735	60.1	8.2
Okinawa to Tokyo Haneda	1553	1	BC737	138.1	7.4
Orlando to Chicago O'Hare	1619	0	AA738	180.4	35.5
Osaka Itami to Sendai	615	0	JLE70	75.0	10.8
Osaka Kansai to Sapporo Chitose	1083	0	MM320	113.2	14.4
Oulu to Helsinki	510	1	D873H	65.0	5.0
Paris Charles de Gaulle to Amsterdam	1880	2	CZ321	77.7	19.5
Paris Charles de Gaulle to Geneva	1099	2	AF321	69.9	9.6
Paris Charles de Gaulle to Rome Fiumicino	398	2	AF321	124.5	11.8
Paris Orly to Marseille Provence	626	1	AF320	75.0	6.3
Penang to Kuala Lumpur Subang/KLIA	323	1	AK320	60.3	19.4
Penang to Singapore Changi	600	1	AK320	82.7	22.0
Perth to Singapore Changi	3907	1	SQ333	319.6	24.6
Philadelphia to Atlanta Hartsfield	1070	0	DLM88	139.9	35.6
Philadelphia to Boston Logan	449	0	B6E90	81.8	24.7
Phoenix to Los Angeles Int'l	594	0	WN73W	80.4	13.2
Phoenix to Salt Lake City	816	0	WN73W	90.2	12.1
Phoenix to Seattle-Tacoma	1778	0	AS73J	177.7	18.7
Recife to Sao Paulo Guarulhos	2099	1	JJ321	202.1	21.5
Reno to Las Vegas	555	0	WN73W	73.8	11.7
Rome Fiumicino to Catania	538	2	FR73H	89.0	23.5
Rome Fiumicino to London Heathrow	1442	2	BA321	165.8	18.6
Rome Fiumicino to Paris Charles de Gaulle	1099	2	AF321	130.0	11.0
Saigon to Hanoi	1159	2	VJ320	125.0	14.6
Salt Lake City to Phoenix	816	0	WN73W	95.6	14.6
San Diego to Denver	1370	0	WN73W	136.2	17.5
San Francisco Int'l to Dallas-Ft Worth	2351	0	AA32B	209.7	34.7
San Francisco Int'l to Las Vegas	665	0	VX320	90.5	28.6
San Francisco Int'l to New York Kennedy	4150	1	B632S	332.0	15.5
San Francisco Int'l to Newark	4117	0	UA757	324.4	26.4
San Jose Mineta to Las Vegas	618	0	WN73W	79.9	15.3
Sao Paulo Guarulhos to Bueons Aires Pistarini	1722	1	G3738	171.7	19.5
Sao Paulo Guarulhos to Recife	2099	1	JJ321	181.6	11.6
Sapporo Chitose to Osaka Kansai	653	1	AV320	132.5	28.2
Sapporo Chitose to Sendai	1083	0	MM320	70.0	12.0
Seattle-Tacoma to Phoenix	1778	0	AS73J	165.7	14.1
Sendai to Osaka Itami	615	0	JLE70	82.0	14.6
Sendai to Sapporo Chitose	518	0	HD737	75.0	17.0
Singapore Changi to Jakarta Soekarna-Hatta	880	2	GA738	112.6	26.3
Singapore Changi to Kuala Lumpur Subang/KLIA	296	2	AK320	65.8	19.9
Singapore Changi to Penang	600	1	AK320	81.5	12.7
Singapore Changi to Perth	3907	1	SQ333	311.4	12.0
Singapore Changi to Taipei Taoyuan	3219	2	CI333	282.9	33.1
Singapore Changi to Tokyo Narita	5354	2	NH77W	422.4	40.0
St Louis to Chicago O'Hare	415	0	AAM80	81.2	35.8
St. Petersburg Pulkovo to Moscow Sheremetyevo	599	1	SU321	76.1	9.6
Sydney Kingsford-Smith to Adelaide	1164	1	QF73H	127.9	22.6
Sydney Kingsford-Smith to Auckland	2158	2	QF73H	187.9	23.4
Taipei Taoyuan to Hong Kong	805	2	CX333	121.4	36.6
Taipei Taoyuan to Singapore Changi	3219	2	SQ333	273.1	11.9
Tokyo Haneda to Okinawa	1553	1	BC737	172.0	33.6
Tokyo Narita to Manila Aquino	3048	2	JL763	290.9	30.9
Tokyo Narita to Singapore Changi	5354	2	NH77W	439.9	29.3
Toronto Pearson to Edmonton Int'l	2688	1	AC320	252.1	17.5
Toronto Pearson to Montreal Dorval	505	1	AC320	76.2	16.8
Toronto Pearson to New York LaGuardia	571	2	ACE90	93.2	22.5
Toronto Pearson to Vancouver Int'l	3344	2	AC321	308.4	23.3
Vancouver Int'l to Toronto Pearson	3344	2	WS73H	267.8	17.1
Washington Dulles to Atlanta Hartsfield	856	0	DLM88	116.8	33.1
Washington Regan to Atlanta Hartsfield	518	0	HD737	119.5	31.2
Washington Regan to Boston Logan	879	1	DLM90	88.5	14.5
Washington Regan to Dallas-Ft Worth	639	1	AA319	210.0	41.8
Washington Regan to New York LaGuardia	1914	1	AA738	80.6	26.2
Wellington to Auckland	480	1	NZ320	65.0	18.7
Zurich to Frankfurt-am-Main	285	2	LH319	64.1	15.6
Zurich to London Heathrow	785	2	LX320	110.0	17.0

between un-congested airports help provide more observations on shorter block times that are achievable for the same distance (see Table 1).

2.1. Data overview

From the 200 directional non-stop routes (airport pairs), a total of 15,180 airline-aircraft-route combinations was extracted, with an average flight distance of 1526 km. Excluding those combinations with 53 or fewer frequency in a specific year, equivalent to an infrequent schedule of one flight a week and likely corresponding to ad-hoc aircraft utilization, there are 10,738 airline-aircraft combinations for further econometric analysis, encompassing 7,300,456 scheduled one-way flights and a total of 959,395,405 min of scheduled block time. The average scheduled block time in the data used in further econometric analyses is 151.2 min per flight. Just over half the airline-aircraft-route combinations, or 50.2%, are wholly within North America, 19.8% wholly within East Asia, and 14.3% wholly within Europe. Among the 192 directional airport pairs with non-stop service in 1986, only 8 record a reduction in block times when averaged across all airlines and aircraft types from 1986 to 2016. The median increase in average block times among the 192 airport pairs is 16.14 min in the same period, and the median percent increase is 12.5%. The average increase in block time in this period is 15.5 min, with the average block time being 140.8 min in 1986.

To provide an overview of the block times over the years, the average scheduled block times across all airlines and aircraft types in select airport pairs over the years are shown for comparison. Fig. 1 shows several directional airport pairs between 296 and 343 km in great-circle distance in an eastward direction: Washington National (DCA) to New York LaGuardia (LGA), LGA to Boston (BOS), Paris Charles de Gaulle (CDG) to Amsterdam (AMS), and Kuala Lumpur (KUL) to Singapore (SIN). Overall, all four airport pairs show a sizable increase in block times over the years, but the first three both start with a higher baseline in 1986 (around 60 min) and end with higher block times in 2016 (between 77 and 83 min) than the last, likely as a result of more severe congestion at and around airports in the first three airport pairs. Even for the last airport pair, situated wholly within South-east Asia, the increase in block time has been notable, from 50 min in 1986 to 64 min in 2016 on average. In particular, the increase for KUL to SIN happened in spite of the fact that the new KUL airport, which came on line in 1998, actually reduced the flight distance from 335 km to 297 km for this route. The flight distances for DCA to LGA and for KUL to SIN after 1998 are virtually the same, at 296–297 km, yet the two routes differ by 19 min in block time in 2016.

Fig. 2 shows the scheduled block times for four slightly longer airport pairs in a westward direction between 415 and 476 km in distance: St Louis (STL) to Chicago O'Hare (ORD), London Heathrow (LHR) to Dublin, Stansted (STN) to DUB, and Durban (DUR) to Johannesburg (JNB). All four airport pairs show a general increase in block times over the years, in spite of periodic declines every now and then. For DUR to JNB, the increase is the smallest, from 60 min in 1986 to 66 min in 2016. STL to ORD begins in 1986 with a comparable 62 min of block time, but then increases to 81 min in 2016 – an increase of 19 min, or a whopping 30% increase. In 2016, both LHR to DUB and STL to ORD feature the same average block time, potentially suggesting that the two routes suffer similar congestion. Interestingly, STN to DUB averages a longer block time (flown primarily by budget carriers), at 85 min, than LHR to DUB, at 81 min, in 2016.

Fig. 3 shows the scheduled block times of four even longer airport pairs in a southward direction between 1722 and 1880 km: Beijing (PEK) to Guangzhou, New York LaGuardia (LGA) to Miami (MIA), Seattle-Tacoma (SEA) to Phoenix (PHX), and Sao Paolo Guarulhos (GRU) to Buenos Aires Pistarini (EZE). SEA to PHX shows the smallest increase over these years, from 164 min in 1986 to 170 min in 2016. GRU to EZE shows a slightly higher increase, from 160 min to 176 min in 2016. LGA to MIA starts at a higher base of 170 min in 1986 and soars to 200 min in 2016: a net increase of 30 min. PEK to CAN shows a similar increase over the years as LGA to MIA, suggesting that the rapid rise of aviation activity in China has likely created congestion problems comparable to those in north-eastern U.S.

Fig. 4 shows the scheduled block times of four airport pairs in the 2430 to 2688 km range of flight distance in a westward

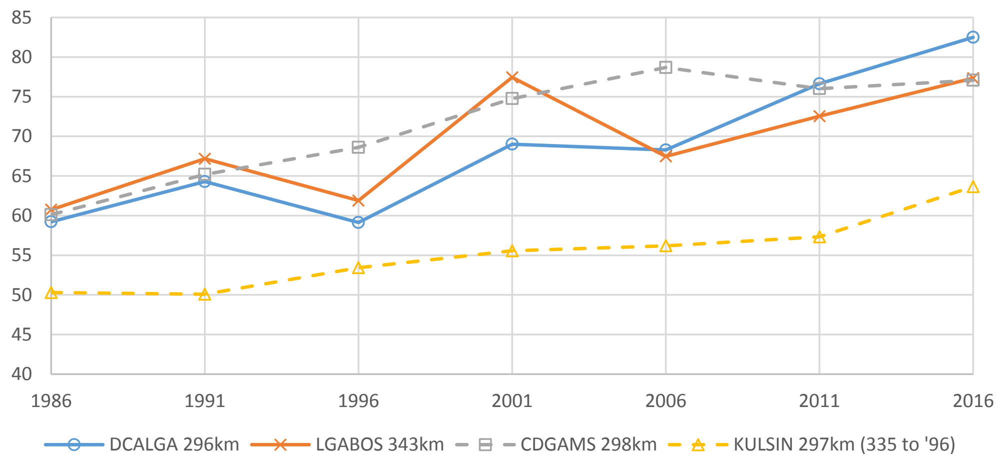

Fig. 1. Average block times in minutes of some of the shortest city-pairs sampled.

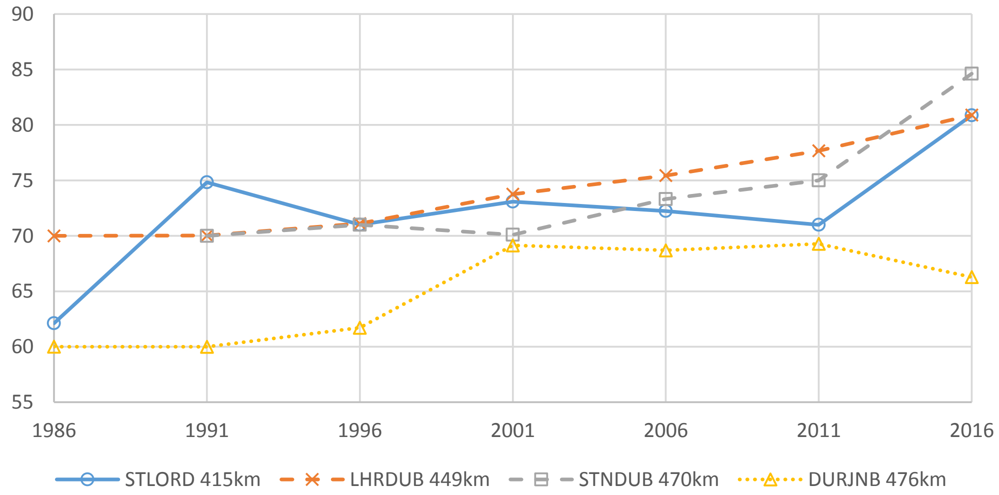

Fig. 2. Average block times in minutes of several city-pairs 410–480 km in distance.

