# Der Boardingprozess bei Passagierflugzeugen

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Simone Neumann

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| | |
|---|---|
| Erstgutachter: | Prof. Dr. Florian Jaehn |
| Zweitgutachter: | Prof. Dr. Jens O. Brunner |
| Drittgutachter: | Prof. Dr. Robert Klein |
| Vorsitzender der mündlichen Prüfung: | Prof. Dr. Michael Krapp |
| | |
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# Verzeichnis der Beiträge

Die Dissertation beinhaltet die folgenden Beiträge, welche bei internationalen Zeitschriften veröffentlicht bzw. eingereicht wurden. Die jeweils angegebene Kategorie bezieht sich auf das Zeitschriftenranking JOURQUAL 3 des Verbands der Hochschullehrer für Betriebswirtschaft e.V. (VHB).

**Beitrag 1:**
Jaehn, F. und Neumann, S. (2015). Airplane Boarding. European Journal of Operational Research, 244(2): 339-359. DOI: http://dx.doi.org/10.1016/j.ejor.2014.12.008
*Veröffentlicht, Beitrag der Kategorie A*

**Beitrag 2:**
Neumann, S. (2018). Is the Boarding Process on the Critical Path of the Airplane Turn-around?

Dies ist ein Vorabdruck eines im European Journal of Operational Research veröffentlichten Artikels. Die finale Fassung ist online verfügbar unter:
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*Beitrag der Kategorie A*

**Beitrag 3:**
Hutter, L., Jaehn, F., und Neumann, S. (2018). Factors Influencing Airplane Boarding Times.

Dies ist ein Vorabdruck eines in Omega veröffentlichten Artikels. Die finale Fassung ist online verfügbar unter: https://doi.org/10.1016/j.omega.2018.09.002
*Beitrag der Kategorie B*

# Inhaltsverzeichnis



*Anmerkung:* Die Nummerierung von Abbildungen, Tabellen, Hypothesen und mathematischen Gleichungen erfolgt fortlaufend innerhalb der Kapitel. Ein Literaturverzeichnis befindet sich am Ende jedes Kapitels.

# I Einleitung

“It is possible to fly without motors,
but not without knowledge and skill.”

*(Wilbur Wright, US-amerikanischer
Flugpionier, 1867 – 1912)*

Der Traum vom Fliegen – seit Anbeginn der Menschheit besteht der Wunsch, sich wie ein Vogel in die Lüfte zu erheben. In der griechischen Mythologie erfindet Dädalus Flügel, mit denen sein Sohn Ikarus so hoch in den Himmel aufsteigt, dass er der Sonne zu nahe kommt, die Flügel schmelzen und er in die Ägäis stürzt. Leonardo da Vinci fertigte um 1500, inspiriert durch die Natur, bereits zahlreiche Skizzen von Hubschraubern, Fallschirmen und Gleitern an, die er jahrelang weiterentwickelte und immer komplexere Konstrukte entwarf. Er realisierte jedoch keine dieser Ideen und es ist kein Flugversuch dokumentiert (Harf und Teschner, 2017). Erst 1783, fast 300 Jahre später, bauten die Brüder Montgolfier einen Heißluftballon, mit dem in Frankreich die erste bemannte Ballonfahrt stattfand. Die Deutschen Otto und Gustav Lilienthal führten knapp 100 Jahre später diverse Testreihen durch, um ein der Anatomie der Vögel nachempfundenes Fluggerät zu entwickeln. Ihre auf zahlreichen Messungen basierende Theorie erklärte erstmals die Grundlagen der Aerodynamik und beschrieb die notwendigen Eigenschaften und Beschaffenheit von Flügeln. So entwickelte der Ingenieur Otto Lilienthal schließlich seinen *Normal-Segelapparat*, mit dem er, auf einem Hügel startend, bis zu 250 Meter zurücklegte. Er erlangte nicht nur Berühmtheit, sondern konnte sogar acht Exemplare davon verkaufen – bis er 1896 bei einem seiner Flüge tödlich verunglückte (Lohre, 2017). Es war erneut ein Brüderpaar, die Amerikaner Orville und Wilbur Wright, das, inspiriert durch Lilienthal und durch geduldiges Tüfteln, den nächsten großen Erfolg in der Luftfahrt für sich verbuchen konnte und als Pioniere der Luftfahrt in die Geschichte einging: Ihnen gelang 1903 der erste bemannte Motorflug und ihr Flugapparat kann als Vorläufer unserer heutigen Flugzeuge bezeichnet werden (Mesenhöller, 2017). Seitdem wurden immer mehr erfolgreiche Flugversuche mit motorisierten oder auch nicht-motorisierten Fluggeräten absolviert. 1909 wurde der Ärmelkanal mit einem Motorflugzeug überquert und der Serienbau von Flugzeugen gestartet, in den folgenden Jahren wurde in mehreren Ländern mit dem Aufbau von Luftstreitkräften begonnen und 1914 fand in Florida der erste Linienflug statt, der zweimal am Tag angeboten wurde und eine Strecke von 40 Kilometern zurücklegte. Die erste Atlantiküberquerung mit einem Flugzeug und ohne Zwischenstopps fand 1919 durch die Engländer John Alcock und Arthur Whitten Brown statt, die in 16 Stunden von Neufundland nach Irland flogen. Die Strecke von New York nach Paris, wofür bereits im Jahr 1919 vom Pariser Hotelier Raymond Orteig ein Preisgeld in Höhe von 25.000 US-Dollar ausgesetzt wurde, wurde erstmals am 20. Mai 1927 vom damals 25-jährigen Amerikaner Charles Lindbergh geflogen, der damit auch die erste Alleinüberquerung des Atlantik vollbrachte und mit seinem über 30 Stunden dauernden Flug in die Geschichte einging.

In den Anfangszeiten der Passagierluftfahrt wurden zunächst umgerüstete Kampfflugzeuge aus dem ersten Weltkrieg genutzt. Im Deutschen Reich wurde 1919 durch den Versailler Vertrag der Bau und Einsatz von Motorflugzeugen jedoch größtenteils verboten, weshalb dort bis zu der Aufhebung des Verbots 1926 der Fokus auf der Weiterentwicklung von Segelflugzeugen lag. Im Jahr 1926 wurde die *Deutsche Luft Hansa AG* gegründet und es wurden immer mehr Flugzeuge speziell für die Passagierluftfahrt gebaut. 1929 wurde das von Dornier ursprünglich für die Marine entwickelte Flugboot *Do X*, ein Wasserflugzeug, das 169 Passagiere transportieren konnte und somit das größte Flugzeug weltweit war, über dem Bodensee getestet. Obwohl große Hoffnungen in es gesetzt wurden, konnten nur zwei Exemplare verkauft werden und die Produktion wurde eingestellt (Bischoff, 2017). Die Ursache dafür war, dass sich der Luftverkehr in eine andere Richtung entwickelte – es wurden kleinere Flugzeuge mit ca. 30 Sitzplätzen gefertigt, beispielsweise vom deutschen Flugzeugbauer Junkers, aber auch von den amerikanischen Herstellern Boeing und Douglas. Die *Douglas DC-3*, die 1935 ihren Erstflug absolvierte und danach mehr als 16.000-mal gefertigt wurde, ist bis heute das meistproduzierte Flugzeug der Welt. Mit der steigenden Anzahl an Flughäfen wurde auch die vermehrte Nutzung des Flugzeuges als Verkehrsmittel möglich, sodass Fluggesellschaften Ende der 1930er

Jahre weltweit etwa zwei Millionen Passagiere pro Jahr transportierten (Mischer, 2017; Teschner, 2017).

Mit dem Beginn des zweiten Weltkriegs, der zu großen Teilen auch in der Luft geführt wurde, kam die Passagierluftfahrt in vielen Ländern weitgehend zum Erliegen. Allerdings führte die Entwicklung neuer Fluggeräte während des Krieges direkt danach dazu, dass die Passagierluftfahrt einen Aufschwung erlebte: Die neuen Fluggeräte ermöglichten ein deutlich günstigeres Reisen und auch die Flugverbindungen über den Atlantik wurden ausgebaut. Obwohl bereits während des zweiten Weltkriegs entwickelt, begann in den 1960er Jahren das Zeitalter des Düsenantriebs und die Propellermaschinen wurden Schritt für Schritt abgelöst. Flugreisen entwickelten sich zur Alternative zur Bahn und am 23. Juni 1964 landete der zehnmillionste Passagier der Lufthansa in Stuttgart. In den folgenden Jahrzehnten wuchs der Personenflugverkehr rasant: In den 1950er und 60er Jahren betrug das jährliche Wachstum durchschnittlich fast 15 Prozent, in den 70er Jahren ca. 10 Prozent und ab den 80er Jahren ca. 4 Prozent (Doganis, 2002; Pompl, 2007; Schlegel, 2010). Man konnte nun also von einem Massenverkehrsmittel sprechen. Auch wenn es immer wieder Einschnitte gab und die Passagierzahlen in Deutschland im Jahr 2009 als Folge der Finanzkrise beispielsweise um 4,6 Prozent gesunken sind, setzte sich dieses starke Wachstum fort. Der weltweite Luftverkehr wuchs von 2009 bis 2015 sogar um 40 Prozent, was hauptsächlich auf die Entwicklungen in den asiatischen Ländern zurückzuführen ist, welche Nordamerika mittlerweile, bezogen auf das Passagieraufkommen, von Platz 1 verdrängt haben. In Deutschland konnten im Jahr 2015 fast 110 Millionen Einsteiger auf deutschen Flughäfen verzeichnet werden (Berster et al., 2016).

Fluggesellschaften standen stets vor großen Herausforderungen. In den Anfangsjahren waren es vorwiegend die hohen Investitionskosten, dann der durch die 1978 in den USA beginnende Deregulierung des Flugverkehrs aufkommende Preiskampf, die Auswirkungen verschiedener Ereignisse wie zuletzt des 11. Septembers 2001 sowie der Finanzkrise und mittlerweile beschränkte Flughafenkapazitäten. Dies führte über die Jahre hinweg zu zahlreichen Insolvenzen von Fluggesellschaften, aber auch stets zu neuen Wettbewerbern. Gerade durch den Einzug von sogenannten Billigfluggesellschaften in den Markt mussten bestehende Anbieter ihre Preisstruktur überarbeiten und führten Preisdifferenzierung für Flugtickets ein, um auch für preissensible Kunden attraktiv zu bleiben. Durch diesen neu aufkommenden Konkurrenzkampf entstand bei vielen Fluggesellschaften außerdem unweigerlich das Bestreben, Kosten einzusparen, um wettbewerbsfähig zu bleiben.

Ansatzpunkte zur Kostenreduzierung lassen sich nach Swan und Adler (2006) aus folgender Kostenstruktur von Fluggesellschaften ableiten: Die Anschaffungskosten der Fluggeräte belaufen sich auf fast ein Drittel der Gesamtkosten eines Fluges. Die übrigen zwei Drittel der Kosten umfassen (neben einem kleinen Anteil für Versicherungen, der weniger als ein Prozent beträgt) zu ähnlich großen Teilen Kosten für Treibstoff, die Kabinencrew, die Piloten, Instandhaltung- und Wartung, Flugsicherung und Flughafengebühren.

Natürlich kann jeder dieser Bereiche isoliert betrachtet und optimiert werden. Eine Strategie, mit der jedoch gleich mehrere der genannten Faktoren berücksichtigt werden, ist die Reduzierung der Turnaround-Zeit eines Flugzeuges. Diese Zeit, in der sich ein Flugzeug zwischen Landung und erneutem Start am Gate oder auf einer Vorfeldposition befindet und für den nächsten Flug vorbereitet wird, verursacht Kosten, ohne dass ein direkter Gegenwert geschaffen wird. Kostenschätzungen reichen von US$30 bis US$250 pro Minute und Flugzeug (Horstmeier und de Haan, 2001; Nyquist und McFadden, 2008; Steiner und Philipp, 2009). Das Ziel ist daher, diese Zeit zwischen zwei Flügen so kurz wie möglich zu halten.

Der Flugzeug-Turnaround besteht vor allem aus den Prozessen, die das Aus- und Einladen von Gepäck, Catering, Auffüllen der Treibstoff- und Wassertanks, Reinigen der Flugzeugkabine und das Aus- und Einsteigen von Passagieren betreffen (Jaehn und Neumann, 2015). Da davon ausgegangen werden kann, dass der Boardingprozess, welcher das Einsteigen der Passagiere in das Flugzeug beschreibt, für Kurz- und Mittelstreckenflüge auf dem kritischen Pfad des Turnarounds liegt (Neumann, 2018), führt eine Reduzierung dieser Zeit im Normalfall zu einer verkürzten Turnaround-Zeit. Durch eine solche Reduzierung werden nicht nur die erwähnten Kostenfaktoren berücksichtigt, indem die teuren Ressourcen Flugzeuge, Gates und Personal effizienter genutzt werden, sondern es können durch die damit einhergehende Reduzierung von Abflugverspätungen weitere Kosten eingespart werden und darüber hinaus auch die Kundenzufriedenheit gesteigert werden, welche neben wettbewerbsfähigen Preisen für Flugtickets ein entscheidender Punkt im Kampf um Passagiere ist.

In dieser Dissertation soll der Fokus auf die Untersuchung der Boardingzeit als Teilprozess der Turnaround-Zeit gelegt werden. Die Boardingzeit beginnt, wenn der erste Passagier das Flugzeug betritt und endet, wenn der letzte Passagier auf seinem zugewiesenen Sitzplatz sitzt (Van Landeghem und Beuselinck, 2002). Die Beschränkung der Untersuchungen auf den Prozess des Boardings und auch auf das Verkehrsmittel Flugzeug ist legitim, da dieser innerhalb der Turnaround-Zeit den größten Anteil und gleichzeitig das größte Potenzial für Einsparungen innehat. Darüber hinaus kann der Boardingprozess bei Flugzeugen als zeitkritisch eingestuft werden, was bei anderen Verkehrsmitteln nicht zwingend der Fall ist: Verzögerungen beim Einsteigevorgang beispielsweise bei Bussen haben nicht solch weitreichende Auswirkungen wie dies bei Flugzeugen der Fall ist.

In den folgenden Kapiteln werden der Aufbau und die Ziele der Dissertationsschrift vorgestellt sowie die drei Beiträge kurz zusammengefasst und die Hauptergebnisse erläutert.

## 1 Struktur und Zielsetzungen der Dissertation

Die folgende Tabelle 1 gibt einen Überblick über den Aufbau sowie die Zielsetzungen der verschiedenen Teile der Dissertationsschrift:

Tabelle 1: Struktur und Zielsetzungen der Dissertation

| | |
|---|---|
| **I Einleitung** | |
| Ziel I.1: | Motivation und Hinführung zur Problemstellung |
| Ziel I.2: | Strukturierung der Arbeit und Zielsetzungen |
| Ziel I.3: | Vorstellung der Forschungsfragen und Hauptergebnisse der Beiträge |
| **II Beitrag 1** | |
| Ziel II.1: | Einordnung und Definition des Boardingproblems |
| Ziel II.2: | Darstellung und Klassifizierung bestehender Boardingmethoden |
| Ziel II.3: | Detaillierter Überblick über relevante Literatur |
| Ziel II.4: | Zusammenfassung des aktuellen Forschungsstandes und Aufzeigen weiterer potentieller Forschungsfelder |
| **III Beitrag 2** | |
| Ziel III.1: -Zeit | Darstellung der Zusammenhänge zwischen Boardingzeit, Turnaround und Abflugverspätungen |
| Ziel III.2: | Empirische Analyse, ob sich der Boardingprozess auf dem kritischem Pfad des Flugzeug-Turnarounds befindet |
| **IV Beitrag 3** | |
| Ziel IV.1: | Empirische Analyse zur Identifikation der Einflussfaktoren auf die Boardingzeit |
| Ziel IV.2: | Entwicklung eines Regressionsmodells zur Vorhersage von Boarding-zeiten |
| Ziel IV.3: | Validierung des Modells anhand bestehender Modelle und Vergleich |
| Ziel IV.4: | Ableitung von Handlungsempfehlungen |
| **V Fazit und Ausblick** | |
| Ziel V.1: | Zusammenfassung und kritische Würdigung der zentralen Erkennt-nisse der Dissertationsschrift |
| Ziel V.2: | Reaktionen und Entwicklungen nach Veröffentlichung des Beitrags 1 |
| Ziel V.3: | Aufzeigen zukünftigen Forschungsbedarfs |

## 2 Forschungsfragen und Hauptergebnisse der Beiträge

In den in dieser Dissertation enthaltenen Beiträgen wird im Rahmen des Airport Managements zunächst auf den Boardingprozess im Allgemeinen und einschlägige Literatur eingegangen (Beitrag 1). Anschließend wird untersucht, ob sich der Boardingprozess auf dem kritischen Pfad des Flugzeug-Turnarounds befindet (Beitrag 2), was als notwendige Bedingung dafür gesehen werden kann, mit der Reduzierung der Boardingzeit relevante Kosteneinsparungen zu realisieren. Im darauffolgenden Beitrag 3 werden schließlich potentielle Einflussfaktoren auf den Boardingprozess analysiert, um Prognosen der Boardingzeit zu ermöglichen und Ansatzpunkte für Optimierungsprozesse zu ermitteln. Die drei Beiträge bauen somit aufeinander auf und tragen sukzessive dazu bei, das Boardingproblem wissenschaftlich zu analysieren. Abbildung 1 gibt einen Gesamtüberblick und zeigt die Zusammenhänge zwischen den drei Beiträgen auf.