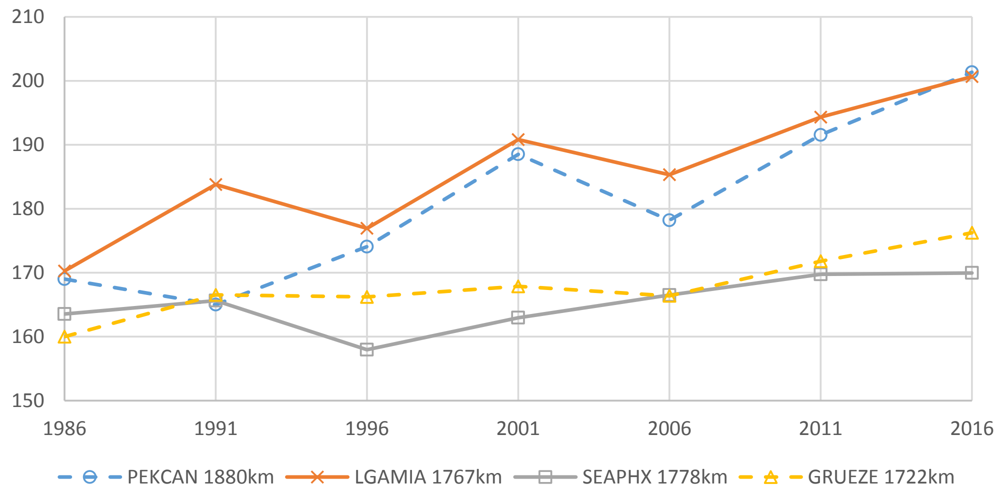

Fig. 3. Average block times in minutes of several city-pairs 1700–1890 km in distance.

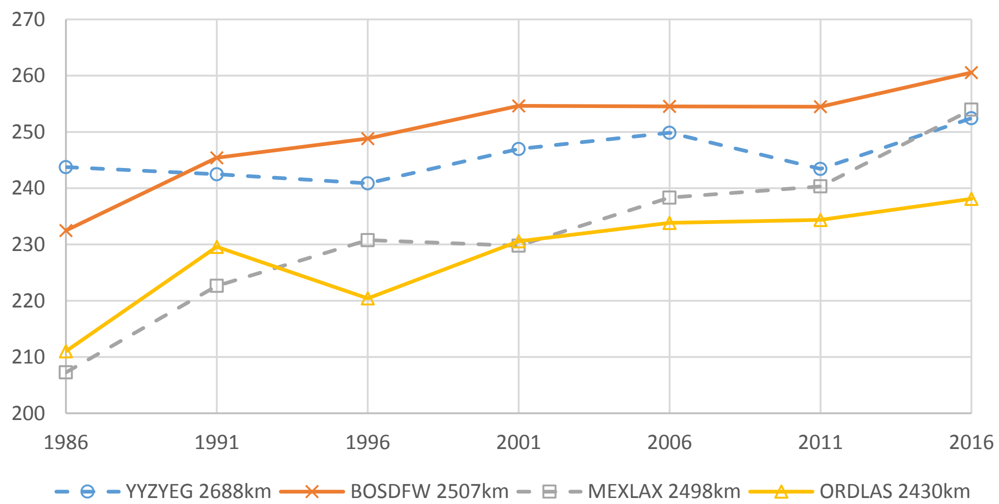

Fig. 4. Average block times in minutes of several city-pairs 2400–2690 km in distance.

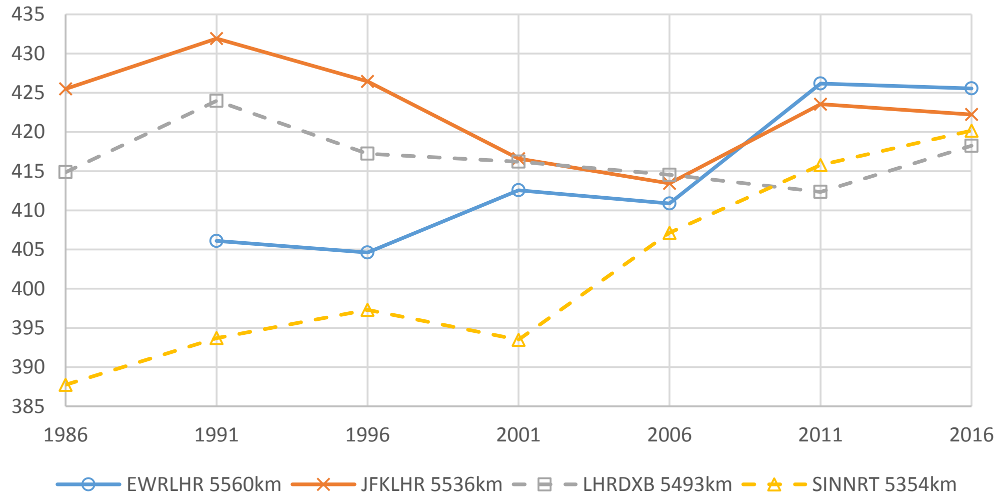

Fig. 5. Average block times in minutes of several longest city-pairs sampled.

direction, about 3.5–4.5 h of flights time: Toronto Pearson (YYZ) to Edmonton International (YEG), Boston (BOS) to Dallas/Fort Worth (DFW), Mexico City (MEX) to Los Angeles International (LAX), and Chicago O'Hare (ORD) to Las Vegas (LAS). There has been an overall increase in block times over the years. The last two airport pairs start with relatively short block times in 1986, around 210 min, but increase to 254 min in 2016 for MEX to LAX (an increase of 46 min) and to 238 min for ORD to LAS (an increase of 27 min). BOS to DFW starts with 233 min of block time in 1986 and increases to 261 min in 2016 (an increase of 28 min). YYZ to YEG starts with the longest block time in 1986, at 244 min, and still records an increase of 9 min in 2016.

Fig. 5 shows the scheduled block times of four eastward airport pairs between 5354 and 5560 km, i.e., in the longest distance band in the sample: Newark (EWR) to London Heathrow (LHR), New York Kennedy (JFK) to London Heathrow (LHR), LHR to Dubai (DXB), and Singapore (SIN) to Tokyo Narita (NRT). LHR to DXB and JFK to LHR begin with higher block times between 415 and 426 min respectively, and both end with similar block times between 418 and 422 min in 2016. JFK to LHR and EWR to LHR have nearly the same flight distances, yet feature a difference of 25 min in 1991. In 2016, this difference shrinks to less than 4 min, with the block times for EWR to LHR having significantly increased. Incidentally, JFK to LHR is one of the few routes that record a reduction in scheduled block times averaged across all airlines. More dramatically, the SIN to NRT route features the shortest block time by far in 1986 among these routes, at 388 min, but has a substantial increase to 420 min in 2016 in line with the other 3 airport pairs.

2.2. Regression model

Three econometric analyses are performed on the sampled data: 10th percentile quantile regression, 15th percentile quantile regression, and ordinary least-squares regression, following the advocate of Gillen et al. (2016) in 'marrying' both traditional regression analyses with percentile measures in estimating flight durations. The first two analyses try to replicate via regression analyses the 10th or 15th percentile flight times (i.e., toward the lower end of the spectrum of flight times observed) used in El Alj (2003) and Skaltsas (2011), while incorporating other factors such as aircraft types. Aiming at locating the sample mean, the third analysis mirrors what many other scholars have used to attribute flight delays to underlying reasons (e.g., Morrison and Winston, 2008).

These model the following equation:

$$\begin{aligned}\mathrm{Block}_{j,y} = a\cdot\mathrm{Yr}_{j,y} + b\cdot\mathrm{Km}_{j,y} + c\cdot\mathrm{Km}^2_{j,y} + d_i\cdot\mathrm{Km}_{j,y}\cdot\mathrm{Hdg}_{i;j,y} + f_i\cdot\mathrm{Km}\cdot\mathrm{Acft}_{i;j,y}\\ + g\cdot\mathrm{Km}_{j,y}\cdot\mathrm{OilChg}_{,y} + h_i\cdot\mathrm{Km}^2_{j,y}\cdot\mathrm{OilChg}_{,y} + k_i\cdot\mathrm{Dum}_{i;j,y} + m_i\cdot\mathrm{Yr}_{j,y}\cdot\mathrm{Dum}_{i;j,y}\\ + Const + e\end{aligned} \tag{1}$$

Indices j and y refer to a specific directional airline-aircraft-route combination, and calendar year respectively. $\mathrm{Block}_{j,y}$ is the average scheduled block time in minutes for the airline-aircraft-city-pair combination j in year y. Index i refers to the different estimated coefficients corresponding to different control variables explained below. The estimated coefficients are a, b, c, d_i, f_i, g, h_i, k_i, m_i. The prime measure of schedule creep is $\mathrm{Yr}_{j,y}$, which denotes the number of years elapsed from 1986, the earliest year sampled, to year y. If a long-run, consistent creep in scheduled block times is detected, coefficient a should be positive and statistically significant. The other variables are discussed below.

2.3. Physical attributes

Several categories of controls are used, with the first several being fixed, i.e., not changing over time. The first groups include physical characteristics of an airport-pair, including route distance, approximate flight heading, aircraft types and airport-specific factors, which do not change over time. $Km_{j,y}$ and $Km_{j,y}^2$ denote respectively the great-circle flight distance in kilometres for the airport-pair (route) described in airline-aircraft-route *j*, and its square. The square term for flight distance is included as longer flights may permit the use of higher cruise altitudes that can marginally shorten flight times. $Hdg_{i;j,y}$, with i = 1, 2, 3…, denote several route heading dummy variables (=1 if headed in the specified direction, 0 otherwise) that represent the approximate heading for the directional airport pair *j* to account for the effect of prevailing winds: East (HdgE), Northeast (HdgNE), Southeast (HdgSE), West (HdgW), Northwest (HdgNW) and Southwest (HdgSW). The effect of directional route heading on block time is modelled through its mathematical product with flight distance: the longer the distance, the more pronounced the change in block times.

$Acft_i$ denotes a list of aircraft dummy variables (=1 if that aircraft type is used, 0 otherwise) that are used in the sampled airline-aircraft-route combinations, including Airbus 300 (acAB3), the Airbus 320 family (ac320), Airbus 330 (ac330), Airbus 340 (ac340), Boeing 727 (ac727), Boeing 737-100 to − 500 (ac737), Boeing 737-600 or higher series (ac73n), Boeing 747 except for −400 (ac747), Boeing 747-400 (ac744), Boeing 757 (ac757), Boeing 767 (ac767), Boeing 777 (ac777), Douglas DC-9 (acDC9), Douglas DC-10 (acD10), Lockheed L-1011 (acL10), Embraer Regional Jets (acEMJ) and propeller aircraft (acPRP). The effect of aircraft type on block time is modelled through its mathematical product with flight distance. In the sample, only 38 out of 10,738 airline-aircraft-city-pair combinations are operated with propeller aircraft, all in short-distance routes where the difference in scheduled block times from jet-operated schedules is small.

Airport-specific flight path peculiarities can contribute to an adjustment in scheduled block times. If a flight departs from or arrives at a list of 22 airports with a high number of airline-aircraft-route combinations, separate dummy variables are assigned to both the departure and arrival airports, respectively with the prefixes 'D' and 'A'. For example, $DATL_{j,y}$ equal 1 if the airline-aircraft-route combination (*j*) involves a departure from Atlanta Hartsfield-Jackson airport, and 0 otherwise; $AFCO_{j,y}$ equals 1 if the nonstop city-pair concerned involves an arrival at Rome Fiumicino Airport, and 0 otherwise. The airports designated with dummy variables are: Atlanta Hartsfield-Jackson (ATL), Boston Logan (BOS), Paris Charles de Gaulle (CDG), Jakarta Soekarno–Hatta (CGK), Washington Reagan National (DCA), Dallas-Fort Worth (DFW), Dubai International (DXB), Newark Liberty (EWR), Rome Fiumicino (FCO), New York Kennedy (JFK), Kuala Lumpur International (KUL), Las Vegas McCarran (LAS), Los Angeles International (LAX), New York LaGuardia (LGA), London Heathrow (LHR), Munich (MUC), Tokyo Narita (NRT), Chicago O'Hare (ORD), Phoenix Sky Harbor (PHX), San Francisco International (SFO), Singapore Changi (SIN), and Toronto Pearson (YYZ).