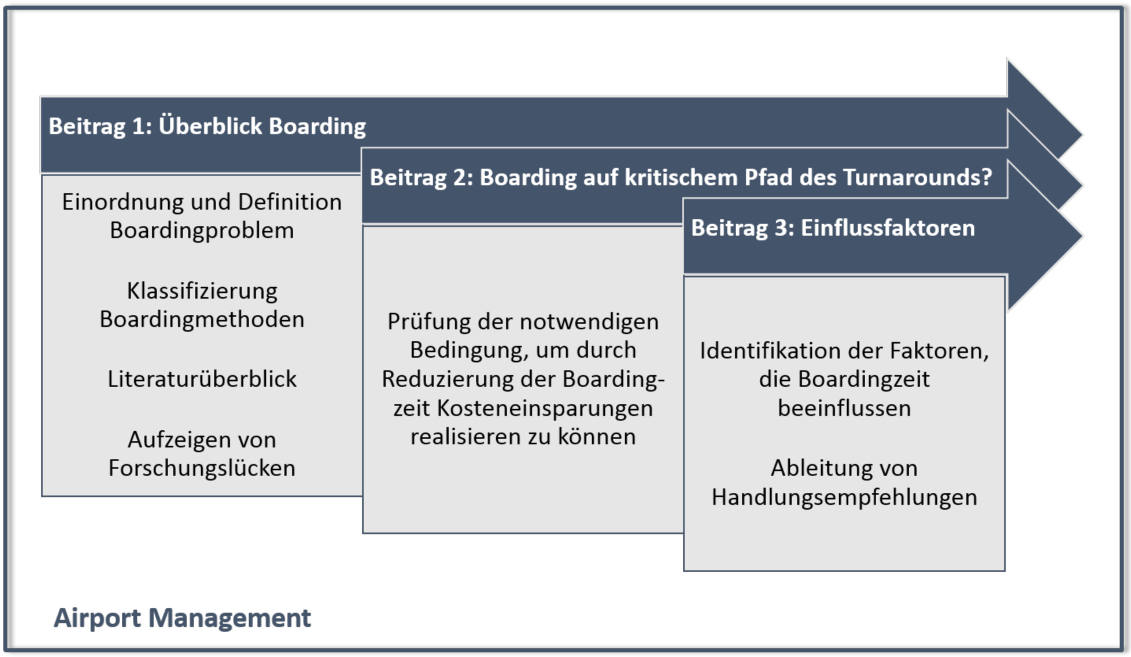


Abbildung 1: Einordnung der wissenschaftlichen Beiträge in den Forschungsrahmen

## 2.1 Kurzbeschreibung Beitrag 1: Airplane Boarding

Das Ziel des in Kapitel 2 enthaltenen wissenschaftlichen Beitrags mit dem Titel *Airplane Boarding* ist es, einen fundierten Einblick in die Thematik des Boardings bei Passagierflugzeugen zu geben und den aktuellen Stand der Forschung zu identifizieren und darzustellen. Der Beitrag stellt einen umfassenden Übersichtsartikel dar, in dem neben der allgemeinen Vorstellung und Einordnung des Boardingprozesses auf verschiedene Boardingmethoden sowie bestehende Literatur eingegangen wird.

Im ersten Teil des Artikels wird das grundlegende Problem beschrieben, in den Kontext des Airport Managements eingeordnet und die relevanten Begriffe werden definiert. Es werden Kurz- und Mittelstreckenflugzeuge wie die Modelle der A320-Familie von Airbus oder der B737-Familie von Boeing mit einem Mittelgang betrachtet, welche über eine Boardingbrücke mit dem Gate verbunden sind und über eine Tür im vorderen Bereich des Flugzeuges geboardet werden. Als zentrale Forschungsfrage des Boardingproblems wurde folgende formuliert: *Wie und in welchem Umfang sollte die Sequenz, in der die Passagiere ein Flugzeug betreten, beeinflusst werden, wenn die Boardingzeit reduziert, gleichzeitig aber auch ein hohes Niveau an Kundenkomfort gewährleistet werden soll?* Anders formuliert wird die optimale Boardingmethode gesucht, bei der der Trade-off zwischen Boardingzeit und Passagierkomfort berücksichtigt wird. Die Boardingzeit beginnt, wenn der erste Passagier das Flugzeug betritt und endet, wenn der letzte Passagier auf seinem zugewiesenen Platz sitzt. Diese Definition weicht von der Auffassung vieler Fluggesellschaften bezüglich der Boardingzeit ab, da diese vor allem die beim Ticketcheck am Gate benötigte Zeit betrachten, die jedoch keinen direkten Einfluss auf den Turnaround-Prozess eines Flugzeuges hat und somit für Optimierungen mit dem Ziel, die Turnaround-Zeit zu reduzieren, nicht geeignet ist.

Im zweiten Teil des Beitrags werden theoretische aber auch von Fluggesellschaften verwendete Boardingstrategien detailliert beschrieben und analysiert und systematisch kategorisiert. Hier wird zunächst unterschieden zwischen random-Boarding, bei dem jeder Passagier zwar einen zugewiesenen Sitzplatz hat (im Gegensatz zur Variante open seating), jedoch keine vorgegebene Einsteigereihenfolge existiert, dem

Gruppenboarding, bei dem die Passagiere in bestimmten Gruppen aufgerufen werden und by-seat-Boardingstrategien, welche die Einsteigereihenfolge Platz für Platz genau festlegen. Neben dem weit verbreiteten random-Boarding wird von Fluggesellschaften vor allem die Gruppenboardingmethode back-to-front eingesetzt, bei der zunächst die hinteren Reihen eines Flugzeuges geboardet werden, anschließend die mittleren und am Ende die Reihen im vorderen Bereich des Flugzeuges. Überraschenderweise ist diese Methode jedoch recht zeitaufwändig und nicht zu empfehlen, wie die Analyse der Literatur zum Thema Boarding im dritten Teil des Beitrags zeigt. Eine wissenschaftliche Überprüfung nicht fundierter Annahmen aus ökonomischer Perspektive kann also sehr sinnvoll sein. Vielmehr überwiegen die Vorteile des simplen random-Boardings, bei dem die Passagiere keine komplizierten Einsteigeregeln befolgen müssen, sondern in beliebiger Reihenfolge das Flugzeug boarden können.

Der Fokus des Beitrags liegt auf der Vorstellung und Analyse relevanter wissenschaftlicher Literatur, welche schematisch dargestellt und nach verwendeter Methodik und untersuchten Flugzeugtypen und Boardingstrategien sortiert wird. In diesem Teil des ersten Beitrags, dem Literaturüberblick, welcher alle relevanten bis dato erschienenen wissenschaftlichen Artikel umfasst, die sich mit dem Boarding von Kurz- und Mittelstreckenflugzeugen mit zugewiesenen Sitzplätzen befassen, werden zwölf wissenschaftliche Paper im Detail präsentiert und deren Ergebnisse zusammengefasst und verglichen. Am häufigsten wurden Computersimulationen durchgeführt, welche die Boardingzeit verschiedener Strategien bestimmen, es existieren jedoch auch einige Arbeiten, die einen analytischen Ansatz verfolgen und sehr vereinzelt wurden kleinere empirische Tests durchgeführt. Die erste Studie zum Thema Boarding bei Passagierflugzeugen erschien im Jahr 1998. Die Hauptergebnisse der verschiedenen Untersuchungen stimmen insofern größtenteils überein, als dass sie by-seat-Methoden als die schnellsten jedoch nur mäßig praktikablen Strategien identifizieren, von back-to-front abraten und zu nicht-traditionellen Gruppenboardingmethoden wie reverse pyramid, einem Mix aus outside-in (zuerst die Fensterplätze, dann die Mittelplätze und zuletzt die Gangplätze) und back-to-front raten. Nach den by-seat-Strategien und outside-in, bei denen Gang- und auch Sitzplatzbehinderungen durch im Gang stehende oder bereits sitzende Passagiere vermieden werden können, schneidet random-Boarding bei den meisten Untersuchungen recht gut ab. Daher wird meist empfohlen, statt komplizierte und kundenunfreundliche by-seat- oder Gruppenboardingmethoden einzusetzen, alle Passagiere zufällig einsteigen zu lassen.

Im vierten Teil des Beitrags *Airplane Boarding* werden verschiedene potentielle Forschungsfelder und -ideen aufgezeigt. Neben der Untersuchung, in welchen Fällen sich der Boardingprozess wirklich auf dem kritischen Pfad des Turnarounds befindet und somit eine Minimierung der Boardingzeit Kosten sparen kann, wird empfohlen, Boardingstrategien im Allgemeinen, aber vor allem auch empirisch zu untersuchen. By-seat-Strategien, die als optimale Boardingmethoden gelten, wurden außerdem noch nicht eingehend analytisch untersucht, könnten aber, wenn eine optimale Strategie bestimmt werden kann, gegebenenfalls als Grundlage für die Entwicklung praxistauglicher Boardingstrategien dienen. Da abgesehen von Untersuchungen zur Performance verschiedener Boardingstrategien kaum Forschung zu den Einflussfaktoren auf die Boardingzeit existiert, ist die empirische Analyse der Auswirkungen potentieller Faktoren wie Auslastung, Destination und Handgepäck dringend nötig. Ein weiterer möglicher Ansatz auf diesem Gebiet könnte die Untersuchung der Faktoren, die die Kundenzufriedenheit beeinflussen, sein. Da ein gutes Servicelevel für viele Fluggesellschaften ein wichtiger Aspekt ist, steckt auch hierin großes Potential.

## 2.2 Kurzbeschreibung Beitrag 2: Is the Boarding Process on the Critical Path of the Airplane Turn-around?

Wie bereits in Beitrag 1 thematisiert wird, ist es zwar die vorherrschende Meinung, dass sich der Boardingprozess bei Kurz- und Mittelstreckenflugzeugen auf dem kritischen Pfad des Turnarounds befindet, es existiert nach unserem Kenntnisstand jedoch keine wissenschaftliche Studie, die dies überprüft. Um durch die Reduzierung der Boardingzeit wesentliche Kosten einsparen zu können, was als Motivation bei den meisten Veröffentlichungen auf diesem Gebiet dient, ist es jedoch eine notwendige Bedingung, dass sich der Boardingprozess auf dem kritischen Pfad befindet. Daher wird in dem Beitrag mit dem Titel *Is the Boarding Process on the Critical Path of the Airplane Turn-around?* eben diese Forschungsfrage untersucht.

Nach einer allgemeinen Einordnung des Boardingprozesses in die Prozesse des Airplane Turnarounds und der Darstellung der Zusammenhänge zwischen Boardingzeit, Turnaround-Zeit und Abflugverspätungen, werden vier Hypothesen aufgestellt, mit deren Hilfe die eingangs gestellte Forschungsfrage empirisch überprüft werden soll. Als Datengrundlage dienen 54 Flüge, deren Boardingzeiten und weitere Flugdaten in einer umfangreichen Feldstudie an einem großen europäischen Flughafen manuell erhoben wurden. Es handelt sich hierbei um Kurz- und Mittelstreckenflüge, welche mit einem Flugzeug mit einem Mittelgang und alle von derselben Fluggesellschaft durchgeführt wurden. Außerdem wurden alle Flüge random geboardet.

Im Rahmen der deskriptiven Statistiken werden die Eckdaten erläutert. Die Turnaround-Zeit beträgt im Mittel 71,5 Minuten, die Boardingzeit knapp 16 Minuten. Unter Anwendung von Regressionsanalysen und statistischer Tests werden im Hauptteil des Beitrags die Hypothesen überprüft. Es kann bestätigt werden, dass die Boardingzeit einen positiven Einfluss auf die Turnaround-Zeit hat, eine längere Boardingzeit also zu einer längeren Turnaround-Zeit führt. Führt man eine multiple Regression der Turnaround-Zeit auf die unabhängigen Variablen geplante Turnaround-Zeit, Ankunftverspätung, Boardingzeit und Push-back-Verzögerung (Differenz zwischen Push-back und Boardingende) durch, so ergibt sich aus einer Verkürzung bzw. Verlängerung der Boardingzeit um ein Prozent eine um 0.25 Prozent kürzere bzw. längere prognostizierte Turnaround-Zeit. Bei den oben genannten Werten der Stichprobe, in der die Boardingzeit knapp ein Viertel der Turnaround-Zeit beträgt, führt also eine um eine Minute kürzere Boardingzeit zu einer um ebenfalls eine Minute kürzer prognostizierten Turnaround-Zeit. Ausgehend von unserem Regressionsmodell zieht eine Einsparung in der Boardingzeit also eine entsprechende Einsparung bei der Turnaround-Zeit nach sich.

Des Weiteren konnte der Einfluss der Boardingzeit auf die Abflugverspätung eines Fluges (Differenz zwischen tatsächlicher und geplanter Abflugzeit) sowie der Einfluss einer den Mittelwert übersteigenden Boardingzeit (bezogen auf Flüge mit dem entsprechenden Flugzeugtyp) auf die Turnaround-Zeit und auf die Abflugverspätung nachgewiesen werden. Mit Hilfe eines weiteren Regressionsmodells wird die Auswirkung einer Veränderung der Boardingzeit um eine Minute auf die Abflugverspätung eines Fluges auf ebenfalls ca. eine Minute geschätzt.

Auf Basis dieser Analysen kann die Forschungsfrage folgendermaßen beantwortet werden: Die Ergebnisse deuten darauf hin, dass sich der Boardingprozess bei Kurz- und Mittelstreckenflugzeugen grundsätzlich auf dem kritischen Pfad des Airplane Turnarounds befindet.