Seven cities feature a complete switch-over from an old to a new airport within the same city have their own dummy variables to represent the change: Denver ($DEN_{j,y}$, equals 1 if the airport pair in combination *j* involves Denver as the departure or arrival airport, and *y* is prior to 1995, and 0 otherwise), Guangzhou ($CAN_{j,y}$, equals 1 if the airport pair involves Guangzhou and *y* is prior to 2004, and 0 otherwise), Haikou ($HAK_{j,y}$, equals 1 if the airport pair involves Haikou and *y* is after 2013, and 0 otherwise), Hong Kong ($HKG_{j,y}$, equals 1 if the airport pair involves Hong Kong and *y* is prior to 1997, and 0 otherwise), Ishigaki ($ISG_{j,y}$, equals 1 if the airport pair involves Ishigaki and *y* is after 2013, and 0 otherwise), Kuala Lumpur ($KUL_{j,y}$, equals 1 if the airport pair involves Kuala Lumpur and *y* is before 1997, and 0 otherwise), and Munich ($MUC_{j,y}$, equals 1 if the airport pair involves Munich and *y* is before 1992, and 0 otherwise). In particular, the flight distance may differ as airport operations are moved from the old to the new airport. For instance, the flight distance between Kuala Lumpur and Penang was 279 km at the Sultan Abdul Aziz (Subang) Airport, but is now 323 km at the new Kuala Lumpur International Airport.

2.4. Fuel cost changes

To investigate the potential impact of fuel cost on scheduled block times, a measure of change in crude oil prices is used as a proxy: $OilChg_y$ = the quotient obtained by dividing the difference between the inflation-adjusted (to 2018) crude oil price per barrel in year *y*-2 and the inflation-adjusted crude oil price per barrel in year 1984 (two years before 1986) by the latter, then subtracting 1 from it to yield a measure of change (U.S. Energy Information Administration, 2018). A lag of two years is used because airline schedules, especially those involving slot-restricted airports, are typically finalized many months in advance of their actual operation. These schedules in turn rely on past trends in crude oil prices. As such, the effect of crude oil prices on scheduled block times is expected to also be similarly lagged. For instance, to calculate the impact of crude oil price on the 1996 scheduled block times, the difference between the inflation-adjusted crude oil prices in 1994 (US$26.46/barrel) and the equivalent in 1984 (US$70.12/barrel) is divided by the latter (yielding −1.623), from which 1 is subtracted (yielding −0.623). As with flight distance, the impact on scheduled block times from changes in oil prices is implemented by its product with both the unit measure and square of flight distance ($KM_{j,y}$, $KM_{j,y}^2$).

2.5. Region-specific influences

Several regional control variables are used to identify region-specific impact on scheduled block times. The region-specific effect is modelled both as a fixed component as well as a variable component that increases as the number of years elapsed since 1986. For instance, $Aus_{j,y}$ equals 1 if the airport pair in airline-aircraft-route combination *j* is situated wholly within Australasia, and 0 otherwise. The same variable $Aus_{j,y}$ is multiplied with the $Yr_{j,y}$ variable to examine whether scheduled flights in Australasia have experienced consistent changes in block times over the years (either increase or decrease). Based on the number of flights sampled, these are the regions of the world with a separate regional dummy variable: Australasia (Aus), East Asia (Eas, includes Northeast and Southeast Asia including China, and excludes South Asia and the Middle East), Europe (Eur), and North America (Nam). Further, an airport pair departing or arriving within north-eastern US gets an additional dummy variable (Nnb) because of the notoriously busy flight movements in that region (e.g., Kim, 2016), where $Nnb_{j,y}$ equals 1 if the combination *j* either takes off from or arrives at an airport in north-eastern U.S. Based on the work of Yakovchuk and Willemain (2005), which shows that geographically close airports track each other's problems in terms of their actual flight times, Boston, Newark, New York Kennedy and Philadelphia are considered part of north-eastern U.S. in recognition of the busy airspace above and around metropolitan New York.

2.6. Airline policies

Airline management policies are also considered in modelling scheduled block times. These effects are modelled based on (i) company-wide policies; (ii) hub-specific policies, (iii) merger-related effects, and (iv) competition effects. In the few years after the OTDR began, Shumsky (1993) documented evidence of company-specific policies on scheduled block times. In particular, he found that the one airline that increased its block times the most (American Airlines) in those years also began with the shortest block times in the start of the sampling period. As a result, company-wide policies are modelled in this study for a number of airlines that represent the largest number of sampled observations: $AA_{j,y}$, $AC_{j,y}$, $BA_{j,y}$, $CO_{j,y}$, $DL_{j,y}$, $LH_{j,y}$, $PA_{j,y}$, $TW_{j,y}$, $UA_{j,y}$, $US_{j,y}$ and $WN_{j,y}$ each equals 1 if a flight is operated by their respective airlines and 0 otherwise: American Airlines, Air Canada, British Airways, Continental Airlines, Delta Airlines, Lufthansa, Pan Am, TransWorld Airlines, United Airlines, US Airways, and Southwest Airlines. Each of these dummy variables is also multiplied with $Yr_{j,y}$ to examine any company-specific schedule creep over time.

In addition to company-wide policies, individual airlines may choose to adjust scheduled block times on flights that start and end at their respective hub airports to minimize missed flight connections where most of their passengers' flight connections are expected to occur (e.g., Baumgarten et al., 2014). To isolate any airline-specific scheduling policies involving on their respective hubs, $HubAA_{j,y}$, $HubCO_{j,y}$, $HubDL_{j,y}$ or $HubUA_{j,y}$ take on the value of 1 if the airport pair in combination *j* involves at least one of the heritage hubs of American Airlines (DFW, ORD), Continental Airlines (EWR), Delta Airlines (ATL, DFW) and United Airlines (ORD, SFO) respectively. Not all the hubs or airlines are included in the analysis of hub-specific effects because of the limited years of schedules sampled. Each of these 'airline-hub' variables is also multiplied by with $Yr_{j,y}$ to examine any related schedule creep over time.

Over the years, a number of airlines have merged together to form a single entity, and these incidents could influence their post-merger policy on scheduled block times. Among the predominant airlines in the sampled observations, six major mergers have taken place in the sampling window. $AA\text{-}US_{j,y}$ takes on the value of 1 if the combination *j* involves American Airlines (AA) after 2013 (after absorbing US Airways), and 0 otherwise. $AA\text{-}TW_{j,y}$ takes on the value of 1 if the combination *j* involves AA after 2001, and 0 otherwise. $DL\text{-}NW_{j,y}$ takes on the value of 1 if the combination *j* involves Delta Airlines (DL) after 2010 (after absorbing Northwest), and 0 otherwise. $UA\text{-}CO_{j,y}$ takes on the value of 1 if the combination *j* involves United Airlines (UA) after 2011 (after merging with Continental), and 0 otherwise. $WN\text{-}FL_{j,y}$ takes on the value of 1 if the combination *j* involves Southwest Airlines (WN) after 2011 (upon absorbing AirTrans), and 0 otherwise. $WN\text{-}TZ_{j,y}$ takes on the value of 1 if the combination *j* involves Southwest after 2009 (upon absorbing ATA).

Several studies have noted that the flight delays for certain U.S. airlines are related to the airlines' competitive landscape. For instance, Prince and Simon (2009) found that an airline's monopoly routes suffered more arrival delays in aggregate as well as a higher proportion of flights arriving at least 30 min late. In other words, a stronger market position induces airlines into allocating shorter block times for their flights. To investigate this phenomenon from the perspective of scheduled block times, three variables are used in this study using historical flight schedule data from *Official Airline Guide*. $RouteShare_{j,y}$ shows the frequency share (e.g., 0.30 represents 30%) of airline in combination *j* in the respective non-stop airport pair. $DepAirportShare_{j,y}$ denotes the total share of departure of the airline in combination *j* at the departure airport of the non-stop airport pair, while $ArrAirportShare_{j,y}$ denotes the corresponding amount at the arrival airport.

2.7. Congestion effects

Several groups of variables are used to attribute increases in scheduled block times to increasing congestion in several areas: (i) crowded skies (causing delays to overflight traffic), (ii) growth in airport traffic, (iii) airport congestion and (iv) effect of aircraft size at airports. While the overall trend for air traffic has been increasing in the past three decades, there have been occasional periods of declines. For instance, many airports in the U.S. experienced a decline in air traffic in the few years after the September-11th attacks in 2001.

To measure the impact of congested airspace on scheduled block times, the increase in total air traffic movements (take-offs and landings) in three busiest air traffic corridors in the world are noted. $Traffic85euro_{j,y}$ represents the growth in air traffic movements in France, Belgium, Germany, the Netherlands and Switzerland recorded in year $y-1$ over the equivalent in 1985 (e.g. 0.20 representing a 20% growth) as a proxy of congested airspace in the middle of Europe if the airport pair in *j* involves flying over these countries, and 0 otherwise. For example, the non-stop airport pair of Helsinki – Oulu, Finland, is within Europe and hence subject to Europe-wide conventions in scheduled block times but does not over-fly the above countries in likely the most crowded airspace in Europe, and hence will see this variable taking on the value of 0 (i.e., not influenced by the crowded skies in Europe). Likewise, $Traffic85usa_{j,y}$ represents the growth in air traffic in the U.S. as a proxy for congested airspace in the northeast and mid-west of the U.S. relative to its baseline in 1985 for airport pairs that over fly that part of the U.S., and 0 otherwise. As a result, the combination *j* that involves the airport pair of Seattle-Phoenix, U.S., will see this variable take on the 0 value (i.e., no impact from congested airspace). $Traffic85chn_{j,y}$ represents the growth in air traffic in China as a proxy for congested airspace there over a baseline of Japan's traffic level in 1985 because of China's relatively immature air transport industry at that time, and takes on the value of 0 for airport pairs that do not ordinarily involve the eastern half of Chinese airspace. The result of this change of base is that this variable takes on 0 values prior to 2001 (because China's aggregate air traffic only caught up to Japan's level in 1985 at that time), representing the first decade of the break-up of the Civil Aviation Administration of China as the sole provider of scheduled air transport in China. Anecdotal evidence suggests that much airspace in China is controlled by the military and is from time to time restricted for civilian flights, exacerbating the block times airlines schedule for their flights over China.

A direct measure on persistent airport crowdedness would be the amount of flight delays observed at certain airports. Unfortunately, only the U.S. reports such statistics for a large number of airports over a long period of time. The Bureau of Transportation Statistics (BTS) under U.S. DoT publishes such delay statistics from 1995. Both the average flight delays experienced and the percent of flights arriving more than 15 min past the scheduled arrival time in year $y-1$ are available, and these two statistics are highly correlated (Pearson's correlation ~ 0.95). As such, only the average flight delay statistic (in minutes per flight) is used for further analysis. In particular, the flight delay statistic is further averaged across all airports and years, and any airport-specific flight delay above this sample average is entered in the variable $\text{DepAirportDelay}_{j,y}$ if the combination j departs from that airport, and in the variable $\text{ArrAirportDelay}_{j,y}$ if j arrives at that airport. Otherwise, these two variables take on the value of 0. A large average delay observed at an airport in a particular year can drive airlines to increase scheduled block times for flights involving that airport. Most major airports outside of the U.S. adopt a slot-based system that limit the total number of scheduled flights allowed, and hence the observed delays at these airports may be more muted in comparison.

Beyond the actual delay data that are available only in the U.S., a broader measure of airport congestion is introduced. Here, the total number of aircraft movements at an airport in year $y-1$ is divided by its projected 'capacity' to provide an indicator of airport congestion. This indicator is computed for all airports in the sample, across all years, and is then averaged across all airport-years. Any difference above this sample average (47.26%) is then reported in either the $\text{DepCongestion}_{j,y}$ or $\text{ArrCongestion}_{j,y}$ variable, depending whether that specific airport is the departure or arrival airport for the sample j. To compute the projected capacity of airports, the count of operational runways at 73 of the largest airports in the sampled observations is first obtained from Air Transport Research Society (mostly post-2000), supplemented with information from Wikipedia for changes (prior to 2000). ATRS also provides the actual number of aircraft movements (take-offs and landings) post-2000, while the pre-2000 figures are obtained from scheduled operations from *Official Airline Guide*. Next, for each number of runways (from 1 to 8), at least two airport-years (involving different airports if possible) with the highest total number of aircraft movements are short-listed to represent a maximum capacity. These short-listed total number of aircraft movements are then regressed over the number of operational runways (Runways), its square and cube to provide the following expression for a projected maximum capacity (Capacity) for an airport:

$$\text{Capacity} = 2386 \cdot \text{Runways}^3 - 41{,}508 \cdot \text{Runways}^2 + 247794 \cdot \text{Runways} - 106{,}914$$

Details of the results of this regression are reported in Table A1 in the Appendix A. In reality, an airport's capacity depends also on the configuration of its runways (e.g., parallel, intersecting, etc.), as well as its prevailing weather conditions. The capacity projected in this exercise merely serves as an approximate measure of capacity that allows a broad measure of congestion to be calculated.