## 2.3 Kurzbeschreibung Beitrag 3: Factors Influencing Airplane Boarding Times

Da aufgrund der Ergebnisse aus Beitrag 2 davon ausgegangen werden kann, dass der Boardingprozess Teil des kritischen Pfades des Airplane Turnarounds ist, ist es sinnvoll, sich eingehender mit der Optimierung der Boardingzeit eines Kurz- oder Mittelstrecken-Flugzeuges zu beschäftigen. Abgesehen von der Untersuchung von Boardingmethoden existiert bisher nur wenig Forschung zu den verschiedenen Einflussfaktoren auf die Boardingzeit. Vor allem empirische Studien werden allerdings als Basis für theoretische Modelle oder Simulationsmodelle benötigt, daher wird in Beitrag 3 *Factors Influencing Airplane Boarding Times* eine umfassende empirische Analyse potentieller Einflussfaktoren auf die Boardingzeit durchgeführt. Das Ziel dieser wissenschaftlichen Arbeit ist es, die Faktoren zu bestimmen, die, abgesehen von der Wahl der Boardingmethode, die Boardingzeit beeinflussen und herauszufinden, welche Richtung und Stärke diese Einflüsse besitzen. Dies führt zu folgender Forschungsfrage: *Welche Faktoren beeinflussen die Boardingzeit und welcher Art ist dieser Einfluss?*

Um dieser Frage nachzugehen, wurden Hypothesen aufgestellt und anhand des Datensatzes, der auch in Beitrag 2 verwendet wurde, statistische Analysen durchgeführt und diese Hypothesen überprüft. Da es sich bei den für diese Fragestellung relevanten Variablen teilweise um andere als die in Beitrag 2 verwendeten handelt, konnten hier vier weitere Flüge, also insgesamt 58 Flüge untersucht werden. Wie bereits zuvor erwähnt, handelt es sich bei den Flügen um Kurz- oder Mittelstreckenflüge, welche random geboardet wurden.

Im ersten Teil des Beitrags wird nach der Abgrenzung des Forschungsrahmens und einigen Begriffsklärungen einschlägige Literatur vorgestellt, welche sich ebenfalls mit Einflussfaktoren auf die Boardingzeit beschäftigt. Anschließend, in Kapitel 2, werden die verwendeten Variablen eingeführt und die Hypothesen entwickelt. Die Hypothesen können in zwei Gruppen unterteilt werden: Zunächst wird ausschließlich der zu untersuchende Einflussfaktor betrachtet, ohne dass weitere Variablen und deren Einflüsse berücksichtigt werden. So können pauschale Aussagen wie: „Je höherer die Kapazität eines Flugzeuges, desto länger ist die Boardingzeit“ gemacht werden. Dass der Effekt auf die Boardingzeit indirekt von der bei einem Flugzeug mit hoher Kapazität normalerweise auch größeren Anzahl Passagiere kommt, ist in diesem Fall irrelevant, da die Aussage allein über den Zusammenhang zwischen Flugzeugkapazität und Boardingzeit getroffen werden soll. Die in diesem Abschnitt aufgestellten Hypothesen besagen Folgendes: Je mehr Passagiere, je höher die Kapazität oder je höher die durchschnittliche Anzahl Handgepäckstücke pro Person, desto länger ist die Boardingzeit; Flüge nach Südeuropa oder Flüge mit Passkontrolle haben längere Boardingzeiten und Inlandsflüge oder Flüge mit mehr als einem Gate Agent haben kürzere Boardingzeiten. Im zweiten Abschnitt werden schließlich die direkten Auswirkungen der entsprechenden Variablen auf die Boardingzeit betrachtet, indem auch andere Einflussvariablen berücksichtigt werden und somit vom Ceteris-Paribus-Fall ausgegangen wird. Grundsätzlich werden hier die gleichen Annahmen getroffen wie im ersten Abschnitt, es wird also dieselbe Wirkungsrichtung einer Variable auf die Boardingzeit angenommen wie wenn ausschließlich die interessierende Variable betrachtet würde, außer bei der Hypothese bezüglich der Auswirkung der Flugzeugkapazität. Hier wird aus oben genanntem Grund nun angenommen, dass je höher die Kapazität eines Flugzeuges unter sonst gleichen Bedingungen ist, desto kürzer ist auch die Boardingzeit. Man vermutet also, dass bei beispielsweise gleichbleibender Passagierzahl eine Erhöhung der Flugzeugkapazität zu einer Verkürzung der Boardingzeit führt.

In Kapitel 3 werden das Forschungsdesign und die Datenerhebung beschrieben und anschließend erfolgen in Kapitel 4 die statistische Auswertung der Daten und die Hypothesentests. Nach der Darstellung einiger deskriptiver Daten werden unter Verwendung linearer Regression zunächst die Hypothesen aus dem ersten Abschnitt getestet, welche den Gesamteffekt der jeweiligen Variable adressieren. Lediglich die erste Hypothese, welche besagt, dass eine höhere Passagierzahl zu einer höheren Boardingzeit führt, kann nach Anwendung des Holm-Bonferroni-Verfahrens, welches etwaige Fehler beim multiplen Testen korrigiert, bestätigt werden. Die Tests der Hypothesen des zweiten Abschnitts ergeben, dass die erste und zweite Hypothese, also diejenigen bezüglich der Passagierzahl und der Flugzeugkapazität, bestätigt werden können, alle anderen Hypothesen können nicht bestätigt werden. Überraschend ist vor allem, dass das Handgepäck hier keinen signifikanten Einfluss auf die Boardingzeit hat. Eine mögliche Erklärung ist, dass eine große Anzahl Handgepäckstücke pro Person vermehrt bei Flügen mit vielen Businesspassagieren auftritt, welche wiederum als flugerfahren und relativ agil eingestuft werden können und den Boardingprozess somit beschleunigen. Dies ist jedoch eine hypothetische Erklärung, welche einer Überprüfung durch weitere Studien bedarf. Die Anzahl der Passagiere hat einen auf dem 5-Prozent-Signifikanzlevel signifikant positiven und die Kapazität eines Flugzeuges einen auf diesem Level signifikant negativen Einfluss auf die Boardingzeit. Ein zusätzlicher Passagier erhöht die Boardingzeit bei sonst gleichen Bedingungen um ca. ein Prozent, ein zusätzlicher Sitzplatz im Flugzeug verkürzt die Boardingzeit um ca. 0,4 Prozent. Das lineare Regressionsmodell mit der logarithmierten Boardingzeit als abhängige Variable und der Anzahl Passagiere und der Kapazität des Flugzeuges als unabhängige Variablen erklärt fast 86 Prozent der Varianz der Boardingzeit. Der kreuzvalidierte Root-Mean-Square-Error (RMSE), welcher die durchschnittliche Abweichung der mit dem Regressionsmodell vorhergesagten Boardingzeit von der tatsächlich beobachteten Boardingzeit angibt, beträgt hierbei 1,9 Minuten.

Im nächsten Teil des Beitrags werden die Ergebnisse mit denen der Modelle aus anderen Forschungen verglichen, um das aufgestellte Regressionsmodells zu validieren. Sowohl der Vergleich mit den Ergebnissen verschiedener Simulationsstudien oder der Vergleich mit den Ergebnissen eines analytischen Modells als auch ein out-of-sample-Test mit in anderen Studien empirisch erhobenen Daten ergeben zumeist recht gute Übereinstimmungen zwischen den von uns prognostizierten Boardingzeiten und denen aus den anderen wissenschaftlichen Arbeiten.

Als Handlungsempfehlung wird am Ende des Beitrags 3 festgehalten, dass Fluggesellschaften, um Verspätungen zu vermeiden, die Boardingzeit unter Berücksichtigung der Anzahl Passagiere und der Kapazität des Flugzeuges prognostizieren und den Startzeitpunkt, wenn möglich, anpassen sollten. Zusätzlicher Fokus auf die Menge des Handgepäcks, wie es in vielen Simulationsmodellen der Fall ist, wird durch unsere Studie nicht gerechtfertigt, weshalb diese kritisch hinterfragt werden sollten.

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# II Beitrag 1: Airplane Boarding

Florian Jaehn, Simone Neumann (Universität Augsburg), 2015

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# III Beitrag 2: Is the Boarding Process on the Critical Path of the Airplane Turn-around?

Simone Neumann (Universität Augsburg), 2018

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## Abstract

One of the effects of increasing cost pressure in airline industry is that airlines strive to realize short turn-around times, i.e., to let the airplanes stay at the gates between flights only as long as necessary. Associated with this is the reduction of the airplane boarding time, which accounts for a large part of the turn-around time. Most of the scientific literature in this area assumes that the boarding process is on the critical path of the turn-around, at least in sufficiently many cases. The aim of this study is to analyze this assumption empirically. In a field study, we manually collected data of short- and medium-haul flights at a large European airport and analyzed them by performing statistical hypothesis testing. Our results indicate that boarding is on the critical path of the airplane turn-around. Hence, when aiming to reduce airplane turn-around time, the focus on the boarding time is reasonable and airlines are recommended to optimize the processes that are related to the boarding procedure.

*Keywords: OR in airlines; airplane boarding; airport operations; field measurement; empirical study*

# 1 Introduction

Passenger numbers in air traffic have almost continuously increased in the last years. For the number of flights in Europe, this led to a growth of 2.8 % in 2016 compared to 2015 (Eurocontrol, 2016a). Large airlines have to cope with several hundred flights each day and it is a challenging task to achieve punctuality and to keep flight schedules as well as meeting safety and airport regulations and a certain service level. In 2016, 43 % of the European flights were delayed on departure ($\geq$ 5 minutes). Nearly 10 % of all flights had a departure delay of more than 30 minutes, whereas most of the primary delays were caused by airline operations and occurred at the gate (Eurocontrol, 2016a,b).

For the U.S., the total cost of domestic flight delays was estimated to be more than $40 billion for 2007 (Schumer and Maloney, 2008). As business travelers are also affected by the delays, they also result in a loss in productivity for employers (Ball et al., 2010). Moreover, Suzuki (2000) showed that passengers consider the experienced on-time performance of an airline when booking a flight – another motivation for avoiding delays.

## 1.1 The Airplane Turn-around

To improve punctuality, the airplane turn-around time (TAT) has to be examined. It is defined as the time an airplane spends at a parking position at the gate or the apron between flights while being prepared for the next take-off. In other words, it is the time between placing the chocks to the airplane wheels after the arrival at the gate (chocks-on, on-blocks) and removing them before push-back (chocks-off, off-blocks). The time of arrival and time of departure of an airplane also correspond to these points in time (and not as it might be thought to the touchdown and take-off time). Hence, the airplane turn-around comprises all processes that are needed to get an airplane ready for the next flight. Several processes are scheduled within that period at the gate. They can be divided into five paths: the passenger handling (deboarding and boarding as well as cabin cleaning), baggage and freight handling (unloading and loading), water handling (pump out waste water and refill fresh water), unloading and loading of catering, and refueling. An overview is given in Figure 1. For further information on ground operation processes see Ashford et al. (2013), Schlegel (2010), and Schmidt (2017).

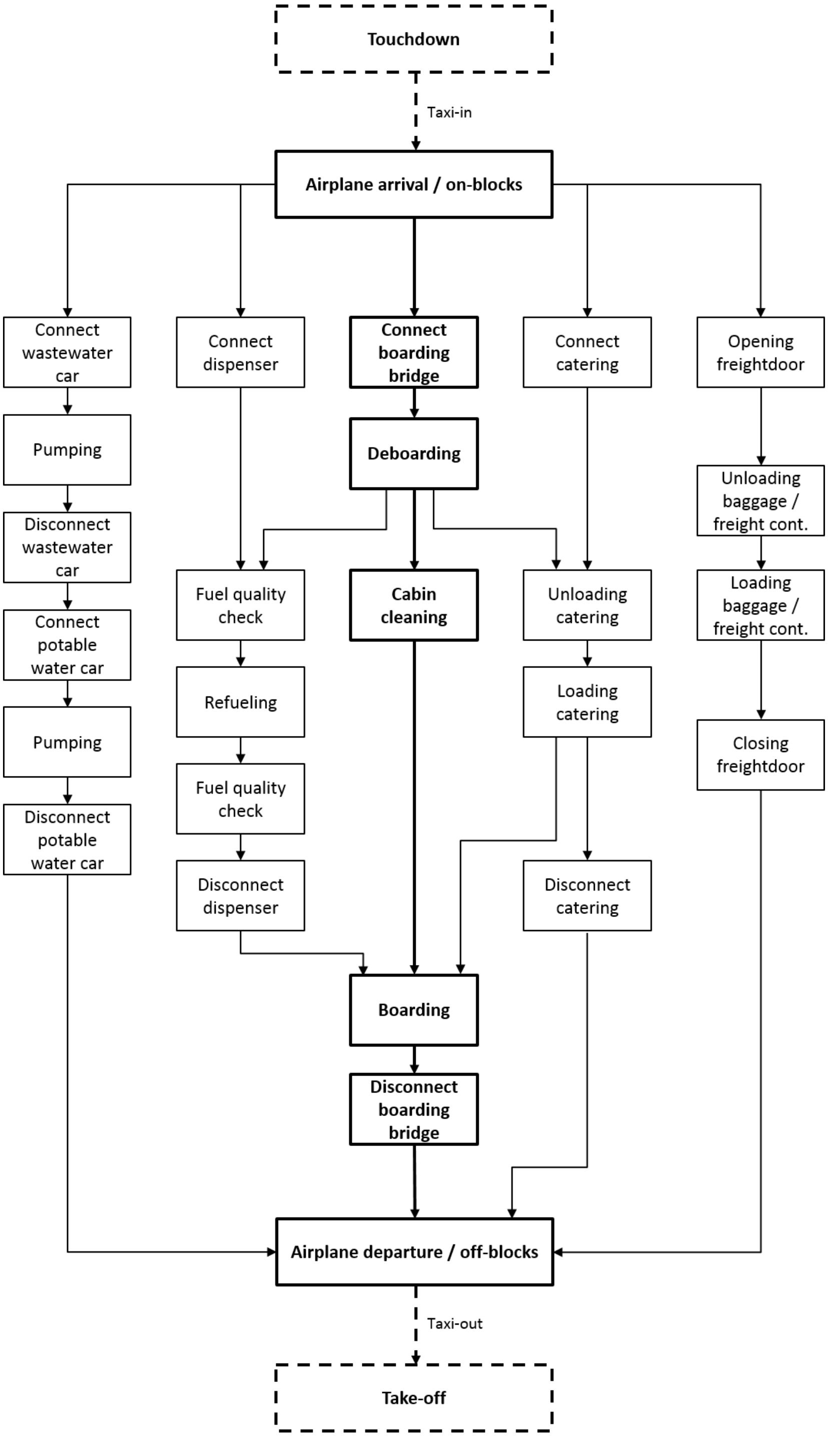


Figure 1: Airplane turn-around time (according to Horstmeier and de Haan (2001)).

As the TAT of a single-aisle airplane often takes less than one hour, it is important for airlines to operate efficiently to hold the schedule. Moreover, as airplanes, gates, and personnel are scarce and costly resources, there is enormous potential for savings. Estimates for possible cost savings due to a reduction of the TAT of one minute range between US$30 and US$250 per flight (Horstmeier and de Haan, 2001; Nyquist and McFadden, 2008; Wu and Caves, 2000), which can sum up to several hundred million dollars per year for a large airline. To accomplish this, especially the processes that are part of the critical path of the TAT should be in the focus for improvement. Being on the critical path means that a delay in one of the particular processes inevitably leads to a delay in the whole process. The prevailing opinion is that the passenger handling processes (primarily deboarding and boarding, see bold path in Figure 1) are on the critical path of the TAT for short- and medium-haul flights (Van Landeghem and Beuselinck, 2002; Schultz et al., 2013; Jaehn and Neumann, 2015). Consequently, when trying to reduce the TAT, the boarding process, which is the most time consuming part of this path and the only one allowing for significant time savings, should be improved.

## 1.2 The Boarding Process

The boarding process describes the process of passengers entering the airplane and includes all activities that define the boarding time, which is the time between "the first passenger enters the plane" and "the last passenger is seated in his assigned seat" (Van Landeghem and Beuselinck, 2002). Consequently, the processes that occur at the gate, e.g., the ticket check, or the time that the first passengers need to walk from the gate to the airplane door, are not part of the boarding process according to our definition (but they are part of it for airlines). Simulations of the boarding process, calculations of the boarding time, and analytical studies are, e.g., performed by Van Landeghem and Beuselinck (2002), Van den Briel et al. (2005), Bachmat et al. (2009), Frette and Hemmer (2012), Brics et al. (2013), Mas et al. (2013), Kierzkowski (2016), and Zeineddine (2017). For a general overview of the literature on the boarding problem see Jaehn and Neumann (2015). Hutter et al. (2018) conducted an empirical study to identify the factors that influence the boarding time using the same data set as in the paper at hand. Although several papers regarding the airplane turn-around time and the boarding problem exist in scientific literature, as far as we know, there is no empirical study on the influencing effect of the boarding time on the turn-around time. So we want to find out if a fast boarding in this context is relevant at all.

### 1.3 Scope of the Study

The aim of this paper is to investigate whether the boarding process is on the critical path of the turn-around. To achieve this objective, flight data were collected at a large European airport and analyzed statistically. As the turn-around is a more critical process for short- and medium-haul flights than it is for long-haul flights, only the former, i.e., airplanes with six seats per row, are considered. Moreover, all observed airplanes parked directly at a gate and were boarded randomly over a boarding bridge and through one door at the front of the airplane. As it is common for most airlines, the passengers have assigned seats.

The remainder of this paper is structured as follows: First, we clarify our research question and define the relevant variables in Sections 2.1 and 2.2. In Section 2.3, we develop our hypotheses. The research design and data collection are described in Section 2.4. Section 3, which comprises our empirical analyses, is the main part of this paper. In Section 3.1, descriptive statistics are provided, and in Section 3.2, we statistically test our hypotheses and present the results. The main results are summarized and discussed in Section 3.3. We conclude the paper with Section 4.

# 2 Research Design

## 2.1 Research Question

In this study, the following research question is analyzed: Is the boarding process on the critical path of the airplane turn-around? To investigate this question and to determine the relevant factors, hypotheses are formulated. We begin by defining the variables used in the study.

## 2.2 Variables

Table 1: List of variables.

| | |
|---|---|
| $TAT$ | (actual) airplane turn-around time [min] |
| $sched\_TAT$ | scheduled airplane turn-around time [min] |
| $diff\_TAT$ | difference between actual and scheduled turn-around time [min] (= $TAT - sched\_TAT$) |
| $delay\_arrival$ | arrival delay of the airplane at the gate [min] |
| $delay\_departure$ | departure delay of the airplane at the gate [min] |
| $bt$ | total boarding time (incl. late passengers) [min] |
| $delay\_pax$ | boarding time delay caused by late passengers [min] |
| $diff\_bt$ | difference between total boarding time of a flight and mean boarding time of the flights with the same airplane type without $delay\_pax$ [min] |
| $last\_seated\_to\_push$ | time gap between last passenger is seated and push back [min] |
| $A319$<br>$A320$<br>$A320neo$<br>$A321$ | airplane type<br>(one dichotomous variable for each type) |

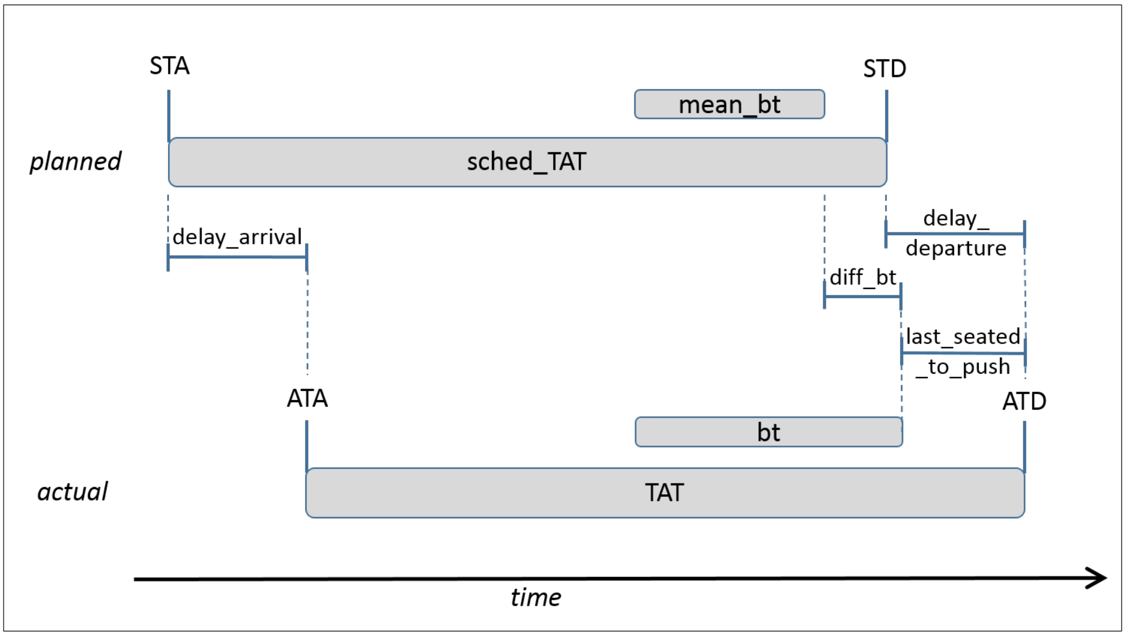


Figure 2: Relationship between variables.

The first variable is the airplane turn-around time ($TAT$), the time the airplane spends at the gate between on-blocks and off-blocks (see Section 1.1). In contrast to this actual TAT, we also determine the scheduled TAT ($sched\_TAT$), which is the difference between the scheduled time of departure (STD) and the scheduled time of arrival (STA). Hence, this time results from the flight schedule, in which the airline also has considered the airplane type and the estimate for the required turn-around time. To get the variable $diff\_TAT$, we calculated the difference between the actual and the scheduled turn-around time, which is the same as the difference between $delay\_departure$ and $delay\_arrival$. $Delay\_arrival$, i.e., the arrival delay of the airplane at the gate, is given by the difference between the actual (ATA) and the scheduled time of arrival (STA). The variable $delay\_departure$, which is equivalent to the delay of the push back, is the difference between the actual (ATD) and the scheduled time of departure (STD). Both variables, as well as $diff\_TAT$, can take negative values. In this regard, we want to note that airlines often use another definition of delay, e.g., when push back is at least 5 minutes after the scheduled time of departure. Further variables are the boarding time ($bt$), which is the time between the first passenger entering the airplane and the last passenger being seated in his assigned seat (see Section 1.2) and $delay\_pax$, when applicable, which is the boarding time delay that is caused by late passengers that enter the airplane when the other passengers are already seated. *Diff_bt* is the difference between the total boarding time of the flight and the mean boarding time of all flights with this respective airplane type without considering delayed passengers. This variable can also take negative values. The variable *last_seated_to_push* describes the time gap between the end of the boarding process (last passenger is seated in his assigned seat) and the departure of the airplane (push back). Finally, we have the dichotomous variables for the airplane type (*A*319, *A*320, *A*320*neo*, and *A*321). An overview of the variables is given in Table 1 and Figure 2.

## 2.3 Hypotheses

To answer our research question, we study the influence of the boarding time on the airplane turn-around time. Assuming that the boarding process is on the critical path of the turn-around, an increase in the boarding time consequently must result in a longer TAT. Hence, we set up the following hypothesis:

Hypothesis 1 (H1): *The longer the boarding time of a flight, the longer the turn-around time.*

When operating a flight, airlines usually have a fixed time at which the boarding process at the gate begins. This time is printed on the boarding passes to ensure that the passengers appear at the gate on time. Hence, the ticket check at the gate and thus also boarding usually cannot begin much earlier than scheduled. According to responsible personnel at airlines, for short- and medium-haul flights this is about 20 to 30 minutes before the scheduled departure time (STD). For more detailed information on the boarding process see Jaehn and Neumann (2015). If an airplane arrives at the gate way ahead of schedule (i.e., the variable *delay_arrival* has a negative value) and boarding does not start much earlier than planned, this can have a direct influence on the TAT. To take this into account, we use the departure delay of the airplane instead of the TAT as dependent variable in our second hypothesis. Like this, the arrival delay of the airplane is not contained in the dependent variable directly, any more. Consequently, we assume that longer boarding times lead to longer departure delays.

Hypothesis 2 (H2): *The longer the boarding time of a flight, the longer the departure delay.*

Our third hypothesis states that the higher the positive deviation of the boarding time of a flight from the mean boarding time, the longer the TAT, and consequently the higher the negative deviation, the shorter the TAT. We herewith analyze the influence of the independent variable $diff\_bt$, which is the difference between the total boarding time of the flight and the mean boarding time of the particular airplane type when delayed passengers are not considered, on the TAT and hence assume that extraordinary long boarding times lead to longer TATs.

Hypothesis 3 (H3): *The higher the delay of the boarding time of a flight, the longer the turn-around time.*

If boarding takes about 15 to 20 minutes and no other irregular incidents occur, the airplane can depart on time. In the case that boarding needs more time than usual, the STD possibly cannot be hold and the flight will depart delayed. To investigate the effect of an unusual long boarding time ($diff\_bt$) on the departure delay of the flight ($delay\_departure$), we built the following hypothesis:

Hypothesis 4 (H4): *The higher the delay of the boarding time of a flight, the longer the departure delay.*

Analogous to H3, the following automatically applies here: The higher the negative deviation of the boarding time of a flight from the mean boarding time of flights with the respective airplane type, the shorter the departure delay. Table 2 gives an overview of the hypotheses:

Table 2: Overview of hypotheses.

| | TAT | delay_departure (=ATD – STD) |
|---|---|---|
| bt | H1 | H2 |
| diff_bt (=bt – mean bt) | H3 | H4 |

## 2.4 Methods and Data Collection

The paper at hand is based on a cross-sectional field study in which data of short- and medium-haul flights were captured at a large European airport. In an earlier study, parts of the data were already analyzed to determine factors that influence the boarding time (Hutter et al., 2018). Table 3 gives an overview which data were collected for which study. In the following, we only outline the process of data collection. For a more detailed description we refer to Hutter et al. (2018). As most other data could be obtained from the airline's system, the focus was on measuring the boarding times. Because airlines do not necessarily define the boarding time in the same way that we do, but consider the time that is needed for the ticket check at the gate, which cannot be used for our analyses, we manually measured the time at which the first passenger entered the airplane and the time at which the last passenger was seated. Moreover, the number of carry-on baggage and the values of *delay_pax* as well as some more data and points in time were measured at the gate to allow for more differentiated statistical analyses. The other variables listed in Table 3 could be taken out of the system. After running two pretests with 13 flights in total, data collection of the main test took place at two days in Summer 2016, and 58 randomly chosen flights were observed by four teams of three. Although data collection was on two different days within two consecutive weeks, there is no measurement bias because of weather conditions or a strike. Our approach was as follows: Two observers, who stood in the boarding bridge near the airplane door, measured the boarding time as well as some more points in time like the time at which late passengers enter the airplane (when applicable). Another observer, who also stood near the airplane door, counted the number of carry-on baggage items of the passengers who entered the airplane. Data collection was completed when the airplane door was closed. Data for the turn-around times was available for 54 of the 58 flights. The other four airplanes were either already standing at the airport (e.g., over night) or they arrived at another gate and then were towed to the departure gate. In the following, all analyses that require data on turn-around times, hence are based on these 54 flights.

Table 3: For empirical studies captured variables.

| variable | Hutter et al. (2018) | this study |
|---|---|---|
| $bt$ | x | x |
| $airplane\_type$ | x | x |
| $pax$ | x | |
| $capacity$ | x | |
| $carry$ | x | |
| $destination\_region$ | x | |
| $doc\_check$ | x | |
| $gate\_agents$ | x | |
| $TAT$ | | x |
| $delay\_arrival$ | | x |
| $delay\_departure$ | | x |
| $delay\_pax$ | | x |
| $last\_seated\_to\_push$ | | x |

## 3 Empirical Analysis

In the following section, we present and discuss the results of our descriptive and predictive analyses.

### 3.1 Descriptive Statistics

In our main test, boarding times and data of 54 short- and medium-haul flights were obtained. Half of the flights were domestic, the other half went to other inner-European destinations. Four different airplane models operated these flights: the Airbus A319, A320, A320neo, and A321. The used airplane configurations had a capacity between 126 and 200 passengers, with a mean of 155.

Table 4: Descriptive statistics.

| variable [min] | mean | std. dev. | median | minimum | maximum |
|---|---|---|---|---|---|
| $TAT$ | 71.50 | 27.87 | 66.50 | 38.00 | 167.00 |
| $sched\_TAT$ | 65.10 | 27.00 | 55.00 | 35.00 | 170.00 |
| $diff\_TAT$ | 6.41 | 11.26 | 6.50 | −22.00 | 50.00 |
| $delay\_arrival$ | −2.83 | 8.23 | −4.50 | −19.00 | 17.00 |
| $delay\_departure$ | 3.57 | 8.60 | 1.00 | −5.00 | 51.00 |
| $bt$ | 15.98 | 5.40 | 14.67 | 7.35 | 34.53 |
| $delay\_pax$ (when applicable) | 3.14 | 3.04 | 2.25 | 0.32 | 13.08 |
| $diff\_bt$ | 0.77 | 5.22 | −0.25 | −7.92 | 17.22 |
| $last\_seated\_to\_push$ | 5.51 | 3.17 | 5.46 | 0.48 | 12.00 |

### 3.1.1 Turn-around Times

The turn-around times of the measured flights ranged from 38 to 167 minutes, with a mean of 71.5 minutes. Accordingly, the airplanes in our sample spent a little more than one hour on average at the gate. As the median of the TAT (66.5) was lower than the mean, the distribution of the TAT is right-skewed, i.e., the data are more concentrated in the lower range (see Figure 3). The scheduled turn-around times were some minutes shorter with an average of 65.1 minutes. For the median, there is a mentionable difference of more than 11 minutes between the scheduled and the actual TAT. This shows that especially in the lower half actual TATs are higher than scheduled. For the flights operated with an Airbus A319, the mean turn-around time was 67 minutes, whereas for flights operated with an A321, the mean time was 80 minutes. As the A321 is a much larger airplane than the A319 (maximum capacities are 200 and 138 passengers, respectively), it is perspicuous that the former has a longer turn-around time. 40 airplanes had a longer turn-around time than scheduled, with an average difference of 6.41 minutes among all flights. 33 flights arrived at the gate before the STA, two flights arrived exactly on time, and 19 flights arrived delayed. As shown in Table 4, the average *delay_arrival* was -2.83 minutes. If only the 19 tardy flights were considered, we had a mean *delay_arrival* of 6.21 minutes, which ranged between 1 and 17 minutes. Concerning the departure of the airplane, we had a mean *delay_departure* of 3.57 minutes in the whole sample and a mean delay of 7.25 minutes under the tardy flights. 13 flights departed before the STD, 9 flights departed on time, and 32 flights were tardy between 1 and 51 minutes. The variable *last_seated_to_push*, which reflects the time between boarding and push back, i.e., the last phase of the turn-around process, ranged from less than one minute to 12 minutes, with a mean of 5.51 minutes.

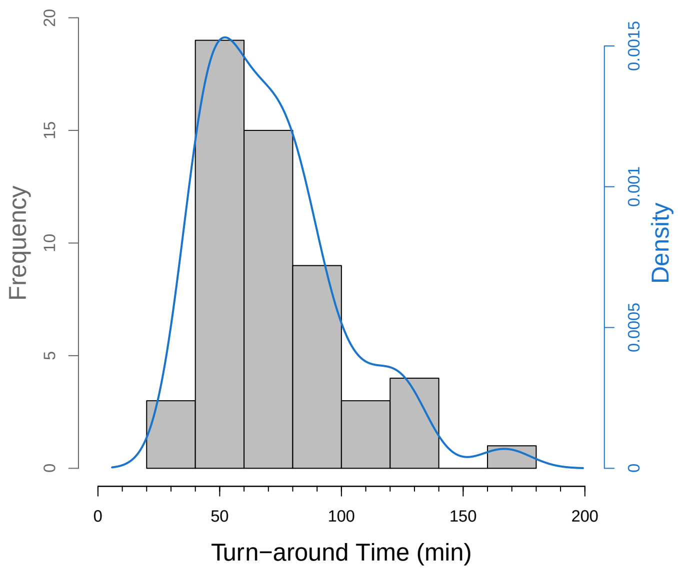


Figure 3: Distribution of $TAT$.