The variables $\text{DepAirportDelay}_{j,y}$, $\text{ArrAirportDelay}_{j,y}$, $\text{DepCongestion}_{j,y}$ and $\text{ArrCongestion}_{j,y}$ may appear to be highly correlated as they in some ways measure the level of airport congestion. However, because of both the method of calculation and the reporting of only the above-average statistic, the Pearson's correlation among any two of these four variables is less than 0.159.

In addition, airports with busy air traffic movements may see a long queue of aeroplanes on the side of its runways waiting to take off, and/or a long queue of aeroplanes in the air waiting to land. The actual flying time of a flight depends on how quickly such queues dissipate, and this also impacts airlines' scheduled block times in the future. An important determinant on how quickly such queues dissipate is the separation distance between successive aeroplanes, and the absolute minimum separation between two departing or arrival aeroplanes is governed by the amount of wake vortices an aeroplane is expected to generate. The aircraft separation minima based on wake vortices are generally larger when a large aeroplane is involved (FAA, 2015). As a consequence, the average aircraft size as approximated by the average number of seats per flight at a particular airport, supplied by ATRS alongside its runway statistics (from 2001 onwards), is used as a variable to measure this effect on scheduled block times. In particular, an average of this variable is determined across 73 airports (at 146.0 seats per flight), and any observed difference in excess of this sample average is recorded in the SeatPerFlight variable (this variable otherwise takes on the value 0). An airline-aircraft-route combination (j) departing from or arriving at a particular airport has the corresponding $\text{DepSeatPerFlight}_{j,v}$ or $\text{ArrSeatPerFlight}_{j,v}$ variable.

Finally, some flight delays occur because of other interactions between different aeroplanes at a specific airport. For instance, one aeroplane requiring more time to manoeuvre out of one runway may have a cascading effect as it delays all other aeroplanes behind it in the queue. This kind of delays likely increases as the sheer volume of air traffic increases at an airport, even as more runways are present to accommodate the large traffic volume – potentially pressuring airlines to increase scheduled block times. To account for the sheer size of increase in air traffic at an airport, a variable is created to calculate a 5-year change in total scheduled air traffic movements (take-offs plus arrivals) by subtracting the air traffic movements in year $y-6$ from the corresponding number in year $y-1$ for each airport in the sample (obtained from *Official Airline Guide*). For the top third of the busiest airports in the sample, a statistic called Growth is created to express this change as the change in percentage points relative to the 80th-percentile air traffic movements across all airport-years – capturing the sheer amount of air traffic growth among the busiest airports in the sample. For the rest of the airports, this variable takes on value 0. The $\text{DepAirportGrowth}_{j,y}$ variable takes on this value if the airline-aircraft-route combination j departs from this airport. The equivalent is formulated for the $\text{ArrAirportGrowth}_{j,y}$ variable if combination j arrives at this airport. Among the airports with non-zero values for these variables, the average is 41.57 percentage points (i.e., 41.57%). These two variables correlate more with $\text{DepCongestion}_{j,y}$ and $\text{ArrCongestion}_{j,y}$ (Pearson's correlation up to 0.55), but do cover the early part of the sample, from 1985 to 2000, where the other statistics do not cover. Moreover, these congestion-related variables do not cause multicollinearity concerns based on their variance inflation factors (Kutner et al., 2004). As such, these variables are still included in the regression analyses.

2.8. Airport slot policy

Last but not least, the sampling procedure includes airports with different slot regimes at comparable flight distances. With the reference group being airport pairs involving airports with no slot regimes (i.e., airlines are relatively free to schedule flights), two variables pertaining to slot regimes are used: $Slot1_{j,y}$ equals 1 if the airport pair in combination *j* involves exactly one airport (either departure or arrival) that adopts Level 3 slot coordination as defined by the International Air Transport Association (IATA) or the equivalent (e.g., High Density Rule in the U.S., noise-based quota system for Tokyo Haneda), and 0 otherwise; $Slot2_{j,y}$ equals 1 if the airport pair in combination *j* involves two airports (both departure and arrival) that adopt the slot coordination procedure, and 0 otherwise. Both $Slot1_{j,y}$ and $Slot2_{j,y}$ are also multiplied with the $Yr_{j,y}$ variable to examine whether there is specific schedule creep for airports in certain slot regimes.

3. Results

The results from the 10th percentile quantile regression, 15th percentile quantile regression, and ordinary least-squares regression models are shown in Table 2. To reduce the effect of heteroscedasticity, the estimated coefficients and their robust standard errors are obtained. The F-tests for the rest of the variables or groups of variables are statistically significant, at $p < 0.001$. Many variables are estimated to have coefficients of the same sign and statistical significance across all three regression analyses.

Overall, the regression results show that in addition to the effects of congested skies and airports as well as a range of other effects, there is a statistically significant and monotonic increase in scheduled block times over the years ($Yr_{j,y}$). This means that schedule creep from 1986 to 2016 is real. The amount of creep is estimated to be between 0.21 and 0.33 min per year depending on the regression model, at $p < 0.001$, or between 6.2 and 9.8 min per flight over 30 years. This effect is in addition to all other effects discussed below.

Table 2
Estimated coefficients in regression of scheduled block times.

Robust coefficients	OLS	15% Quantile	10% Quantile
Global schedule creep			
Yr	0.2061^{***}	0.3281^{***}	0.2718^{***}
	(0.0363)	(0.0249)	(0.0278)
Flight distance			
Km	0.0777^{***}	0.0783^{***}	0.0782^{***}
	(0.0004)	(0.0003)	(0.0005)
Kmsq	$-1.13 \times 10^{-6***}$	$-1.67 \times 10^{-6***}$	$-1.72 \times 10^{-6***}$
	(7.03×10^{-8})	(6.66×10^{-8})	(6.77×10^{-8})
Oil price influence			
Km × OilChg	0.0006	0.0005^{*}	0.0011^{***}
	(0.0004)	(0.0003)	(0.0003)
Kmsq × OilChg	-4.34×10^{-8}	-6.47×10^{-8}	$-1.74 \times 10^{-7**}$
	(8.62×10^{-8})	(7.29×10^{-8})	(6.58×10^{-8})
Heading influences			
Km × HdgE	-0.0052^{***}	-0.004^{***}	-0.0036^{***}
	(0.0002)	(0.0002)	(0.0004)
Km × HdgNE	-0.0029^{***}	-0.002^{***}	-0.0016^{***}
	(0.0003)	(0.0002)	(0.0004)
Km × HdgSE	-0.0019^{***}	-0.0008^{**}	−0.0004
	(0.0003)	(0.0002)	(0.0004)
Km × HdgW	0.0048^{***}	0.0057^{***}	0.0061^{***}
	(0.0003)	(0.0002)	(0.0004)
Km × HdgNW	0.0051^{***}	0.0049^{***}	0.0055^{***}
	(0.0003)	(0.0002)	(0.0004)
Km × HdgSW	0.0036^{***}	0.0032^{***}	0.0033^{***}
	(0.0003)	(0.0003)	(0.0004)
Regional influences			
Aus	-5.4395^{***}	−2.106	-7.4112^{*}
	(0.8737)	(1.6249)	(3.3977)
Eas	−0.9428	−0.4033	$-1.1441^{\dagger}$
	(0.7615)	(0.5370)	(0.6610)
Eur	$1.3329^{\dagger}$	2.7805^{***}	3.4711^{***}
	(0.7426)	(0.3563)	(0.6704)
Nam	-1.7117^{*}	−0.293	-1.8411^{*}
	(0.8002)	(0.4780)	(0.7574)
Nnb	3.7227^{***}	3.6392^{***}	3.9577^{***}
	(0.6002)	(0.5328)	(0.6162)

(*continued on next page*)

Table 2 (*continued*)

Robust coefficients	OLS	15% Quantile	10% Quantile
Aus × Yr	0.2228***	0.0269	0.2641*
	(0.0459)	(0.0686)	(0.1193)
Eas × Yr	0.0237	−0.0767**	−0.1002**
	(0.0359)	(0.0255)	(0.0326)
Eur × Yr	−0.0973**	−0.2031***	−0.2358***
	(0.0349)	(0.0254)	(0.0284)
Nam × Yr	0.1625***	0.0504†	0.0994***
	(0.0357)	(0.0272)	(0.0273)
Nnb × Yr	−0.0063	−0.0223	−0.0518*
	(0.0252)	(0.0180)	(0.0226)
Aircraft influence			
Km × ac320	0.0002	−0.0003†	−0.0003
	(0.0002)	(0.0002)	(0.0002)
Km × ac330	0.0004	0.0001	0.0001
	(0.0003)	(0.0005)	(0.0003)
Km × ac340	−0.001**	−0.0009†	−0.0012***
	(0.0003)	(0.0005)	(0.0002)
Km × ac727	−0.0013***	−0.0017***	−0.0014***
	(0.0003)	(0.0002)	(0.0002)
Km × ac737	0.0010**	−0.00003	0.0002
	(0.0003)	(0.0002)	(0.0002)
Km × ac73n	−0.00001	−0.0001	−0.0001
	(0.0002)	(0.0002)	(0.0002)
Km × ac744	−0.002***	−0.0018***	−0.002***
	(0.0003)	(0.0002)	(0.0005)
Km × ac747	−0.0018***	−0.0016***	−0.0019***
	(0.0002)	(0.0003)	(0.0002)
Km × ac757	8.9×10^{-6}	−0.0002	−0.0002
	(0.0002)	(0.0002)	(0.0002)
Km × ac767	0.0003	−0.0005*	−0.0006***
	(0.0002)	(0.0002)	(0.0002)
Km × ac777	−0.0011***	−0.0009***	−0.0008***
	(0.0002)	(0.0002)	(0.0002)
Km × acAB3	0.0005	0.0004†	0.0006*
	(0.0003)	(0.0002)	(0.0003)
Km × acD10	−0.0023***	−0.0024***	−0.0024***
	(0.0003)	(0.0002)	(0.0003)
Km × acDC9	0.0005	−0.0002	−0.0002
	(0.0005)	(0.0003)	(0.0004)
Km × acEMJ	0.002***	0.0004	−0.0003
	(0.0005)	(0.0009)	(0.0005)
Km × acL10	−0.0024***	−0.0027***	−0.0027***
	(0.0004)	(0.0006)	(0.0003)
Km × acPRP	0.0316***	0.0289***	0.0241†
	(0.0032)	(0.0028)	(0.0134)
Airport slot regime			
Slot1	−1.7879**	−1.3034**	−2.0479***
	(0.5704)	(0.3937)	(0.5153)
Slot2	−0.1418	0.5657	−0.6029
	(0.6710)	(0.5188)	(0.6300)
Slot1 × Yr	0.0525*	−0.0065	0.0072
	(0.0241)	(0.0166)	(0.0207)
Slot2 × Yr	0.0403	−0.0622**	−0.0398
	(0.0281)	(0.0212)	(0.0271)
Airport traffic growth			
Dep Airport Growth	0.0152**	0.0214***	0.0213***
	(0.0044)	(0.0040)	(0.0032)
Arr Airport Growth	0.0239***	0.0266***	0.0226***
	(0.0047)	(0.0044)	(0.0045)
Dep Airport Delay	−0.0549	−0.1088	−0.0607
	(0.0577)	(0.0526)	(0.0399)
Arr Airport Delay	0.0217	0.0302	0.0193
	(0.0461)	(0.0490)	(0.0311)
Dep Congestion	0.0005***	0.0006***	0.0008***
	(0.0001)	(0.0001)	(0.0001)
Arr Congestion	0.0007***	0.0006***	0.0007***
	(0.0001)	(0.0001)	(0.0001)

(*continued on next page*)

Table 2 (*continued*)