### 3.1.2 Boarding Times

The measured boarding times, which also include delays caused by late passengers, were in mean approximately 16 minutes. They ranged from 7.35 minutes to almost 35 minutes. Mean boarding times differed strongly between different airplane types. For an A319, the mean boarding time was less than 15 minutes, whereas for flights operated with an A321, the mean boarding time was 19 minutes. The shortest boarding time and shortest mean (less than 15 minutes) were observed for domestic flights, and the longest boarding time and the longest mean (almost 20 minutes) were observed for flights to Eastern Europe. In our sample, we had 17 flights with late passengers that had an influence on the boarding time of up to 13 minutes. In mean, *delay_pax* was approximately 3 minutes. $Diff\_bt$, which is not directly linked to *delay_pax*, but states the difference between the actual boarding time and the average boarding time of flights with the respective airplane type without considering late passengers, was in mean less than 1 minute but up to more than 17 minutes. The reason for the rather low mean is that half of the flights in our sample had no longer boarding time than the average flight, but were boarded faster than flights with this airplane type in mean (up to 8 minutes), and hence negative values were considered for this variable. Under the flights that had a positive deviation from the mean boarding time, the mean was almost 5 minutes.

### 3.1.3 Correlations

To get an impression of the interdependencies between the different variables, we calculated the correlations (see Table 5). The most interesting value, the correlation between *bt* and $TAT$ is 0.37. Even though this effect is not very strong, it suggests that a longer boarding time leads to a longer turn-around time, as assumed in Hypothesis 1. Although a high correlation between $TAT$ and *sched_*$TAT$ was expected, the strength of the correlation (0.92) is worth noting. The same holds for the correlation between *bt* and $diff$*_bt*, the difference between the actual boarding time and the mean boarding time of flights with the respective airplane type, which is 0.97. The variable $diff\_TAT$, which is the difference between the actual and the scheduled turn-around time, is correlated with *delay_departure*, *bt*, $diff$*_bt*, and (expectedly negatively) with *delay_arrival* within a range of 0.62 to 0.69.

## 3.2 Predictive Analytics

In the following, we perform different statistical analyses to test our hypotheses. According to the results of several tests, the scatterplots, the Q-Q-Plots, and the correlation values, we transformed the dependent variable $TAT$ as well as the independent variables *bt* and *sched_*$TAT$ by taking the natural logarithm in order to achieve an approximate normal distribution. To analyze the dependent variable

Table 5: Correlation matrix.

| | $TAT$ | $ln(TAT)$ | $diff\_TAT$ | $sched\_TAT$ | $ln(sched\_TAT)$ | $delay\_departure$ | $bt$ | $ln(bt)$ | $diff\_bt$ | $delay\_arrival$ | $delay\_pax$ | $last\_seated\_to\_push$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $TAT$ | 1 | | | | | | | | | | | |
| $ln(TAT)$ | 0.98***[a] | 1 | | | | | | | | | | |
| $diff\_TAT$ | 0.28* | 0.33* | 1 | | | | | | | | | |
| $sched\_TAT$ | 0.92*** | 0.87*** | −0.13 | 1 | | | | | | | | |
| $ln(sched\_TAT)$ | 0.90*** | 0.89*** | −0.11 | 0.97*** | 1 | | | | | | | |
| $delay\_departure$ | 0.22 | 0.20 | 0.69*** | −0.06 | −0.06 | 1 | | | | | | |
| $bt$ | 0.37** | 0.39** | 0.66*** | 0.10 | 0.12 | 0.57*** | 1 | | | | | |
| $ln(bt)$ | 0.34* | 0.37** | 0.60*** | 0.10 | 0.12 | 0.48*** | 0.97*** | 1 | | | | |
| $diff\_bt$ | 0.34* | 0.36** | 0.66*** | 0.07 | 0.09 | 0.53*** | 0.97*** | 0.95*** | 1 | | | |
| $delay\_arrival$ | −0.15 | −0.24 | −0.65*** | 0.11 | 0.09 | 0.11 | −0.30* | −0.32* | −0.35** | 1 | | |
| $delay\_pax$ | −0.05 | −0.04 | 0.15 | −0.11 | −0.07 | 0.17 | 0.29* | 0.24 | 0.32* | −0.03 | 1 | |
| $last\_seated\_to\_push$ | 0.29* | 0.28* | 0.13 | 0.24 | 0.25 | 0.13 | −0.20 | −0.25 | −0.17 | −0.05 | −0.05 | 1 |

[a] The correlation is significant (2-tailed) at a level of 0.001 (***), 0.01 (**), 0.05 (*).

$TAT$, we used the maximum likelihood approach of Box and Cox (1964). It led to an estimate of $\lambda$ of 0.00004, which suggests to transform $TAT$. Moreover, we conducted the Shapiro-Wilk normality test and the Jarque-Bera test, which led to p-values that support the transformation of $TAT$, $bt$, and $sched\_TAT$: Without transforming the variables, the p-values apart from one value all were lower than 0.001. After logarithmizing the variables, the p-values apart from one value were higher than 0.1, which suggests that for the logarithmized variables an approximated normality distribution can be presumed. For the variable $last\_seated\_to\_push$ the Shapiro-Wilk and the Jarque-Bera test result in p-values that do not support a transformation of the variable. As the other variables can take negative values, they cannot be logarithmized and anyway, the approach of Box and Tidwell (1962), which is used to check if the independent variables have to be transformed, does not lead to any further reasonable power transformations of these variables.

To test Hypothesis 1, we conduct an ordinary least squares (OLS) regression analysis with $ln(TAT)$ as the dependent and $ln(bt)$ as one of the independent variables and test the estimation of the regression coefficient with the t-test, to check if it differs significantly from 0, and thus if $ln(bt)$ significantly influences $ln(TAT)$. As the influence of an independent variable in a regression model depends on which other independent variables are considered and hence for which variables it is controlled for, we use backward stepwise regression, to select the correct variables and find a good regression model.

### 3.2.1 Stepwise Backward Regression

By applying this approach, starting with a regression model that includes all reasonable independent variables, the variables are deleted step by step, and we get a final regression model, which cannot be improved with respect to Akaike Information Criterion (AIC) by removing further variables. The initial model contains $ln(bt)$, $ln(sched\_TAT)$, $delay\_arrival$, $delay\_pax$, $last\_seated\_to\_push$, and the dummy variables $A320$, $A320neo$, and $A321$ (with $A319$ as reference category) as independent variables, which try to predict the value of the dependent variable $ln(TAT)$. The variables are removed one at a time according to the lowest value of the AIC. Like this, least information is lost and the regression model is improved until the AIC gets higher, again. The procedure is presented in Table 6. AIC, root-mean-square error (RMSE), and $\bar{R}^2$, the adjusted coefficient of determination, refer to the model generated if the corresponding variable is removed from the current model. The latter two, $\bar{R}^2$ and RMSE, are cross-validated with ten-fold cross-validation and the seed set to 1. Both values are for $TAT$ instead of $ln(TAT)$ (Wooldridge, 2013, p. 204 ff.), and hence the RMSE is given in minutes, as it eases interpretation. To control for multicollinearity, we calculated the variance inflation factor (VIF) of all independent variables in the initial model. As the VIF is not higher than 1.5 for any of the variables, we do not have a problem with multicollinearity.

Table 6: Backward stepwise regression of ln(TAT).

| independent variables in current model | model fit if variable is dropped AIC | RMSE | $\bar{R}^2$ | current model fit | |
|---|---|---|---|---|---|
| $ln(bt)$ | −225.04 | 7.78 | 0.9015 | | |
| $ln(sched\_TAT)$ | −116.72 | 23.20 | 0.3258 | | |
| $delay\_arrival$ | −219.41 | 7.46 | 0.8996 | AIC = | −250.69 |
| $delay\_pax$ | −251.71 | 6.17 | 0.9472 | RMSE = | 6.15 |
| $last\_seated\_to\_push$ | −242.65 | 6.56 | 0.9270 | $\bar{R}^2$ = | 0.9450 |
| $A320$ | −252.44 | 6.20 | 0.9439 | | |
| $A320neo$ | −251.16 | 5.78 | 0.9507 | | |
| $A321$ | −252.02 | 5.87 | 0.9475 | | |
| $ln(bt)$ | −226.78 | 7.64 | 0.9041 | | |
| $ln(sched\_TAT)$ | −117.70 | 23.30 | 0.3029 | | |
| $delay\_arrival$ | −219.41 | 7.52 | 0.8983 | AIC = | −252.44 |
| $delay\_pax$ | −253.58 | 6.17 | 0.9467 | RMSE = | 6.20 |
| $last\_seated\_to\_push$ | −244.29 | 6.49 | 0.9262 | $\bar{R}^2$ = | 0.9439 |
| $A320neo$ | −252.51 | 5.86 | 0.9479 | | |
| $A321$ | −253.07 | 5.94 | 0.9458 | | |
| $ln(bt)$ | −228.52 | 7.48 | 0.9106 | | |
| $ln(sched\_TAT)$ | −118.31 | 23.27 | 0.2948 | AIC = | −253.58 |
| $delay\_arrival$ | −220.25 | 7.55 | 0.9000 | RMSE = | 6.17 |
| $last\_seated\_to\_push$ | −245.80 | 6.48 | 0.9303 | $\bar{R}^2$ = | 0.9467 |
| $A320neo$ | −253.44 | 5.85 | 0.9512 | | |
| $A321$ | −254.14 | 5.93 | 0.9485 | | |
| $ln(bt)$ | −226.84 | 6.95 | 0.9180 | | |
| $ln(sched\_TAT)$ | −119.70 | 23.00 | 0.3515 | AIC = | −254.14 |
| $delay\_arrival$ | −222.20 | 7.48 | 0.8996 | RMSE = | 5.93 |
| $last\_seated\_to\_push$ | −247.24 | 6.18 | 0.9355 | $\bar{R}^2$ = | 0.9485 |
| $A320neo$ | −254.30 | 5.54 | 0.9550 | | |
| $ln(bt)$ | −228.49 | 6.73 | 0.9259 | AIC = | −254.30 |
| $ln(sched\_TAT)$ | −121.48 | 22.75 | 0.3532 | RMSE = | 5.54 |
| $delay\_arrival$ | −223.03 | 7.13 | 0.9142 | $\bar{R}^2$ = | 0.9550 |
| $last\_seated\_to\_push$ | −247.91 | 5.86 | 0.9398 | | |

The recommended regression model consequently considers $ln(bt)$, $ln(sched\_TAT)$, $delay\_arrival$, and $last\_seated\_to\_push$ as independent variables. The other variables do not improve the estimate of the turn-around time. Hence, the final model to predict the turn-around time is as follows:

$$\begin{aligned} ln(TAT) = \beta_0 + \beta_1 \cdot ln(bt) + \beta_2 \cdot ln(sched\_TAT) + \beta_3 \cdot delay\_arrival \\ + \beta_4 \cdot last\_seated\_to\_push + \epsilon \end{aligned} \tag{1}$$

After estimating the coefficients, we obtain the following model:

$$\begin{aligned} ln(TAT) = -0.4864 + 0.2513 \cdot ln(bt) + 0.8504 \cdot ln(sched\_TAT) \\ -0.0002 \cdot delay\_arrival + 0.0002 \cdot last\_seated\_to\_push \end{aligned} \tag{2}$$

The cross-validated adjusted coefficient of determination ($\bar{R}^2$) of the overall model is 95.50 % and the regression coefficient of the variable $ln(bt)$ ($\beta_1$) is estimated to 0.2513: A 1 % longer boarding time leads to a 0.2513 % longer turn-around time, assuming that all other independent variables are held constant. Like this, the other independent variables function as control variables and the effect of a delayed arrival or the idle time that can occur between the boarding process and the push back because of various reasons are segregated. As was to be expected, the scheduled turn-around time and the time between boarding and push back have a positive and the arrival delay of the airplane a negative influence on the actual turn-around time.

### 3.2.2 Testing Hypothesis 1

As mentioned before, we use the t-test to analyze the effect of the boarding time on the turn-around time. We check if the null hypothesis $H_0 : \beta_1 \leq 0$ is true, which would imply that the variable $ln(bt)$ does not have a significant influence on $ln(TAT)$.

As we conduct multiple statistical inference tests on the same data set, we apply Holm's method (Holm, 1979) to adjust the p-values and to keep the family-wise error rate (FWER)[1] at a 5 % significance level. This rather conservative stepwise proce-

[1] FWER = the probability of making at least one type 1 error, meaning a null hypothesis is rejected even though it is true

dure is more powerful than classical single-step tests such as Bonferroni correction (Dickhaus, 2014, p. 2). As there are different approaches to perform this correction of the p-values, we decided to choose one of the less extreme ones and only corrected the four p-values of our hypothesis tests (and, e.g., did not perceive the calculation of the correlation values in Table 5 as tests whose p-values have to be corrected). With a Holm adjusted p-value of 0.0000 we can reject the null hypothesis at the indicated 5 % significance level and consequently state that the boarding time has a significant positive influence on the turn-around time. Thus, Hypothesis 1 can be confirmed: The longer the boarding time of a flight, the longer the turn-around time. The effect might seem to be only moderate, but a 1 % longer mean boarding time corresponds to 9.6 seconds in our sample, which prolongs the mean turn-around time by nearly 11 seconds (corresponding to 0.25 % of the mean TAT, see Table 5).
The turn-around time can be predicted as

$$TAT = 1.0039 \cdot e^{-0.4864+0.2513 \cdot ln(bt)+0.8504 \cdot ln(sched\_TAT)-0.0002 \cdot delay\_arrival +0.0002 \cdot last\_seated\_to\_push}, \tag{3}$$

where 1.0039 is a consistent estimator correcting for transformation bias. If we simply exponentiated the predicted value of $ln(TAT)$, the expected value of $TAT$ would be systematically underestimated. This method of moments estimator is obtained by replacing the unobserved error terms with the OLS residuals and calculating the sample average (Wooldridge, 2013, p. 205).

### 3.2.3 Testing Hypothesis 2

Hypothesis 2 states that the longer the boarding time of a flight, the longer the departure delay. Again, we firstly conduct backward stepwise regression to select a good regression model. Instead of $ln(TAT)$ we use $delay\_departure$ as dependent variable. $Ln(bt)$ is again the independent variable to be examined and we additionally consider $ln(sched\_TAT)$, $delay\_arrival$, $delay\_pax$, and $last\_seated\_to\_push$, which function as control variables. As the VIF in the initial model is not higher than 1.4 for any of the variables, we do not have a problem with multicollinearity.

The final model we obtain by applying stepwise regression looks like this:

$$\begin{aligned} delay\_departure = \beta_0 + \beta_1 \cdot ln(bt) + \beta_2 \cdot ln(sched\_TAT) + \beta_3 \cdot delay\_arrival \\ +\beta_4 \cdot last\_seated\_to\_push + \epsilon \end{aligned} \tag{4}$$

After estimating the coefficients, we obtain the following model:

$$\begin{aligned} delay\_departure = -4902.4096 + 1175.7726 \cdot ln(bt) - 388.3963 \cdot ln(sched\_TAT) \\ -0.4019 \cdot delay\_arrival + 1.0838 \cdot last\_seated\_to\_push \end{aligned} \tag{5}$$

The cross-validated $\bar{R}^2$ of the overall model is 54.53 % and the regression coefficient of the variable $ln(bt)$ ($\beta_1$) is estimated to 1175.7726: A 1 % longer boarding time (equivalent to 10 seconds for the mean boarding time) leads to an increase of the departure delay by approximately 12 seconds, assuming that all other independent variables are held constant. To test if this estimate is significant, we check again if the null hypothesis $H_0 : \beta_1 \leq 0$ is true. The parameter estimate $\beta_1$ of this variable is significant at the given 5 % level (Holm adjusted p-value 0.0000), which means that the null hypothesis $H_0 : \beta_1 \leq 0$, claiming that there is no influence of the boarding time on the departure delay can be rejected and therefore Hypothesis 2 can be confirmed.