Robust coefficients	OLS	15% Quantile	10% Quantile
Dep Seat per Flight	0.0287***	0.0481***	0.0526***
	(0.0049)	(0.0035)	(0.0051)
Arr Seat per Flight	−0.0130*	−0.0159*	−0.0083
	(0.0060)	(0.0066)	(0.0066)
Overflight traffic			
Traff85euro	1.1755***	1.5964***	1.9849***
	(0.2189)	(0.1979)	(0.1687)
Traff85usa	3.9673***	5.9072***	6.2205***
	(0.5680)	(0.4927)	(0.5300)
Traff85chn	0.9723***	1.0514***	1.1588***
	(0.1146)	(0.2151)	(0.1536)
Airline Market Share			
Dep Airport Share	−1.4485***	−0.3790	−0.7577**
	(0.3397)	(0.2630)	(0.2650)
Arr Airport Share	−1.1504***	0.3039	0.4279
	(0.3425)	(0.2320)	(0.2738)
Route Share	−1.9751***	−0.6475†	−0.1874
	(0.5215)	(0.3663)	(0.3661)
Company-wide policy			
AA	−0.5154	−0.0312	0.2006
	(1.5727)	(0.7718)	(2.0623)
AC	0.7534	1.4532†	1.1791
	(0.7869)	(0.8628)	(0.8297)
BA	0.4996	0.0389	−0.1899
	(0.8197)	(0.4106)	(0.6993)
CO	5.3806***	4.251***	5.2249***
	(0.9925)	(0.7040)	(0.8838)
DL	−3.249***	−2.7379***	−3.9951*
	(0.9406)	(0.6496)	(1.6198)
LH	3.7118***	2.9653	3.6927***
	(0.9109)	(0.8574)	(0.5146)
PA	0.2427	−0.2136	0.0032
	(1.2577)	(0.4923)	(3.0562)
TW	4.9066**	4.7005***	4.6343*
	(1.5732)	(0.9573)	(2.3559)
UA	2.8974***	4.9527***	5.863***
	(0.6712)	(0.6743)	(0.5802)
US	2.9693***	4.0959***	4.1238***
	(0.7321)	(0.6913)	(0.8242)
WN	−3.516**	0.2852	1.3018
	(1.3522)	(0.7114)	(3.4494)
AA × Yr	0.3827***	0.4222***	0.3706**
	(0.1017)	(0.0890)	(0.1134)
AC × Yr	−0.1235**	−0.0896	−0.0527
	(0.0362)	(0.0358)	(0.0398)
BA × Yr	0.0023	0.0453*	0.1042**
	(0.0410)	(0.0219)	(0.0311)
CO × Yr	−0.1801†	−0.1407†	−0.1146
	(0.0952)	(0.0828)	(0.0843)
DL × Yr	0.294***	0.2096***	0.3081***
	(0.0567)	(0.0420)	(0.0717)
LH × Yr	−0.2213***	−0.1997***	−0.2073***
	(0.0412)	(0.0409)	(0.0310)
PA × Yr	0.2294†	0.0269	0.0434
	(0.1329)	(0.0834)	(0.7774)
TW × Yr	−0.2848†	−0.4501*	−0.4001†
	(0.1692)	(0.1891)	(0.2305)
UA × Yr	−0.1874***	−0.2234***	−0.2442***
	(0.0424)	(0.0402)	(0.0322)
US × Yr	−0.0756†	−0.1656*	−0.1725**
	(0.0450)	(0.0758)	(0.0614)
WN × Yr	0.0661	−0.0827†	−0.1123
	(0.0907)	(0.0468)	(0.1816)
Company-hub Policy			
HubAA	0.5435	−0.9215	−1.4463
	(1.5689)	(0.9564)	(1.9771)

(*continued on next page*)

Table 2 (*continued*)

Robust coefficients	OLS	15% Quantile	10% Quantile
HubCO	1.7077	3.393**	3.4656**
	(1.4742)	(1.0194)	(1.1061)
HubDL	2.0984*	1.5983*	3.3488*
	(1.0662)	(0.7187)	(1.5268)
HubUA	−0.3743	−2.7836***	−3.5574***
	(1.0219)	(0.7044)	(0.8069)
HubAA × Yr	−0.0362	−0.029	0.0164
	(0.0700)	(0.0439)	(0.0907)
HubCO × Yr	0.0586	−0.0048	−0.0652
	(0.1122)	(0.0937)	(0.0965)
HubDL × Yr	−0.2427***	−0.1998***	−0.314***
	(0.0519)	(0.0312)	(0.0631)
HubUA × Yr	0.1334**	0.2045***	0.223***
	(0.0510)	(0.0297)	(0.0410)
Merger influence			
AA-US	−1.2435	−0.8692	−0.6808
	(0.9857)	(0.9421)	(1.1050)
AA-TW	−6.9606***	−7.7174***	−7.0300***
	(1.1070)	(1.5725)	(0.8960)
DL-NW	1.6144†	2.2767**	1.8835**
	(0.9028)	(0.7116)	(0.5545)
UA-CO	5.4258***	4.6638***	4.9561***
	(0.8886)	(0.6585)	(0.5874)
WN-FL	−4.7156***	−3.3533***	−4.4694*
	(0.9433)	(0.5276)	(1.7951)
WN-TZ	2.2278†	3.2618***	3.9842***
	(1.2766)	(0.6362)	(1.2874)
New airports			
CAN	0.4851	−1.0504	−0.4038
	(1.8731)	(1.3950)	(1.6690)
DEN	−2.7222**	−2.9509***	−3.3583***
	(0.7864)	(0.7564)	(0.5004)
HAK	−10.658***	−6.4118**	−5.0086**
	(1.1103)	(1.8873)	(1.6480)
HKG	2.835***	5.3184***	6.7908***
	(0.7186)	(0.5540)	(1.2246)
ISG	−4.8978**	−0.8897	1.3241†
	(1.6827)	(2.0270)	(0.7360)
KUL	1.005	0.2117	−0.0401
	(0.8728)	(0.5323)	(0.7688)
MUC	4.7857***	4.9247†	2.8541
	(1.0010)	(2.6207)	(1.7478)
Departing Airport			
DATL	−1.1131	−1.3746	−1.8215***
	(0.6509)	(0.4426)	(0.4347)
DBOS	6.7328***	7.9477***	8.2735***
	(0.5739)	(0.6468)	(0.4954)
DCDG	5.4655***	7.1918***	6.492***
	(0.5754)	(0.5030)	(0.5355)
DCGK	−0.9864	−0.4399	0.3203
	(0.6041)	(0.5542)	(0.5515)
DDCA	2.1757***	3.7568***	4.8915***
	(0.5833)	(0.4679)	(0.5141)
DDFW	−5.8993***	−6.522***	−6.9582***
	(0.6187)	(0.8211)	(0.4174)
DDXB	2.3973	1.0625	1.262
	(0.7644)	(0.6128)	(0.8358)
DEWR	6.292***	7.7002***	7.381***
	(0.5763)	(0.6248)	(0.5695)
DFCO	1.2454	1.921	1.2232
	(0.4988)	(0.6916)	(0.4982)
DJFK	11.7384***	13.7424***	14.9718***
	(0.9021)	(0.7327)	(1.1046)
DLAS	−2.7467***	−1.2659	−0.6451
	(0.5394)	(0.4745)	(0.5235)
DLAX	−3.5368***	−2.3104***	−2.7899***
	(0.4738)	(0.3488)	(0.2967)

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Table 2 (*continued*)

Robust coefficients	OLS	15% Quantile	10% Quantile
DLGA	13.3013***	12.0092***	10.4658***
	(0.6615)	(0.5354)	(1.1668)
DLHR	7.9541***	6.9409***	6.6252***
	(0.6350)	(0.4470)	(0.4498)
DMUC	−1.3232	0.5051	−0.0614
	(0.5557)	(0.4086)	(1.4048)
DNRT	6.9072***	12.9505***	11.4336***
	(1.6333)	(1.8566)	(1.8946)
DORD	−3.169***	−3.6894***	−5.2845***
	(0.6827)	(0.5085)	(0.6897)
DPHX	−2.694***	−1.6195	−1.6334
	(0.5046)	(0.4899)	(0.5156)
DSFO	−9.3034***	−7.5098***	−6.4954***
	(0.9643)	(0.9643)	(0.8671)
DSIN	1.1704†	1.9319***	3.2177***
	(0.6171)	(0.4286)	(0.5004)
DYYZ	2.9274***	4.5031***	5.4763***
	(0.6694)	(0.5457)	(0.7207)
Arriving airport			
AATL	1.5075**	2.0634**	1.7562**
	(0.7182)	(0.6303)	(0.5835)
ABOS	1.6895†	1.3094*	1.7093**
	(0.5671)	(0.6340)	(0.5444)
ACDG	0.9996	4.5278***	5.1936***
	(0.5504)	(0.4453)	(0.528)
ACGK	−3.8834***	−3.6793***	−2.4348***
	(0.6833)	(0.5063)	(0.5426)
ADCA	−0.1159	−0.5451	0.6063
	(0.6916)	(0.5967)	(0.5389)
ADFW	5.3783***	4.0312***	3.1521***
	(0.6718)	(0.8304)	(0.6237)
ADXB	−5.4505***	−4.4806	−6.1303***
	(0.8295)	(1.5826)	(1.1448)
AEWR	5.7746***	4.4818***	4.0947***
	(0.5804)	(0.5612)	(0.5434)
AFCO	−0.4722	−0.3031	−1.1845
	(0.5459)	(0.3512)	(1.1736)
AJFK	−4.135***	−16.408***	−16.5100***
	(1.1038)	(0.7379)	(1.2350)
ALAS	3.8332***	1.4479	2.1582***
	(0.6306)	(0.4262)	(0.5697)
ALAX	1.6936**	2.3252***	2.2593***
	(0.5563)	(0.4736)	(0.4499)
ALGA	5.8815***	5.9236***	6.2814***
	(0.6057)	(0.4858)	(0.613)
ALHR	5.131***	8.0387***	6.2063***
	(0.6040)	(0.5640)	(0.4907)
AMUC	−7.1429***	−6.2038***	−8.1351***
	(0.5882)	(1.4507)	(1.0449)
ANRT	4.4306***	5.5815***	5.1440**
	(1.2533)	(0.9185)	(1.6019)
AORD	0.6778	2.0667***	1.4667
	(0.6976)	(0.5738)	(0.5649)
APHX	0.2500	0.7444	1.0804
	(0.4895)	(0.4468)	(0.4857)
ASFO	6.816***	7.2891***	7.3859***
	(0.6729)	(0.4673)	(0.6893)
ASIN	−5.2198***	−2.1053***	−1.40698
	(0.6036)	(0.5675)	(0.6660)
AYYZ	0.3818	1.9941	3.3349***
	(0.6636)	(0.6008)	(0.7733)
Constant	28.1607***	19.2618***	19.2381***
	(0.8366)	(0.4537)	(0.7013)
(Pseudo-)R-squared	0.9945	0.8908	0.8821

Number of observations: 10,738; *** statistical significance with $\alpha < 0.001$; ** statistical significance with $\alpha < 0.01$; * statistical significance with $\alpha < 0.05$; † statistical significance with $\alpha < 0.10$. Standard error in parentheses.

The 10th percentile and 15th percentile regression models estimate a constant of 19.2 and 19.3 min respectively, while the OLS estimates a constant of 28.2 min. The pseudo-R-squared values for the former two models are high, at 0.8908 and 0.8821 respectively, as is the R-squared value for the ordinary least-square regression, at 0.9945.

3.1. Effect of physical attributes

In general, scheduled block times increase with flight distance ($Km_{j,y}$) but decrease with the square of flight distance ($Km_{j,y}^2$), both at $p < 0.001$. The flight heading variables confirm that eastward flights are shorter than westward ones, in accordance with the earth's prevailing winds.

All three regression models show that different aircraft types can have different impacts on scheduled block times. The use of several twin-aisle aircraft types, including the Boeing 747's, Boeing 777, Douglas DC-10 and Lockheed L1011, equates to shorter block times. At a flight distance of twice the sample average, at 3052 km (90% between Toronto and Vancouver, Canada), using an Boeing 777 reduces the block time by 3.3 min compared with a Boeing 737 or Airbus 320, representing only a fraction of the global schedule creep over 30 years discussed earlier.

The new airport dummy variables reveal, for instance, that scheduled block times for flights operating at the old Hong Kong Kai Tak Airport are 2.8 to 6.8 min longer ($p < 0.001$) than those at the new Hong Kong Chep Lap Kok International Airport, depending on the regression model. The new Haikou Airport contributes to a reduction of 10.7 min of average scheduled block times (from the OLS model) and a reduction of 5.0 to 6.4 min of the 15th or 10th percentile block times.