### 3.2.4 Testing Hypothesis 3

In Hypothesis 3, we have a look at the influence of the deviation of the boarding time of a flight from the mean boarding time and claim that a higher positive deviation leads to a longer turn-around time. We do not have a regression model with $ln(TAT)$ and $diff\_bt$, yet, consequently, we again conduct stepwise regression. As $ln(bt)$ and $diff\_bt$ are highly correlated, $ln(bt)$ is left out to avoid multicollinearity among the independent variables. Like this, all VIF have a maximum value of 1.4.

This leads to the following model:

$$\begin{aligned} ln(TAT) &= \beta_0 + \beta_1 \cdot diff\_bt + \beta_2 \cdot ln(sched\_TAT) + \beta_3 \cdot delay\_arrival \\ &+\beta_4 \cdot delay\_pax + \beta_5 \cdot last\_seated\_to\_push + \beta_6 \cdot A320neo + \beta_7 \cdot A321 + \epsilon \end{aligned} \tag{6}$$

After estimating the coefficients, we obtain the following model:

$$\begin{aligned} ln(TAT) = 1.170 + 0.0003 \cdot diff\_bt + 0.8551 \cdot ln(sched\_TAT) \\ -0.0002 \cdot delay\_arrival - 0.0001 \cdot delay\_pax + 0.0002 \cdot last\_seated\_to\_push \\ +0.0872 \cdot A320neo + 0.0703 \cdot A321 \end{aligned} \tag{7}$$

The model has a high cross-validated $\bar{R}^2$ of 94.07 and the parameter estimate of the variable $diff\_bt$ reveals that a one minute deviation in the boarding time from the mean boarding time of flights with the respective airplane type results in an approximately one minute longer TAT. The test if $\beta_1 \leq 0$ shows that the estimate is highly significant, which also holds true after adjusting it with the Holm method. Consequently, H3 can be confirmed. However, as we have seven independent variables in our model, which is a lot for the size of our sample, this model should be interpreted with caution. When transforming the equation, we have to multiply with 1.0033 as the consistent estimator correcting for transformation bias and get the following regression model to predict the turn-around time:

$$\begin{aligned} TAT = 1.0033 \cdot e^{1.170+0.0003 \cdot diff\_bt+0.8551 \cdot ln(sched\_TAT)-0.0002 \cdot delay\_arrival} \\ {}^{-0.0001 \cdot delay\_pax+0.0002 \cdot last\_seated\_to\_push+0.0872 \cdot A320neo+0.0703 \cdot A321} \end{aligned} \tag{8}$$

### 3.2.5 Testing Hypothesis 4

Finally, with Hypothesis 4, we combine H2 and H3 and address the influence of a delay of the boarding time on the departure delay. The correlation between the variable $diff\_bt$ and $delay\_departure$ is 0.53. Again, we conduct backward stepwise regression to select a good regression model and obtain the following final model, which has a cross-validated $\bar{R}^2$ of 56.90 %:

$$\begin{aligned} delay\_departure = 2726.8117 + 1.2308 \cdot diff\_bt - 341.2977 \cdot ln(sched\_TAT) \\ +0.4220 \cdot delay\_arrival + 0.9096 \cdot last\_seated\_to\_push \end{aligned} \tag{9}$$

We used this model to analyze the estimates of the regression coefficient $\beta_1$ of the variable $diff\_bt$ and to decide whether or not the null hypothesis $H_0 : \beta_1 \leq 0$ can be rejected. According to the adjusted p-value of the corresponding t-test, the null hypothesis is rejected and thus Hypothesis 4 can be confirmed (p-value = 0.0000) and we can state that the higher the positive deviation of the boarding time from the mean boarding time of flights with the respective airplane type, the longer the departure delay.

### 3.3 Results

Even with using the rather conservative Holm correction of the p-values, all four hypotheses that have been tested in the previous section can be confirmed at the preassigned 5 % significance level. Hence, we can state that the boarding time of a flight has a significant positive influence on its turn-around time and the departure delay. Though the variable $ln(sched\_TAT)$ alone explains nearly 80 % of the actual logarithmized turn-around time, which suggests that flight schedules are met relatively well, the stepwise regression leads to the result that the boarding time, the arrival delay of the airplane, and the variable $last\_seated\_to\_push$ are also significant influencing factors. Our first regression model (Equation 2) shows that a 1 % longer boarding time leads to a 0.25 % longer turn-around time. With a mean TAT of over 70 minutes in our sample and a mean boarding time of less than 16 minutes, this means that with each minute the boarding process takes longer, the TAT is prolonged by more than one minute. According to our second regression model (Equation 5), the impact of a 1 % longer boarding time, which is approximately 10 seconds in mean, on the departure delay is nearly 12 seconds. Moreover, the higher the deviation of the boarding time of a flight from the mean boarding time of flights with the respective airplane type ($diff\_bt$), the longer the turn-around time and the departure delay (see Equations 8 and 9). If the boarding process were not on the critical path of the turn-around, a delay of the boarding time might not lead to a departure delay. These interrelations, which all show the influence of the boarding time on the airplane turn-around time (directly or indirectly), let us answer our research question posed at the beginning, which was: *Is the boarding process on the critical path of the airplane turn-around?* The results indicate that the boarding process is generally on the critical path of the airplane turn-around.

## 4 Conclusion

In the paper at hand, an empirical study on the influence of the boarding time on the airplane turn-around time has been conducted. On the basis of real flight data, which have been collected in a field study at a large international airport, we conducted detailed statistical analyses. According to our regression models that were obtained by conducting stepwise backward regression, influencing factors on the turn-around time are (primarily) the scheduled turn-around time, the boarding time, the arrival delay of the airplane, and the time gap between the last passenger being seated and push back. We tested four hypotheses that are connected with the question whether the boarding process is on the critical path of the airplane turn-around. As all four hypotheses could be confirmed, we conclude that the boarding process seems to be on the critical path of the turn-around. Of course, these results have to be interpreted with caution. Flights with very low load factors, which are usually boarded quite fast, are not supposed to be on the critical path. The reason for this is that if the boarding process is finished earlier than planned, other processes, e.g., loading the baggage, could become time critical. Moreover, if disruptions occur, e.g., caused by bad weather conditions or maintenance issues, boarding is not necessarily on the critical path any more. Delayed feeder flights are another reason for a flight delay, which, in contrast, can lead to a longer boarding time, when waiting for late passengers. In this case, however, measures to accelerate the boarding process are of no value. Nevertheless, the managerial implications we can derive from these insights are that when trying to reduce the turn-around time, it generally is a good option for airlines to optimize the boarding process.

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# IV Beitrag 3: Factors Influencing Airplane Boarding Times

Leonie Hutter [a], Florian Jaehn [b], Simone Neumann [a], 2018
([a] Universität Augsburg, [b] Helmut-Schmidt-Universität – Universität der Bundeswehr Hamburg)

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## Abstract

The topic of airplane boarding is receiving increasing attention in practice and in the scientific literature. Shorter boarding times can reduce the time an airplane spends at the gate (the airplane turn-around time), resulting in annual cost savings of several hundred thousand dollars per airplane. Although several researchers have analyzed the boarding process purely theoretically or with simulation models, little empirical research has been performed, even though empirical research is the basis for any theoretical or simulation model. In this paper, we provide the fundamentals for this research area by presenting the results of an empirical study conducted at a large European airport. To the best of our knowledge, this is the first time such an extensive field study and statistical analyses of the data have been reported in detail. The aim of this study was to determine whether and to what extent certain factors, such as the number of passengers, the capacity of the airplane, and the amount of carry-on baggage, influence boarding times. Boarding times and additional data for short- and medium-haul flights with single-aisle airplanes were manually collected in

a field study and analyzed. The analyses yielded the counter-intuitive result that a significant effect on the boarding time of a flight by the average amount of carry-on baggage per passenger could not be demonstrated. Finally, we developed a regression model to predict boarding times based on the number of passengers and the capacity of the airplane.

*Key words: Airplane Boarding, Airport Operations, Field Study, Econometric Analysis*

# 1 Introduction

## 1.1 Practical Situation and Motivation

The airplane boarding process is usually part of the critical path of the airplane turn-around time, the time that an airplane spends at the gate between flights (Neumann, 2018). Because airplanes, gates, and personnel are scarce and costly resources, this 'lost' time should be minimized. Cost calculations for the turn-around time range between US$30 (Nyquist and McFadden, 2008) and US$250 (Horstmeier and de Haan, 2001) per minute that an airplane is on the ground. Similar results are obtained by Wu and Caves (2000). Based on these numbers, there is enormous potential for cost savings if an airline with several hundred flights a day can reduce the turn-around time even by only a few minutes each flight. However, most processes of the turn-around can hardly be shortened or they barely affect the turn-around time. The former include the fueling or baggage handling, while the latter comprise gate assignment (Dorndorf et al., 2007, 2008), towing (Du et al., 2016), or routing (Safaei and Jardine, 2017). In this paper, we study the boarding process, which is a crucial part of the airplane turn-around and for which time savings are commonly assumed to be possible (Horstmeier and de Haan, 2001; Nyquist and McFadden, 2008; Schultz et al., 2013).

Although several studies on the airplane boarding problem have been published in the scientific literature, an empirical analysis of the factors influencing the boarding time has not been conducted. Some papers mention empirical tests, but no empirical study with more than eight flights has been reported in detail, and in most cases, information about the data is vague. Consequently, no extensive statistical analyses, e. g., with hypothesis testing, have been conducted. Because the theoretical models are based on certain assumptions, there is a strong demand for such data to validate the results obtained by simulations and analytical models. Moreover, correlations between various factors and the boarding time can be studied much better with empirically gathered data than with purely theoretical models. Such analyses are provided here to fill this research gap.

### 1.2 Scope of the Study

The aim of this paper is to investigate whether and how certain factors, such as the number of passengers and carry-on baggage items, influence the total boarding time. To achieve this objective, the boarding times and potential influencing factors, such as passengers, destination, carry-on baggage, and seat capacity, are measured and documented for short- and medium-haul flights at a large central European airport. As our focus is on the effects of these factors on the boarding time, we restrict ourselves to one of the most commonly used boarding strategies: *random boarding*. In the random boarding method, all passengers have reserved seats (which are usually assigned at check-in), and any passenger is allowed to pass through the ticket check as soon as boarding begins. Random boarding stands in contrast to group boarding strategies, where specific parts of the airplane are sequentially called to board (e. g., the last ten rows first). The data are analyzed and connections and interdependencies are identified using statistical methods such as regression modeling. In this way, it is possible to estimate or even reduce the boarding time, potentially resulting in lower turn-around times and fewer departure delays. We consider only flights with single-aisle airplanes with six seats per row. Moreover, all passengers board over a boarding bridge and through one door at the front of the airplane.

The remainder of the paper is structured as follows. We give definitions and present relevant aspects of the related literature in Sections 1.3 and 1.4, and we describe our research questions and hypotheses in Section 2. In Section 2, we discuss the research design and the data collection. Descriptive statistics and analyses are provided in Section 3, and the results are evaluated. Moreover, we validate our regression model against other models and data from the literature in Section 4.4. Recommended actions and managerial implications are developed in Section 5. Finally, we summarize the main results and outline aspects that should be considered in future research in Section 4.

### 1.3 Definitions

To keep the paper self-contained, we present some relevant definitions from the literature.

"The *boarding problem* comprises all decisions and activities that influence the passengers' experience from the gate to their seats, including decisions regarding which boarding strategy to use and its implementation, announcements by the gate agent, the handling of carry-on baggage, lining up in front of the gate, the ticket check, the walk from the gate to the plane and the search for a seat, the stowing of carry-on baggage and settling into one's seat" (Jaehn and Neumann, 2015, p. 340).

*Boarding* in general is "the process of passengers entering an airplane" (Jaehn and Neumann, 2015, p. 340).

For this study, the most important term is the *boarding time*, which "starts when the first passenger enters the plane and ends when the last passenger is seated in his assigned seat" (Van Landeghem and Beuselinck, 2002, p. 296).

We also define the terms *aisle interference* and *seat interference*. *Aisle interference* occurs if a passenger is standing in the middle aisle, e. g., stowing his or her carry-on baggage, and blocking other passengers who want to pass to get to their assigned row. *Seat interference* is caused by passengers who are already sitting in the row in an aisle or middle seat and are blocking access for other passengers who want to get to the middle or window seat. Both cases lead to congestion in the aisle. The implementation of specific boarding strategies, e. g., outside-in, aims to reduce these interferences.

### 1.4 Related Literature

Apart from more general research papers on airport operations, such as Etschmaier and Rothstein (1974), to the best of our knowledge, all scientific papers concerning the airplane boarding problem have appeared during the last twenty years, many within the last five years. Most articles on the topic are based on simulation models or analytical approaches, and few authors have collected empirical data. These studies are briefly summarized in the following section.

#### 1.4.1 Empirical Studies

One way to collect relevant data is experimental tests with volunteers boarding a mock airplane. Although this approach potentially enables data to be rapidly collected for different scenarios, volunteers do not accurately represent real passengers. The group of volunteers might differ from real passengers with respect to age, walking speed, carry-on baggage or other characteristics. Moreover, a learning effect is likely to appear if boarding is repeatedly performed by the same volunteers.

Marelli et al. (1998) conducted in-service observations and experimental tests at Boeing to validate their simulation model. However, they performed no more than six tests to compare the performance of four different scenarios.

Similarly, Steffen and Hotchkiss (2012) conducted experimental tests in a mock airplane to compare boarding strategies and to confirm that the Steffen method is faster than common strategies. However, they only performed one test per strategy, and the airplane model consisted of no more than 72 seats. Furthermore, it is possible that the limited set of volunteers led to a learning curve effect, which is why the authors admit that their results might be systematically biased.

Gwynne et al. (2018) carried out small-scale tests using a mock airplane and simulating the boarding procedure with 35 test persons. Their focus was on investigating and quantifying individual passenger movement depending on factors such as seat distance or carry-on baggage.

Data on boarding can also be gathered by observing actual flights, but this requires immense effort. Thus, most empirical data found in the literature is restricted to a few flights. For instance, DeVries (2009) presented empirical data on the actual boarding times of ten flights boarding back-to-front but used the data only to highlight the potential for improvement and not for statistical analyses. Moreover, the origin of the data is vague.

One of the most extensive empirical studies so far was conducted by Steiner and Philipp (2009), who analyzed data from eight flights at Zurich Airport to calibrate a discrete event simulation model. Moreover, conclusions regarding the effect of carry-on baggage, seat interferences, and passenger queues on the boarding time were drawn from the small sample. Due to the limited number of observations, the analysis is mainly descriptive in nature and cannot be used for statistically firm results.

Recently, Schultz (2017) presented highly aggregated, non publicly available data, which was collected in collaboration with an airline. The data is used to calibrate a simulation model.

To date, the literature related to the airplane boarding problem has mainly investigated the boarding strategy as an influencing factor on the boarding time. For a review of fundamental literature on the airplane boarding problem and a detailed overview of boarding strategies, the interested reader is referred to Jaehn and Neumann (2015). Some scientific articles mentioning other influencing factors at least in passing are summarized in the following section.

### 1.4.2 Passengers and Capacity

Van Landeghem and Beuselinck (2002) included the occupancy level as an independent variable in their simulation model and concluded that an increase in occupancy level increases the boarding time and slightly reduces boarding velocity (rate of passengers per minute) for most strategies. This result implies a disproportionately, positive effect of the occupancy level on the boarding time.

Ferrari and Nagel (2005) tested the sensitivity of the boarding time to airplane type and occupancy level in their simulation model. Fewer rows with more seats per row was found to increase the boarding time. Moreover, for most strategies, an almost linear correlation was observed between the occupancy level and the boarding time; however, there was a tendency for a disproportionate increase in boarding time. The same result was obtained from the simulation performed by Qiang et al. (2016b). In simulation experiments, Schultz (2010), Fonseca i Casas et al. (2013), and Mas et al. (2013) all observed not only a linear relationship between the occupancy level and the boarding time for random boarding, but also a disproportionate, positive relationship for back-to-front boarding.