Airport departure and arrival dummy variables show much variation in terms of their estimated coefficients. Consistent with expectations of the near-chronic congestion at New York LaGuardia (LGA), scheduled block times for flights departing from there are between 10 and 13 min longer ($DLGA_{j,y}$) while block times for flights arriving at that airport are between 5.9 and 6.3 min longer ($ALGA_{j,y}$) than flights not involving LGA at all. Interestingly, some airports have opposing influences on scheduled block times depending whether it is used for departure versus arrival. For instance, New York Kennedy adds between 12 and 15 min of block time for flights departing there ($DJFK_{j,y}$), but subtracts 4 to 17 min of block time for flights arriving there ($AJFK_{j,y}$), depending on the regression model. This could be indicative of congestion-related delays on departure and somewhat fast-tracked arrivals, possibly due to air traffic control policies. Neighbouring Newark Liberty does not show a similar effect. San Francisco International Airport (SFO) adds between 6 and 7 min of block time to flights arriving there but subtracts between 6 and 9 min from flights departing there, depending on the regression model. Nearby Los Angeles International Airport does not show such a strong contrasting effect on departing versus arriving flights.

3.2. Effect of fuel cost changes

Changes in crude oil prices have a positive impact on scheduled block times in both the 10th and 15th percentile regression ($p < 0.001$ and $p < 0.05$ respectively), but there is no statistical significance in the OLS regression. This means that in the wake of rising crude oil prices, the shortest scheduled block times for the respective flight distances witness an increase but the average scheduled block times remain the same. In the sample, the impact of changes in crude oil prices on the scheduled block times ranges between -0.0007 min (i.e., a 'reduction') to 0.004 min (i.e., an 'increase') based on results in the 10th percentile quantile regression – an imperceptible amount.

3.3. Effect of region-specific influences

Australasia in 1986 conjures up an image of reasonably uncongested skies. This is indeed reflected in the estimated coefficients. In both the 10th percentile quantile and OLS regression, the block times for routes wholly within Australasia ($Aus_{j,y}$) can be between 5.4 ($p < 0.0001$, OLS) and 7.4 ($p < 0.05$, 10th percentile) minutes shorter than other routes not wholly within East Asia, Europe and North America, i.e., 'reference routes'. The scheduled block times for routes wholly within East Asia can be 1.1 min shorter than reference routes in the 10th percentile quantile regression ($Eas_{j,y}$, $p < 0.10$), and decreases at 0.1 min per year in the same model ($Eas_{j,y} \times Yr_{j,y}$, $p < 0.01$). The block times for routes wholly within Europe ($Eur_{j,y}$) are 1.3 to 3.5 min longer than reference routes, and decrease year-on-year ($Eur_{j,y} \times Yr_{j,y}$), at about 0.1 to 0.2 min per year depending on the regression model. While the block times for routes wholly within North America are 1.7 or 1.8 min shorter than reference routes in the 10th percentile quantile and OLS regression, and increase ($Nam_{j,y} \times Yr_{j,y}$) between 0.05 and 0.16 min per year depending on the regression model. Moreover, routes involving an airport in north-eastern U.S. start by requiring an additional 3.7 to 4.0 min ($Nne_{j,y}$), depending on the model, but decrease at 0.05 min a year ($Nne_{j,y} \times Yr_{j,y}$) according to the 10th percentile quantile and OLS regression, in addition to the North American ($Nam_{j,y}$) and other effects.

3.4. Effect of airline policies

Different airlines also tend to pursue different company-wide policies regarding scheduled block times, and this effect is in addition to other effects discussed above and below. Some airlines, like Lufthansa (LH) and United Airlines (UA), start with longer block times than the sample average, but then consistently reduce their block times over the years relative to the average airline in the data set (subject also to other prevailing effects). For United Airlines, its 10th percentile scheduled block times starts out being 5.9 min ($UA_{j,y}$) longer than those of reference airlines (those without their own dummy variables) in 1986, and decrease by 0.24 min every year ($UA_{j,y} \times Yr_{j,y}$), or a total of 7.3 min's reduction from 1986 to 2016 relative to reference airlines. This means that in 2016, the 10th percentile scheduled block times for United Airlines flights are actually $7.3 - 5.9 = 1.4$ min shorter than those in reference airlines, in addition to other effects. Delta Airlines (DL) is in the opposite camp, starting with 4.00-min ($DL_{j,y}$) shorter scheduled block times than reference airlines in 1986 but gradually increasing them at 0.31 min per year ($DL_{j,y} \times Yr_{j,y}$) – ending up being $9.24 - 4.00 = 5.24$ min longer than those of reference airlines.

For routes involving at least one of the heritage hubs of the airline, Delta Airlines (AA) starts with longer block times (1.6–3.3 min longer depending on the model, $HubDL_{j,y}$) than its other routes but decrease them over time (0.20–0.31 min per year depending on the model, $HubDL_{j,y} \times Yr_{j,y}$) – ending up being 6.0 min shorter ($3.3 - 30 \times 0.31 = -6.0$) than other routes in 2016. Instead of increasing the block times for routes involving its busy hub airports, Delta Airlines might have realized that it could accomplish the same kind of schedule 'buffers' by increasing aircraft's ground time at its hubs between flights. This effect is once again in addition to other effects reported.

Moreover, a number of airline mergers have significant impacts on their post-merger scheduled block times. After acquiring TransWorld Airlines, scheduled block times at American Airlines are 7.0 to 7.7 min shorter ($AA\text{-}TW_{j,y}$) than before. However, there is no significant impact when American Airlines merges with US Airways ($AA\text{-}US_{j,y}$). Interestingly, after acquiring ATA ($WN\text{-}TZ_{j,y}$), Southwest's scheduled block times increase between 2.2 and 4.0 min but reduces by between 3.4 and 4.7 min after subsequently acquiring AirTrans Airways ($WN\text{-}FL_{j,y}$). Both Delta and United Airlines report longer scheduled block times after integrating with Northwest ($DL\text{-}NW_{j,y}$) and Continental ($UA\text{-}CO_{j,y}$) respectively.

In terms of the effect of an airline's competitive positions on its scheduled block times, the effect varies depending on the model. In the OLS model, all three market share variables – an airline's frequency share at the departure airport ($DepAirportShare_{j,y}$), its frequency share at the arrival airport ($ArrAirportShare_{j,y}$), and its frequency share on the airport-pair ($RouteShare_{j,y}$) – report negative and statistically significant coefficients. This means that a greater degree of market dominance as indicated by a greater frequency share translates into shorter scheduled block times – airlines with market dominance believe that they can still be competitive with perhaps greater flight delays in the eyes of their customers. The sample average for these three variables are respectively 0.224, 0.224 and 0.129, and the standard deviations 0.241, 0.240 and 0.139 respectively. This means that an increase in frequency share of one standard deviation in each of these three variables would result in a combined reduction of ($0.241 \times 1.449 + 0.240 \times 1.150 + 0.139 \times 1.975 =$) 0.90 min of average scheduled block times – relatively small compared with the overall schedule creep ($Yr_{j,y}$). This finding is consistent with complementary findings in prior studies (Prince and Simon, 2009 reports the flight delay performance, not block times). However, in each of the 10th and 15th percentile quantile regression models, only one of these variables has a negative and statistically significant coefficient, possibly because there is not much 'slack' in the 10th and 15th percentile block times for airlines to reduce.

3.5. *Effect of congested skies and airports*

Several groups of variables are used to represent the different effects of congested skies and airports. The first group of variables try to account for the impact of crowded skies – $Traff85euro_{j,y}$, $Traff85usa_{j,y}$ and $Traff85chn_{j,y}$ – and all three of them have positive and statistically significant coefficients in all three regression models. In particular, the magnitude of their estimated coefficients is largest in the 10th percentile quantile regression, and smallest in the OLS – meaning that crowded airspace increases the 10th percentile scheduled block times more than the 15th percentile and also the average scheduled block times. For the year 2016, the $Traff85euro_{j,y=2016}$, $Traff85usa_{j,y=2016}$ and $Traff85chn_{j,y=2016}$ variables take on the coefficients 2.10, 0.71 and 7.65 respectively. This means that the crowded skies in the core of Europe, USA and China contribute to an increase in average scheduled block times of ($2.10 \times 1.1755 =$) 2.5 min, ($0.71 \times 3.9673 =$) 2.8 min and ($7.65 \times 0.9723 =$) 7.4 min respectively to flights overflying the core of these three regions, relative to other flights not overflying these regions according to the OLS model. The corresponding increases to the 10th percentile scheduled block times are respectively 4.1 min, 4.4 min and 8.9 min. In particular, the 7.4 to 8.9 min added to flights overflying China is in the same range as the 6.2 to 9.8 min attributed to an overall schedule creep from 1986 to 2016.

Interestingly, the flight delay variables ($DepAirportDelay_{j,y}$, $ArrAirportDelay_{j,y}$) do not have statistically significant coefficients. This may be because airlines in the U.S. (these variables are only available for U.S. airports) do not consistently adjust their scheduled block times based on the amount of delays observed. In view of the three variables on frequency shares ($DepAirportShare_{j,y}$, $ArrAirportShare_{j,y}$, $RouteShare_{j,y}$) which have statistically significant coefficients in all three regression models, the lack of statistical significance in the coefficients for the flight delay variables suggests that competitive pressures trump passenger comfort in motivating airlines to adjust their block times.

Derived from the ratio of actual air traffic movements to an airport's projected capacity, the runway congestion variables ($DepCongestion_{j,y}$ and $ArrCongestion_{j,y}$) have positive and statistically significant coefficients in all three models. Across non-duplicate airport-year observations with a non-zero value of these variables, the average is 21.00 (21.00%), translating into an increase of ($0.0008 \times 21.00 =$) 0.02 min in the 10th percentile scheduled block time if that particular airport is the departure point for that flight. The magnitude of this effect is certainly small.

To detect the effect of the average aircraft size operating at an airport on the scheduled block times, the two variables on the number of seats per flight – $DepSeatperFlight_{j,y}$, $ArrSeatperFlight_{j,y}$ – have opposite signs in their estimated coefficients: positive for the former and negative for the latter. This means that the equivalent increase in aircraft size as a result of adding one more seat on every flight operating at a particular airport adds 0.029 min to the average block times for flights departing from this airport but subtracts 0.013 min to the average block times for flights arriving at this point, based on the sample average. For the 15th percentile block times, the same increase would add 0.048 min for flights departing from this airport and subtracts 0.016 min for flights arriving at this airport. An increase in aircraft size would therefore result in a net increase in scheduled block times when the combined effect on a pair of arriving and departing flights is considered: (+ 0.048 – 0.016 =) a net increase of 0.032 min for the 15th percentile block times. While this magnitude is small, this effect is worth considering when airport planners advocate the use of larger aircraft as a means to reduce flight delays ultimately brought about by an increase in demand from passengers.

The two variables that account for the sheer size of traffic growth at specific airports, $\text{DepAirportGrowth}_{j,y}$ and $\text{ArrAirportGrowth}_{j,y}$, both have positive and statistically significant coefficients. Among those airport-years that report a non-zero value for these variables, the average is 41.57%, translating to an increase of $(41.57 \times 0.021 =)$ 0.87 or $(41.57 \times 0.023 =)$ 0.94 min in the 10th percentile scheduled block time if a flight involves that particular airport on departure or arrival respectively.

3.6. *Effect of airport slot policy*

Airport slot regimes have an impact on scheduled block times. The regression results show that routes involving only one airport with slot coordination ($\text{Slot1}_{j,y} = 1$) shorten their block times between 1.3 and 2.0 min compared with those involving no airports with slot coordination ($p < 0.01$ or $p < 0.001$), depending on the regression model. In the 15th percentile quantile regression, routes involving only one slot-coordinated airport ($\text{Slot1}_{j,y} = 1$) are 1.3 min shorter than those with no such airport, while routes involving both airports with slot coordination ($\text{Slot2}_{j,y} = 1$) see block times decrease by 0.06 min a year ($\text{Slot2}_{j,y} \times \text{Yr}_{j,y}$, $p < 0.01$), or a reduction in block times of 1.9 min from 1986 to 2016. In the OLS regression, routes involving only one slot-coordinated airport ($\text{Slot1}_{j,y} = 1$) are 1.8 min shorter than those with none, and these routes see their scheduled block times decrease ($\text{Slot1}_{j,y} \times \text{Yr}_{j,y}$) by 0.05 min a year ($p < 0.05$), or a reduction in block times of 1.6 min from 1986 to 2016.

4. Discussion

4.1. *Robustness of analysis*

Three regression analyses are used in this study: the 10th percentile, 15th percentile, and OLS. Using these three regression analyses itself increases the robustness of the finding that there has been a steady and significant increase in scheduled block times around the world in the past three decades. The econometric analyses are based on 200 directional airport pairs drawn from the world's busiest by the number of available seats per year. The fact that these airport pairs draw significant traffic means that airlines have to operate many flights on these routes, and that any increase in the block times would have to be judiciously balanced with the potential benefits. Still, over the past three decades, these routes witness a significant increase in block times, meaning that the cost of not doing so would be even more significant.

The sampling procedure requires an airport pair to be among the top 1000 between 1986 and 2016 by the number of available seats. The sampling procedure includes a number of airport pairs that include relatively uncongested airports, such as Cartagena (Colombia), Kona (Hawaii, US), Oulu (Finland), St.Petersburg (Russia), Sendai (Japan) and Wellington (New Zealand). These airports should contribute toward yielding a lower estimate for the 10th and 15th percentile regression. Meanwhile, this sampling procedure can create a bias toward North America and Europe, and against East Asia or the Middle East, as the latter regions saw phenomenal growth only in the past decade or so. The growth of aviation in these two regions in the past decade or so has been nothing short of phenomenal (Adler and Hashai, 2005; Ryerson and Ge, 2014; Fan and Lingblad, 2016; Fan, 2019). Further studies can perhaps focus more on routes in these regions.

The preceding econometric analyses highlights the different policies airlines have on assigning block times to the same routes, and how they vary their policies over time. Similarly, airport pairs in different regions of the world are subjected to different scheduling practices and variations over time, after accounting for differences in aircraft types, heading directions, airport slot regimes, airport-specific anomalies and recent changes in oil prices. Above all, the analyses confirm a positive, statistically significant phenomenon of schedule creep ($\text{Yr}_{j,y}$), demonstrating a consistent increase in block times in flight schedules worldwide. The analyses shows that substituting a faster twin-aisle aeroplane with a single-aisle aeroplane likely results in a longer block time, but that increase still pales in comparison to the schedule creep worldwide over the past three decades. Similarly, changes in block times in response to changes in oil prices are small compared with the monotonic schedule creep over the past three decades. In short, schedule creep is real and affects flights around the world.

Questions can arise whether the worldwide schedule creep is in fact too simplified: airlines could have mounted a more dramatic increase in their block times shortly after the OTDR of 1987, and be slowing in terms of further increases by 2016. To test this possibility, a square term of the baseline creep ($\text{Yr}_{j,y}^2$) is introduced. The estimated coefficient of this square term, however, is not significant. Moreover, applying one version of this baseline creep squared to data from 1986 to 2001, and another version to data in 2001 through 2016, also does not yield a statistically significant coefficient. This refutes the possibility that schedule creep accelerates only after the introduction of OTDR, or that the schedule creep has slowed by 2016.

In incorporating data on flight delays and oil price changes, an alternative formulation involving cumulative measures has also been attempted. Cumulative measures of these variables assume that airlines continuously update their scheduled block times based on the latest information they receive. However, the estimated coefficients in this alternative formulation are often not statistically significant or at times inconsistent with expectations or with one another. This finding reduces the probability that airlines in general continuously update their scheduled block times based on the latest information they receive, and supports the notion that they adjust from certain 'hard' benchmarks that may be derived from their flight planning systems.

The inclusion of the flight route heading variables likely account for the effect of different directions in prevailing winds at flight altitudes. Such winds often occur in opposing north-south directions in the northern compared with the southern hemispheres. To correctly account for effect of prevailing winds in routes wholly within the southern hermisphere, the north-south direction in their headings should be reversed. In an alternate set of regression analysis, this reversal of north-south direction in the flight route heading is instituted. This means that a uni-directional route wholly within the southern hemisphere that ordinarily heads in the northwesterly direction (as in Durban to Johannesburg) is recorded as being headed in the southwesterly direction to provide for the same effect from prevailing winds as in flights wholly in the northern hemisphere. The regression analyses of this alternate formulation generate coefficientes that are qualitatively and quantitatively similar to those reported in Table 2, largely because of the overwhelming number of flights in the northern hemisphere in this study. The only three exceptions in terms of notable differences in this alternate analysis is that in the 10th percentile quantile regression, (i) the estimated coefficient for Km × HdgSE variable becomes -0.00069 and is now statistically significant ($p < 0.05$), (ii) the estimated coefficient for Slot1 × Yr becomes -0.04468 and is now significant ($p < 0.10$), and (iii) the estimated coefficient for Slot1 becomes -1.67605 ($p < 0.001$).

The econometric analyses include a total of 141 variables. It is possible that the main effect on the schedule creep is only visible after including all these variables. To address this concern, separate regression analyses are conducted that include only the variables on the long-run schedule creep and flight distances, namely $\mathrm{Yr}_{j,y}$, $\mathrm{KM}_{j,y}$ and $\mathrm{KM}_{j,y}{}^2$. The estimated coefficients for these variables in this skeletal analysis still show the same signs and statistical significance, meaning that the effect of schedule creep has been evident all along. The continued significance of the main schedule creep ($\mathrm{Yr}_{j,y}$) in light of a host of explanatory variables opens more question as to what actually drives this long-run schedule creep that spans different regions. It is possible that airlines are simply adding more buffers to their flight times to account for an increasing array of possibilities that can delay their flights. Aircraft systems today are much more complicated and electronically driven than those from decades ago. Unlike their mechanical counterparts, electronic systems do not necessarily exhibit more failures as they age. This means that failures in these systems may be more difficult to predict, and there is a greater need to provide some kind of blanket buffer. Meanwhile, airport systems and air traffic control – with many more aeroplanes in them today than decades ago – are much more complicated than before, more varied disruptions can occur and can cascade delays through many flights within a region or an airline's network. Instead of responding to individual problems, airlines could simply be providing a blanket buffer to marginally reduce the 'pain' of occasional but severe disruptions.

4.2. Comparing to other related concepts: schedule padding and 'baseline' block times

This section discusses how this study is related to a handful of related concepts: schedule padding and flight delays. Schedule creep can very well be an important part of an airline's tactic to improve its on-time performance, and is therefore related to the notion of schedule padding. Schedule padding refers to airlines' practice to increase their block times to result in more flights arriving on time relative to the scheduled arrival time (Skaltsas, 2011). Empirically, those airlines that institute longer block times have been found to correlate with better on-time performance (Mazzeo, 2003).

In reality, however, schedule padding can be a misnomer when one considers the distribution of actual block times (time elapsed 'from departure gate to arrival gate'): flights simply do not uniformly have the same block times. For example, in an analysis of actual block times for U.S. domestic flights in 2009, Skaltsas (2011) observes that more than a quarter (28%) of flights arrive more than 15 min earlier than the scheduled arrival time, another quarter (27%) arrive at the gate earlier than scheduled, and another quarter (27%) arrive more than 15 min past the scheduled arrival time. In all, about 9% of flights arrive more than one hour past the scheduled arrival time. This general pattern exists both for all the flights sampled and for a specific directional airline-city-pair combination. As a result, while the scheduled block times can be regarded as 'padded' for the 55% of flights (28% + 27% = 55%) that arrive before their scheduled arrival times, the scheduled block times cannot be considered as 'padded' for the 27% of flights that arrive more than 15% past the scheduled arrival time, and certainly not for the 9% of flights that arrive more than one hour past the scheduled arrival time. In other words, it is unrealistic to expect airlines to set a scheduled block time such that all of their flights would arrive on time. The amount of schedule padding is in fact an artefact of airlines' trade-off between committing to more resources with longer scheduled block times with certainty and being liable for more resources (and disruption) when flights are delayed beyond these block times.

What the 1986 baseline for scheduled block times can do, from the preceding analyses, is to provide a realistic estimate of minimum 'feasible' block times that are devoid of effects from further increased congestion and other unexpected flight delays. In the U.S., the Airline Deregulation Act was signed into law in 1978, but full routing flexibility for airlines only began in 1982 and full pricing flexibility in 1983. In other words, airlines were still learning to adjust to the new regulatory regime in 1986, and much of the rest of the world still operated with substantial regulation. Put simply, the substantial growth post-deregulation in passenger and flight movements had barely begun in 1986, and it is not unreasonable to consider scheduled block times in 1986 to reflect what airlines could achieve in the absence of unanticipated delays. After all, a significant portion of flights in 1986–1987 did arrive on time (Shumsky, 1993).

Based on the regression results from the 10th percentile quantile regression, a projected 1986 baseline can be computed using current aircraft types, airline frequency shares, etc, but devoid of any creep from the different variables, This projected value is then subtracted from the 2016 actual average block time for each of the airline-aircraft-route combinations to produce a projected change in block time. This change in block time for the sampled routes is shown in the rightmost column in Table 1 for reference. The average of such a change among all observations in 2016 among the sample is 24.0 min per flight, and the median is 23.1 min per flight. Using coefficients from an alternate formulation reversing the north-south direction heading for routes wholly within the southern hemisphere, the average of this change among all all observations in 2016 becomes 24.3 min, with a median of 23.5 min. Counting only those airport pairs that are wholly within the U.S. in 2016, the average difference between actual 2016 and projected 1986 block times is 27.5 min using estimates from Table 2.

Skaltsas' (2011) approach to looking for a baseline block time is to look for the 10th percentile of flight time (time when wheels down minus time when wheels up, within 2009) and then add to that an estimate of unimpeded taxi-out and taxi-in times. Skaltsas (2011) called the difference between a flight's actual block time and its baseline block time its 'buffer', and derives an average buffer of 18.36 min from the 2009 flight data. In the data from this study, the closest years to 2009 in Skaltsas's (2011) analysis would be 2006 and 2011. For airport pairs wholly within the U.S. in this study, the average difference between a flight's actual block time and its baseline block time is 21.8 and 24.1 min per flight in 2006 and 2011 respectively – strikingly close to Skaltsas' (2011) estimate of an average buffer of 18.36 min per flight in 2009.

4.3. Evolution of scheduled block times – specific examples

The projected 1986 scheduled block times computed in the previous section are based on current market, airspace and airport conditions. To understand how the effect of these changing conditions contribute to changes in the projected block times, two examples are used. The first is the London Heathrow (LHR) – Rome Fiumicino (FCO) flights operated by British Airways' Airbus 320 aircraft, at 1442 km. Fig. 6 decomposes the scheduled block time for this flight as an illustration based on results from the 10th percentile quantile regression. Based on the physical attributes of the flight (e.g., distance, aircraft type, heading, airport-specific effects and slot situation in 1986), the basic scheduled block time of 138.49 min is computed (close to the historical actual of 140.00 min by the 757-200). Based on the airline's frequency shares at the two airports and on this non-stop airport-pair in 1986, 0.40 min is deducted from the 138.49 min, leaving 138.49 − 0.40 = 138.09 min. From 1986 to 2016, there is a baseline schedule creep of + 8.15 min. This route being in Europe is subjected to a region creep of −7.07 min (Eur × Yr). There is also an airline-specific creep of +3.13 min (BA × Yr). These three kinds of 'creep' sum to 4.21 min, and push the 138.09 min running total to 142.30 min. Further, the more crowded skies in Europe (Traff85euro) add a further +4.14 min, while the more crowded departure and arrival airports add another +7.69 min. The airline's change in its airport and route frequency shares over the years subtracts 0.09 min from the running total, resulting in a total projected scheduled block time of 154.04 min, which is only 1.51 min more than the actual total of 152.53 min. In this example, the increasingly crowded airspace and airports add (4.14 + 7.69 =) 11.83 min to the base of 138.09 min, amounting to 8.6%.

The second example is the Chicago O'Hare (ORD) – Orlando (MCO) flights by United Airlines' Airbus 320, at 1619 km. Fig. 7 decomposes the scheduled block time for this flight as an illustration based on results from the 10th percentile quantile regression. Based on the physical attributes of the flight (e.g., distance, aircraft type, heading, airport-specific effects and slot situation in 1986), the basic scheduled block time of 134.17 min is computed. Based on the airline's frequency shares at the two airports and on this non-stop airport-pair in 1986, 0.36 min is deducted from the 134.17 min, leaving 134.17 − 0.36 = 133.82 min (close to United's historical actual of 143.3 min by its 727-200 in 1986). From 1986 to 2016, there is a baseline schedule creep of +8.15 min. This route being in North America is subjected to a region creep of +2.98 min (Nam × Yr). There is also an airline-specific creep of −0.73 min (UA × Yr). These three kinds of 'creep' sum to 10.41 min, and push the 133.82 min running total to 144.22 min. Further, the more crowded skies in the U.S. (Traff85usa) add a further +1.41 min, while the more crowded departure and arrival airports add another +1.09 min. The airline's change in its airport and route frequency shares over the years subtracts 0.10 min from the running total, resulting in a total projected scheduled block time of 146.62 min, which is still 18.41 min short of the actual total of 165.03 min. In this example, the increasingly crowded airspace and airports add (1.41 + 1.09 =) 2.50 min to the base of 134.17 min, amounting to only 1.9%.