Mas et al. (2013) also assessed boarding strategies using different airplane types. The results allow us to conclude that larger aircraft slightly reduce boarding times for a given number of passengers.

In their small empirical observation, Steiner and Philipp (2009) discovered that a queue of passengers forces the passengers in front to hurry, thereby reducing the boarding time.

### 1.4.3 Gate Operations

Although not explicitly included in their simulation study, Van Landeghem and Beuselinck (2002) remarked that gate operations determine the arrival rate of passengers at the airplane door.

From computer simulations of their analytical model, Van den Briel et al. (2005) concluded that using a second gate agent reduces the inter-arrival time of passengers and thus shortens the boarding time. However, if the inter-arrival times drop below a certain level, no further reductions in boarding time are possible. The same result was observed by Schultz et al. (2013), Qiang et al. (2014), Giitsidis and Sirakoulis (2016), and Qiang et al. (2016a), who confirmed that there is a critical value for the inter-arrival time regarding the behavior of the queue length and its effect on the boarding time. Below this critical value, passengers queue outside the airplane, and the boarding time is not greatly affected by changes in the inter-arrival time. Therefore, Qiang et al. (2016a) advised against increasing arrival rates (e. g., by checking tickets faster) to shorten the boarding time, as it will not have the desired effect if the inter-arrival time is already below the critical value (which is rather likely in reality), and passenger comfort will be reduced. By contrast, based on simulation results, Steiner and Philipp (2009) recommended using a pre-boarding area or increasing the number of gate agents to reduce the boarding time.

### 1.4.4 Carry-on Baggage

According to Tang et al. (2012), the size of a passenger's carry-on baggage influences his or her attributes such as speed and safe distance. If a boarding strategy does not consider these individual properties, passengers with more carry-on baggage will block others and increase the boarding time.

Van Landeghem and Beuselinck (2002) included carry-on baggage as an independent variable in their simulation model. Increasing the amount of carry-on baggage from 1.5 to two items per passenger increased the total boarding time of random boarding by only 9 %. However, in the worst case (boarding in half-blocks from the back to the front, skipping one block), the boarding time increased by 28 % due to the additional carry-on baggage.

Canzani and Lechner (2014) analyzed disruptions due to carry-on baggage in a system dynamics model and found that they increased the boarding time by eight to twelve minutes. Disruptions occurring later and in the middle-rear part of the aisle have an especially strong effect on the boarding time.

The amount of carry-on baggage had an exponential influence on the boarding time in the simulation model of Notomista et al. (2016). This effect was confirmed by the simulation results of Milne and Kelly (2014), Qiang et al. (2014), and Qiang et al. (2016b), who all used a bin occupancy model that accounted for the fact that stowing carry-on baggage takes longer as the overhead bins fill up. Steiner and Philipp (2009) also observed that the amount of carry-on baggage exponentially increases the boarding time and provided a log-linear regression for this relation. Yet, their sample only consisted of eight observations, which makes statistical inference problematic.

The work by Nicolae et al. (2016) does not consider boarding directly, but they empirically analyzed the effect of checked baggage fees on flight delays. One might expect that checked baggage fees lead to a higher amount of carry-on baggage. However, the implementation of checked baggage fees led to a reduction in average departure delays.

## 2 Theoretical Development

The research questions of the study at hand are the following: What factors influence the boarding time and how do they influence it? We formulated specific hypotheses to investigate these questions and to determine the relevant factors. We begin by defining the variables used in the study.

### 2.1 Variables

Based on our research questions, the dependent variable is the total boarding time ($bt$). An overview of the independent variables is given in Table 1. The occupancy level of the airplane ($occupancy$) can be calculated by dividing $pax$ by $capacity$. The

Table 1: List of variables.

| | |
|---|---|
| $bt$ | total boarding time (sec) |
| $ln(bt)$ | natural logarithm of total boarding time |
| $pax$ | number of passengers |
| $A319$ | airplane type |
| $A320$ | (one dichotomous variable for each type) |
| $A320neo$ | |
| $A321$ | |
| $capacity$ | total capacity of the airplane in the used configuration |
| $occupancy$ | occupancy level (%) |
| $carry$ | total amount of carry-on baggage |
| $carry\_pp$ | average amount of carry-on baggage per passenger |
| $domestic$ | region of the destination airport |
| $NorthernEurope$ | (one dichotomous variable for each region) |
| $EasternEurope$ | |
| $SouthernEurope$ | |
| $doc\_check$ | passport control (0 - no, 1 - yes) |
| $gate\_agents$ | number of gate agents > 1 (0 - no, 1 - yes) |

dichotomous variable *doc_check* indicates whether there is a passport control in addition to the automated ticket check at the gate, and the dichotomous variable *gate_agents* indicates whether there is more than one gate agent assisting the passengers.

## 2.2 Hypotheses

Our first set of hypotheses (H1A-H6A) considers each independent variable separately as if it was the only factor influencing the boarding time. The effect can also result from other variables that are interrelated with the boarding time and therefore influence it indirectly. The second set (H1B-H6B) considers the direct effect of an independent variable ceteris paribus, hence, the effect of the other independent variables is controlled. Assuming that *carry* is highly correlated with *pax* and that *occupancy* is determined by *pax* and *capacity*, we do not propose any hypotheses with *carry* and *occupancy*, as these variables are unlikely to provide any additional benefit.

As depicted in Section 1.4, there are several opinions and assumptions in the literature concerning the influence of different factors on the boarding time. Based on these reports, we build the following hypotheses.

A positive correlation with the total boarding time is expected for the number of passengers (see Van Landeghem and Beuselinck (2002), Ferrari and Nagel (2005), and Qiang et al. (2016b)).

Hypothesis 1A (H1A): *The more passengers boarding an airplane, the longer the total boarding time.*

As airplanes with higher capacity are usually used on flights with more passengers, following from H1A, we assume that the number of seats in an airplane (capacity) would have a positive effect on the boarding time if capacity was the only influencing factor. However, this effect is indirectly caused by the higher number of passengers.

Hypothesis 2A (H2A): *The larger the total capacity of an airplane, the longer the total boarding time.*

Stowing carry-on baggage items takes time and can produce aisle interferences during boarding. Therefore, a positive correlation with the total boarding time is expected for the average amount of carry-on baggage per passenger (see Van Landeghem and Beuselinck (2002), Steiner and Philipp (2009), Milne and Kelly (2014), and Qiang et al. (2016b)).

Hypothesis 3A (H3A): *The higher the average amount of carry-on baggage per passenger in an airplane, the longer the total boarding time.*

We also conducted interviews with responsible persons at airlines who have observed the boarding process for several years. They reported that the boarding times for flights to Southern Europe appear to be longer than those for flights to other European regions. With this information, and considering that the percentage of passengers who fly on business and are used to the boarding procedure is higher on domestic flights, we assume that there is a positive correlation between boarding time and flights to Southern Europe and a negative correlation between boarding time and domestic flights. Hence, we consider the following hypotheses:

Hypothesis 4.1A (H4.1A): *Flights to Southern Europe have longer boarding times than flights to other regions.*

Hypothesis 4.2A (H4.2A): *Domestic flights have shorter boarding times than flights to other regions.*

We do not consider any hypotheses for the variables $NorthernEurope$ and $Eastern$ $Europe$. In agreement with the results in the literature and with the statements by the responsible persons at the airlines, we anticipate a positive correlation between the variable *doc_check* and the boarding time, as passengers who have to show their passport before they enter the boarding bridge are expected to slow the boarding process (Van Landeghem and Beuselinck, 2002; Qiang et al., 2014). The probability of passport control depends on the region of the destination airport. Domestic flights do not usually require passport control.

Hypothesis 5A (H5A): *Flights with passport control have longer boarding times than flights without passport control.*

Gate agents, who usually help passengers through the ticket check, are expected to accelerate the boarding process (Van den Briel et al., 2005; Steiner and Philipp, 2009). Consequently, we assume a negative correlation between the variable *gate_agents* and boarding time.

Hypothesis 6A (H6A): *Flights with more than one gate agent have shorter boarding times than flights with only one gate agent.*

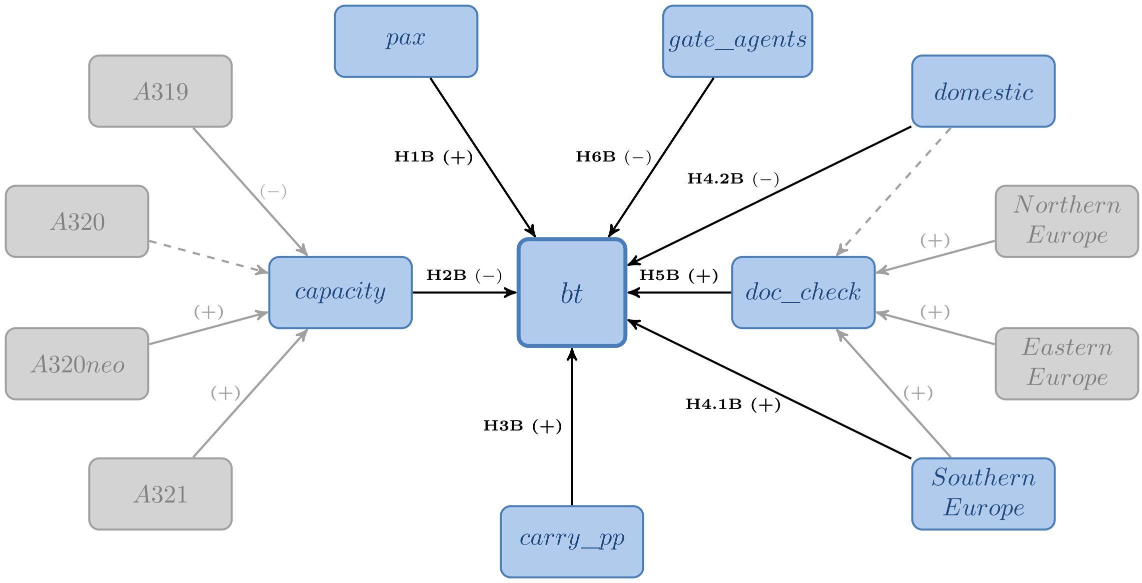


Figure 1: Hypotheses H1B to H6B (influencing factors ceteris paribus).

We now consider the combination of different variables and examine the influence of an independent variable under the assumption that the values of all other variables remain the same, i. e., the other variables are controlled for, and the effect is solely attributed to the relevant variable. The direction of most influences is expected to be the same as when analyzed separately. However, the larger the capacity (ceteris paribus, hence not more passengers), the less time that should be necessary for boarding because more space is available in the aisle, allowing for more parallel stowing of carry-on baggage and leading to less congestion (see Van Landeghem and Beuselinck (2002), Mas et al. (2013), and Qiang et al. (2016b)).

Hypothesis 1B (H1B): *The more passengers boarding an airplane, ceteris paribus, the longer the total boarding time.*

Hypothesis 2B (H2B): *The larger the total capacity of an airplane, ceteris paribus, the shorter the total boarding time.*

Hypothesis 3B (H3B): *The higher the average amount of carry-on baggage per passenger in an airplane, ceteris paribus, the longer the total boarding time.*

Hypothesis 4.1B (H4.1B): *Ceteris paribus, flights to Southern Europe have longer boarding times than flights to other regions.*

Hypothesis 4.2B (H4.2B): *Ceteris paribus, domestic flights have shorter boarding times than flights to other regions.*

Hypothesis 5B (H5B): *Ceteris paribus, flights with passport control have longer boarding times than flights without passport control.*

Hypothesis 6B (H6B): *Ceteris paribus, flights with more than one gate agent have shorter boarding times than flights with only one gate agent.*

An overview of the hypotheses is given in Figure 1. Additional obvious connections are displayed in gray. The dashed arrows indicate the reference category for the categorical variables.

# 3 Research Design

## 3.1 Methods

We conducted a cross-sectional field study by measuring the boarding times of short- and medium-haul flights at a large European international airport. To rule out biases caused by different conditions and regulations, we only observed flights that were performed by a single airline. In addition to measuring boarding times, we documented the total amount of carry-on baggage and received several flight and airplane data sets (number of passengers, capacity of the airplane, important times, etc.) from the airline. Our approach was as follows: After developing the research design, we ran a pretest in which nine flights were observed and data were collected. This pretest led to some adaptations of the data collection process, and the new procedure was rechecked in a second pretest in which four flights were observed. To prevent biases, the results of the pretests were not used in our statistical analysis.

The main test was conducted on two days within two consecutive weeks by four teams of three people each. A briefing of all involved persons occurred some days before to avoid measurement biases. The sample size of the main test was 58 randomly chosen flights. The main challenge in collecting data is that, even for a single flight, extensive effort is required. The actual boarding time, which influences the critical path, cannot be measured automatically; thus, manpower is necessary, which in turn implies bureaucratic hurdles due to security regulations at airports. On average, the manpower required for a single flight is almost an hour; therefore, collecting data on numerous flights implies substantial effort.

## 3.2 Data Collection

For our analyses, we require the following data for each flight: boarding time, number of passengers, capacity of the airplane, total amount of carry-on baggage, destination of the flight, number of gate agents, and information about whether there is a passport control at the gate. Several data sets were obtained from the airline's system (general data such as destination, planned departure time, airplane model, the number of regular and priority passengers who boarded the airplane, the capacity in the used configuration, the maximum capacity, the time at which the first passenger passed the ticket check, the time at which the airplane door was closed, the time at which the airplane was off blocks, and the time at which the airplane was airborne). Because airlines do not necessarily define the boarding time in the same way that we do (see Section 1.3), these data do not contain all the points in time that we are interested in. The most important time points, i.e., the time at which the first passenger enters the airplane and the time at which the last passenger is seated, had to be measured. We also noted the number of gate agents and whether there was additional passport control after the ticket check. We collected the data directly at the gate with three people observing each flight. All three observers stood in the boarding bridge near the airplane door. Two observers were responsible for measuring the boarding time, and the other observer was responsible for documenting the total amount of carry-on baggage, neither of which was measured by the airline. Observers 1 and 2 recorded the following time points: first priority passenger enters the airplane, first regular passenger enters the airplane, last passenger enters the airplane, last passenger leaves the door area, last passenger is seated in his or her assigned seat, late passenger enters the airplane (when applicable), and door is closed. Observer 3 counted the number of carry-on baggage items of the passengers who entered the airplane. Data collection was completed by recording the time at which the airplane door was closed.

# 4 Empirical Analysis

The results of our descriptive and predictive analyses are presented in the following section. A detailed interpretation and evaluation of the results is given in Section 4.3.

## 4.1 Descriptive Statistics

As mentioned above, we measured the boarding times of 58 short- and medium-haul flights. Four different airplane models operated these flights. More than one third of the flights were operated with an Airbus A319, another third with an A320, and the remaining flights with an Airbus A320neo or A321. The maximum capacities (if no additional regular seats were used for business passengers) ranged from 138 (for the A319) to 200 passengers (A321). The capacities in the actually used configurations ranged from 126 to 200 passengers, with a mean of 157. The destinations were classified into four regions. More than half of the flights were domestic, eleven flights went to Northern Europe, eight flights went to Eastern Europe, and nine flights went to Southern Europe.

### 4.1.1 Boarding Times

The most interesting observations, the boarding times, ranged from approximately 6 minutes to almost 30 minutes, with a mean of 15 minutes. For the flights operated with an Airbus A319, the mean boarding time was 13.5 minutes, whereas for flights

Table 2: Descriptive statistics.

| variable | mean | std. dev. | median | minimum | maximum |
|---|---|---|---|---|---|
| *bt* (sec) | 902.45 | 303.67 | 852.00 | 384.00 | 1,772.00 |
| *pax* | 113.34 | 37.44 | 112.00 | 37.00 | 196.00 |
| *occupancy* | 72.24 | 20.07 | 75.96 | 28.21 | 103.03[a] |
| *carry* | 84.12 | 32.70 | 78.00 | 39.00 | 184.00 |
| *carry_pp* | 0.75 | 0.16 | 0.79 | 0.41 | 1.14 |

[a]An occupancy of over 100 % is possible, e. g., if employees of the airline are on the flight as passengers and sit on a jumpseat.

operated with an A321, the mean time was more than 17 minutes. The shortest boarding time and shortest mean (less than 14 minutes) were observed for domestic flights, and the longest boarding time and the longest mean (more than 18.5 minutes) were observed for flights to Eastern Europe. The mean boarding times for destinations in Northern and Southern Europe were 14 and 17 minutes, respectively.