These two examples show that the different components of block times and changes in them can be very different in different

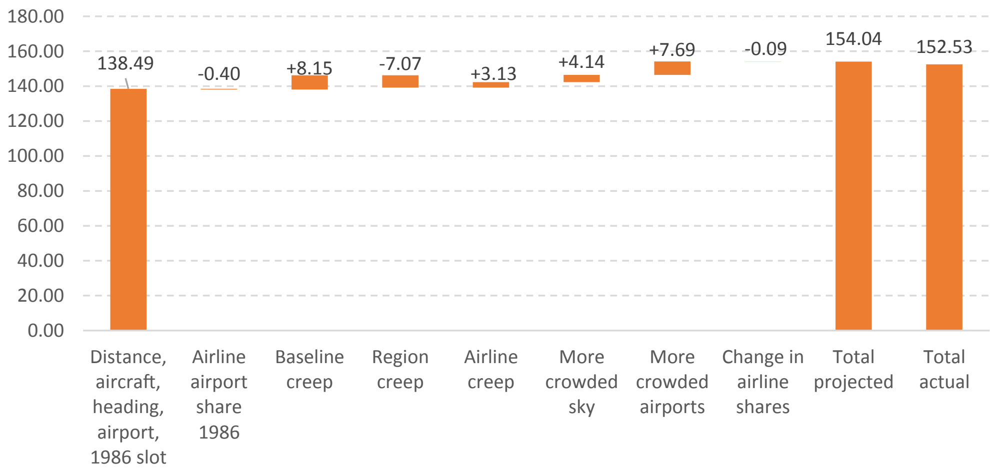

Fig. 6. Decomposition of the 2016 block time for LHR to FCO on British A320, 1442 km. Scheduled block time in minutes (10th percentile projection).

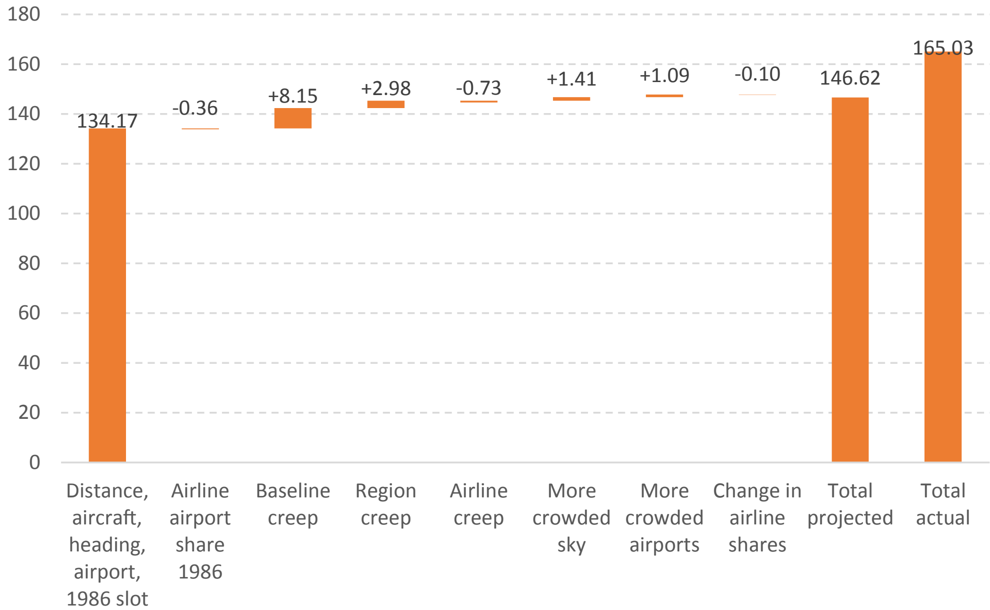

Fig. 7. Decomposition of the 2016 block time for ORD to MCO on United A320, 1619 km. Scheduled block time in minutes (10th percentile projection).

regional contexts. In the LHR-FCO route, the overall schedule creep of +8.15 min is almost completely negated by the −7.07-min creep applicable to Europe-wide flights. In the ORD-MCO route, the overall schedule creep of +8.15 min add to the region-specific creep of +2.98 min. As well, the impact of crowded skies also differs markedly in these two routes, showing a far more prominence in the former than in the latter.

4.4. Implications for public policy

This study demonstrates that airlines worldwide have generally been increasing their scheduled block times for the same non-stop routes over past three decades, and this has been the case after accounting for differences in aircraft types over the years. Specific airlines have also been found to increase or decrease their scheduled block times over past three decades, and some also have a contrasting policy for non-stop flights involving some of their hubs. This has important implications for public policy.

First, decision-makers for public policy should take on-line statistics such as airlines' so-called 'on-time performance', reported by the U.S. Department of Transportation, based on scheduled arrival times with caution. With scheduled block times shifting from time to time, and from one airline to another, even a 90% on-time statistics – meaning that 90% of flights arrive no later than 15 min past the scheduled arrival time – will not guarantee a lack of congestion on runways and in the airspace around an airport. To achieve this statistics, airline would simply have to increase their scheduled block times, without having to take any effort to resolve the underlying issue of having too many flights take off or land at the same airport around the same time. Crafting laws with on-time statistics as the end-goal may therefore not result in material changes in how flights are planned beyond a cosmetic change in scheduled block times. Similarly, such on-time statistics should not be used as the sole performance benchmark for investments in expanding capacity in handling more aircraft movements.

Second, policy analysts must face the reality that airlines are far from innocent in inadvertently resulting in flight delays. In fact, the regression results show that airlines are content to schedule shorter block times on routes or at airports where they have large frequency shares, and that flight delay statistics do not systematically influence scheduled block times. This study therefore highlights the causality between airlines' deliberate managerial decisions based on competitive pressures and their willingness to artificially induce greater flight delays on certain routes as they try to cut costs by scheduling a minimal block time. An upshot for small, young entrant carriers competing against large, networked carriers is that it costs the former much less to schedule longer block times as a means to achieve better on-time performance as a marketing ploy to compete with the latter, simply because there are by definition fewer flights operated by the former than the latter (Fan, 2010).

Third, the changing scheduled block times, and the inconsistency thereof among different airlines, advocate the use of minimum feasible times as benchmark block times in non-stop airport pairs. In line with Skaltsas' (2011) study, Gillen et al. (2016) advocates the use of, and Britto et al. (2012) specifically employ percentile statistics (specifically, the 10th percentile and 20th percentile of actual block times) to derive minimum feasible block time for routes in the U.S. These percentile statistics are typically obtained without adjusting for differences in aircraft types. The present study shows that for short- to medium-haul routes, the difference in flight times achieved by different aircraft types, based on their associated scheduled bock times, may be sufficiently small to make any difference. The present study, with the numerous estimated coefficients from regression models, also provide policy makers with convenient rules-of-thumb to calculate approximate minimum feasible block times. Alternatively, more resource-intensive avenues to obtain minimum feasible block times include the examination of actual flight plans and unimpeded taxi times (Morrison and Winston, 2008), and the use of four-dimensional aircraft trajectory models to obtain route-specific minima (Ryerson et al., 2014).

Fourth, the present study attempts to quantify the impact of crowded airspace on scheduled block times by differentiating those flights that over-fly crowded airspace from others that do not. This is a novel approach and the results show different impacts of crowded airspace depending on the region. Flights over-flying eastern China can add up to almost 9 min in block times compared with those that do not. This highlights how the problem of congestion can and should also be studied from a more comprehensive perspective, acknowledging how flight delays are probably only one component of the congestion phenomenon.

Fifth, the importance of slot-based administrative procedures cannot be under-stated. The regression analysis shows that flights involving only one airport with slot coordination shorten their average block times by 1.8 min compared with other flights involving no such airports. This represents a potentially enormous savings for airlines, beyond the reduced flight delays that slot coordination would normally accomplish. Interestingly, flights between two airports with slot coordination do not have significantly different block times than flights between two airports without slot coordination. The apparent lack of benefits on reducing scheduled block times for flights between two airports with slot coordination (relative to flights involving only one such airport) may have to do with the difficulty in adjusting block times at both airports to better reflect reality. Moreover, airports with slot coordination may be inherently busy to begin with, and airlines as a result may want to designate block times that allow for a certain amount of operational irregularity.

5. Conclusions

An analysis of 200 directional non-stop airport pairs worldwide, accounting for the effect of aircraft type, flight heading, airport slot policy, other airport-specific anomaly, airline-specific policies and the impact of oil price changes, shows that scheduled block times have been growing at a speed between 0.23 and 0.31 min per year depending on the regression model, or a total of between 6.9 and 9.2 min per flight from 1986 to 2016. This schedule creep shows no abatement toward 2016, and the total increase over 30 years is larger than increases in scheduled block times due to a change from faster to slower aircraft types on the same route. Slot coordination practice at airports does have a significant impact on scheduled block times, but interestingly, the scheduled block times for those airport pairs between two airports that both practice slot coordination have been increasing in certain models. Airport pairs wholly within certain continents witness a further adjustment, with those in North America growing at 0.24 to 0.26 min per year on top of the global ‘creep’. Those routes with at least one airport in north-eastern U.S. add a further 3.4 to 4.3 min to their scheduled block times. Airline-specific policies also influence scheduled block times, with some airlines like Air Canada beginning with longer times in 1986 and reducing theirs over the years while others like Delta Airlines beginning with shorter times in 1986 and increasing theirs over the years. There is some evidence that airlines also adjust the scheduled block times of flights to and from their hubs in addition to network-wide changes. The econometric analyses allow the increase from 1986 to 2016 scheduled block times to be decomposed. The overall increase from the projected baseline block times in 1986 to the actual scheduled block times in 2016 is 24.0 min per flight.

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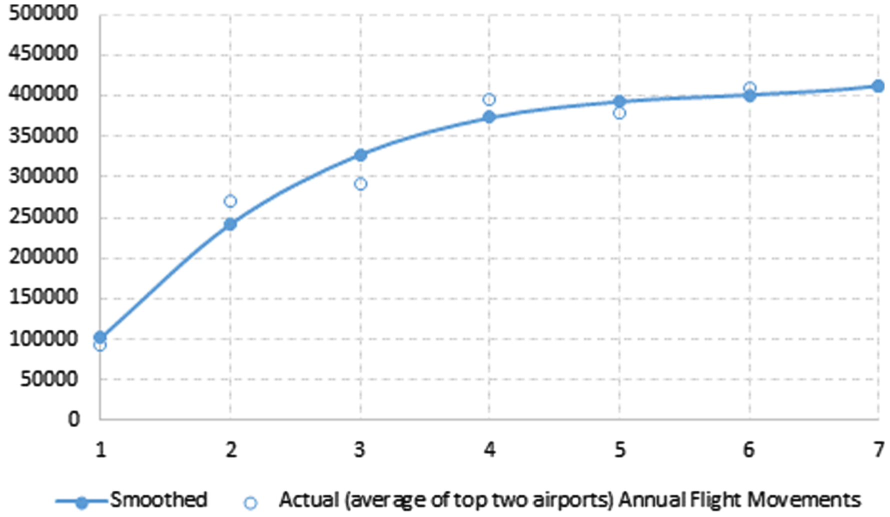
Appendix A. Estimated coefficients of ordinary least-square regression of airport capacity

Estimated coefficients	OLS
No. of runways cubed	2386†
	(1099)
No. of runways squared	−41508*
	(14980)
No. of runways	247794**
	(59721)
Constant	−106914
	(66001)
R-squared	0.9689

Number of observations: 15; *** statistical significance with $\alpha < 0.001$; ** statistical significance with $\alpha < 0.01$; * statistical significance with $\alpha < 0.05$; † statistical significance with $\alpha < 0.10$. Standard error in parentheses.

A plot of the annual total aircraft movements (departures + arrivals) versus the number of runways based on the above regression model:



Appendix B. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tra.2019.01.006.

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