### 4.1.2 Number of Passengers

The total number of boarded passengers ranged from 37 to 196, with a mean of 113, and was distributed nearly symmetrically. The minimum and maximum numbers of passengers occurred on domestic flights, where the mean was 102 passengers. The highest average number of passengers (137) was on flights to destinations in Southern Europe. There were 110 passengers on average on flights to Northern Europe and 135 on flights to Eastern Europe. On flights with an Airbus A319, the mean number of passengers was 93; on flights with an A320 or A320neo, it was 116; and on flights with an A321, it was 147.

### 4.1.3 Occupancy Level

Half of the measured flights had an occupancy level under 76 %, and the mean was 72.24 %. Similar to the number of passengers, there was a wide range, from only 28 % occupied seats in the airplane to full occupancy. With a mean of 86.75 %, flights to

Eastern Europe had the highest average occupancy level, and domestic flights had the lowest average occupancy level of 66.36 %. The mean occupancy levels of the different airplane models were nearly equivalent.

### 4.1.4 Carry-on Baggage

The total amount of carry-on baggage ranged between 39 and 184 items. As the mean was 84.12 and the median was 78.00, the distribution was right-skewed, which means that the data were more concentrated in the lower range. The average amount of carry-on baggage per passenger ranged from 0.41 to 1.14 items and was distributed nearly symmetrically, with a mean of 0.75 items per passenger. The highest mean of the average amount of carry-on baggage per passenger was observed on flights with an A319 and to domestic destinations (both 0.78), whereas the lowest mean (0.68) appeared on flights to Southern Europe.

### 4.1.5 Gate Operations

As there is an automated ticket check at the gates (the passengers have to scan their boarding passes to walk through the gate), most of the flights (41 out of 58) were operated with only one gate agent who belongs to the ground crew of the airline. For 15 flights, two gate agents were standing at the gate, and in two cases, three gate agents were present. A separate passport control (*doc_check*) was conducted on twelve flights, which means additional staff controlled the passports after the passengers had passed the ticket check.

### 4.1.6 Correlations

Table 3 shows the correlations between the different variables. For now, we focus on the correlations between independent variables. The highest correlation is between *occupancy* and *pax*. Moreover, there is a high correlation of *carry* with *pax* and *occupancy*. All these correlations are highly significant. The variable *carry_pp* is negatively correlated with *pax* (−0.21) and *occupancy* (−0.29). The variable *doc_check* is hardly correlated with any variable other than *domestic*, with which a highly significant negative correlation exists. The variable *gate_agents* is moderately correlated with *pax*, *occupancy* and *carry*.

Table 3: Correlation matrix.

| | *bt* | *ln(bt)* | *pax* | *capacity* | *occupancy* | *carry* | *carry_pp* | *domestic* | *SouthernEurope* | *EasternEurope* | *doc_check* | *gate_agents* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *bt* | 1 | | | | | | | | | | | |
| *ln(bt)* | 0.98***[a] | 1 | | | | | | | | | | |
| *pax* | 0.84*** | 0.87*** | 1 | | | | | | | | | |
| *capacity* | 0.29* | 0.30* | 0.56*** | 1 | | | | | | | | |
| *occupancy* | 0.84*** | 0.88*** | 0.88*** | 0.12 | 1 | | | | | | | |
| *carry* | 0.80*** | 0.77*** | 0.83*** | 0.48*** | 0.71*** | 1 | | | | | | |
| *carry_pp* | −0.07 | −0.18 | −0.21 | −0.09 | −0.26 | 0.33* | 1 | | | | | |
| *domestic* | −0.24 | −0.25 | −0.32* | −0.17 | −0.30* | −0.19 | 0.17 | 1 | | | | |
| *SouthernEurope* | 0.16 | 0.18 | 0.27* | 0.30* | 0.18 | 0.12 | −0.19 | −0.44*** | 1 | | | |
| *EasternEurope* | 0.28* | 0.27* | 0.23 | −0.04 | 0.29* | 0.20 | −0.07 | −0.41** | −0.17 | 1 | | |
| *doc_check* | 0.15 | 0.14 | 0.12 | 0.07 | 0.09 | 0.14 | 0.05 | −0.53*** | 0.02 | 0.29* | 1 | |
| *gate_agents* | 0.33* | 0.32* | 0.33* | 0.02 | 0.38** | 0.32* | 0.02 | −0.21 | 0.25 | 0.07 | 0.05 | 1 |

[a]The correlation is significant (2-tailed) at a level of 0.001 (***), 0.01 (**), 0.05 (*).

## 4.2 Predictive Analytics

Log-linear models are considered in the following ordinary least squares (OLS) regression analyses. The natural logarithm of the dependent variable is taken, as we assume the relationship between the boarding time and possible influencing factors to be best expressed in terms of percentages. The scatterplots of *pax* and *occupancy* in Figure 2 also suggest that their influence on *bt* might be nonlinear. For instance, the first passenger is likely to cause a smaller absolute increase in *bt* than the hundredth. This transformation is confirmed by the maximum likelihood approach of Box and Cox (1964), with an estimated power $\lambda = 0.1082$, which suggests to replace the variable *bt* with its natural logarithm. Table 3 shows that correlations with $ln(bt)$ are slightly stronger than those with *bt* on average.

In addition, the sampling distribution of $ln(bt)$ is symmetric (median = mean =

6.75) and approximately normal (p-value of Shapiro-Wilk test = 0.9445, p-value of Kolmogorov-Smirnov test = 0.9991, p-value of Jarque-Bera test = 0.8659), which is desirable for statistical inference. By contrast, *bt* was not normally distributed in the sample (p-value of Shapiro-Wilk test = 0.0271, p-value of Kolmogorov-Smirnov test = 0.8823, p-value of Jarque-Bera test = 0.0337).
Moreover, the approach of using the logarithm of the boarding time as the dependent variable has been established in related literature. Horstmeier and de Haan (2001) also assume a log-normal distribution of boarding times. Similarly, Steiner and Philipp (2009) regress the natural logarithm of the 'cabin time' of a passenger on his or her amount of carry-on baggage and whether there are seat interferences or passengers waiting to pass.
The approach of Box and Tidwell (1962) does not lead to any reasonable power transformations of the independent variables, which is why they are all included in the regression analyses without any changes.

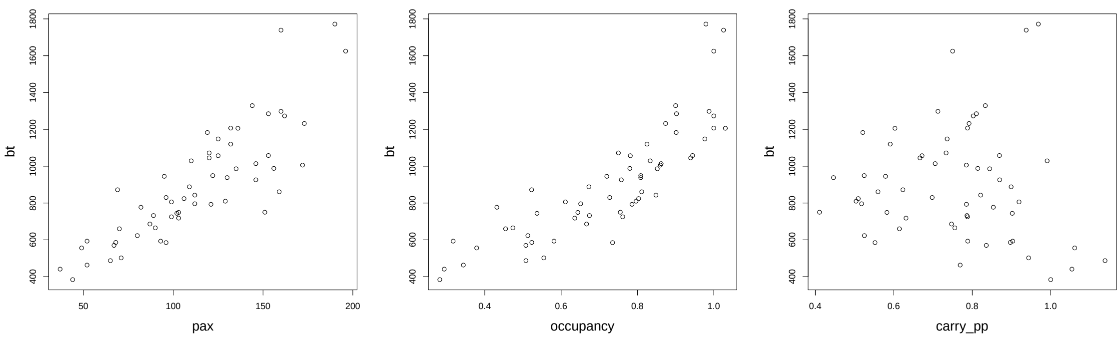


Figure 2: Scatterplots of different variables and *bt*.

#### 4.2.1 Hypothesis Testing

Initially, the effect of each possible influencing factor on the boarding time is considered separately (H1A to H6A). A regression of $ln(bt)$ on each single independent variable is considered to assess the effect and test the significance of each predictor variable. Table 4 shows the results of the single regressions.

Table 4: Tests of H1A to H6A (separate influencing factors): linear regression models of ln(bt) on single predictor variables.

| hypothesis | independent variable | parameter estimate | unadjusted p-value | Holm-Bonferroni adjusted p-value | model RMSE (in sec) | model $\bar{R}^2$ |
|---|---|---|---|---|---|---|
| H1A | intercept | 5.8668 | | | 134.43 | 0.7767 |
| | *pax* | 0.0078 | 0.0000 | 0.0000 | | |
| H2A | intercept | 6.0721 | | | 287.05 | 0.2692 |
| | *capacity* | 0.0043 | 0.0215 | 0.2370 | | |
| H3A | intercept | 7.0212 | | | 300.41 | 0.2271 |
| | *carry_pp* | −0.3604 | 0.1846 | 1.0000 | | |
| H4.1A | intercept | 6.7243 | | | 295.78 | 0.1950 |
| | *SouthernEurope* | 0.1627 | 0.1873 | 1.0000 | | |
| H4.2A | intercept | 6.8353 | | | 294.28 | 0.2594 |
| | *domestic* | −0.1658 | 0.0617 | 0.6173 | | |
| H5A | intercept | 6.7264 | | | 298.68 | 0.1494 |
| | *doc_check* | 0.1121 | 0.3113 | 1.0000 | | |
| H6A | intercept | 6.6803 | | | 280.65 | 0.3687 |
| | *gate_agents* | 0.2364 | 0.0141 | 0.1692 | | |

To maintain the family-wise error rate (FWER) at a 5 % significance level, the Holm-Bonferroni correction, a rather conservative stepwise rejective FWER-controlling multiple test procedure, is applied to adjust the p-values in Table 4 (Holm, 1979).

According to the adjusted p-values of the t-tests of whether the corresponding parameter estimates differ significantly from 0, Hypothesis 1A can be confirmed at the 0.05 significance level. An additional passenger increases the boarding time by $(e^{0.0078} - 1) \cdot 100\,\% \approx 0.78\,\%$. As indicated by the adjusted coefficient of determination ($\bar{R}^2$), the number of passengers alone explains almost 80 % of the variance in *bt*.[1]

After the conservative Holm-Bonferroni adjustment of the p-value, H2A cannot be confirmed as $0.2370 > 0.05$. However, in the sample, the capacity had a positive influence on *bt*, as expected.

[1] Root-mean-square error (RMSE) and $\bar{R}^2$ have been adjusted to determine how well the model with $ln(bt)$ as the dependent variable explains *bt* (Wooldridge, 2013, p. 204 ff.). Moreover, they are cross-validated via ten-fold cross-validation with the seed set to 1.

Hypothesis 3A also cannot be confirmed. In accordance with the negative correlation in Table 3, more carry-on baggage per passenger was even associated with shorter boarding time in the sample.

H4.1A and H4.2A cannot be confirmed for the population, but the tendencies in the sample meet our expectations: on average, flights to Southern Europe tend to have longer boarding times than flights to other regions, whereas the opposite is true for domestic flights.

Hypothesis 5A cannot be confirmed, but the effect in the sample is as anticipated since boarding took longer if passport control occurred.

As $0.1692 > 0.05$, the number of gate agents does not have a significant effect on *bt* after the Holm-Bonferroni adjustment of the p-value. However, Hypothesis 6A would still not be confirmed without this conservative adjustment because the direction of the effect is counterintuitive: the total boarding time with more than one gate agent is *longer* than that with only one gate agent.

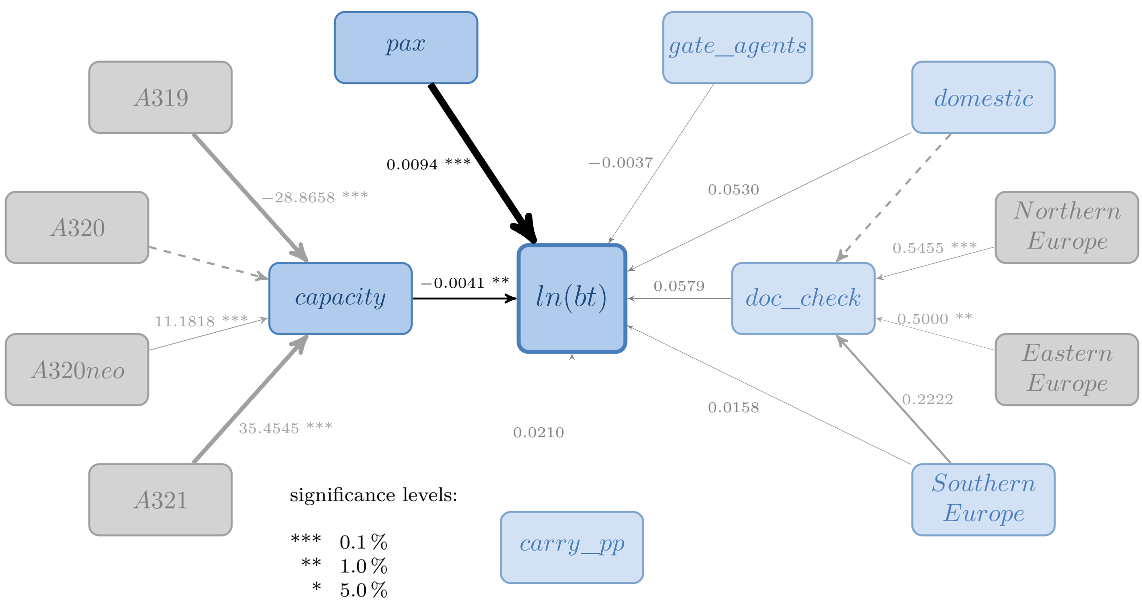


Figure 3: Tests of H1B to H6B (influencing factors, ceteris paribus) in a structural equation model.

Next, the joint effects of the predictor variables on *bt* are tested. The structural equation model (SEM) in Figure 3 shows the results. Again, the Holm-Bonferroni test is used to adjust the p-values and control the FWER. A faded independent variable indicates that the associated hypothesis cannot be confirmed. The arrow's thickness represents the relative importance of the corresponding independent variable in predicting the outcome and is based on the standardized regression coefficients.

Hypothesis 1B is confirmed because the positive effect of *pax* on *bt* is highly significant. One additional passenger, ceteris paribus, increases the boarding time by $(e^{0.0094} - 1) \cdot 100\,\% \approx 0.94\,\%$.

In contrast to H2A, Hypothesis 2B is confirmed. The higher the total capacity of an airplane, ceteris paribus, the shorter the total boarding time. If the values of all other predictor variables remain unchanged, an additional seat in an airplane changes the boarding time by $(e^{-0.0041} - 1) \cdot 100\,\% \approx -0.41\,\%$. We additionally tested how the capacity of the airplane is determined by the airplane type. On average, there are approximately 29 fewer usable seats in an Airbus A319 than in an Airbus A320. By contrast, Airbus A320neo and A321 are configured to have approximately 11 and 35 seats more, respectively, than an Airbus A320.

Hypothesis 3B cannot be confirmed. The average amount of carry-on baggage per passenger is not found to effect the total boarding time.

H4.1B and H4.2B also cannot be confirmed. The boarding times of domestic flights and flights to Southern Europe do not differ significantly from the boarding times of flights with destinations in other regions if all other factors are equal. In the sample, the boarding time of flights to Southern Europe was slightly longer than that of flights to other regions on average, which is in accordance with our expectations. However, against our expectations, domestic flights also had longer boarding times than flights to other regions in the sample if all other factors were kept constant.

Hypothesis 5B cannot be confirmed. In the sample, flights with passport control had slightly longer boarding times than flights without passport control, but this effect is not significant in the population. We further tested the relationship between the region of the destination airport and the probability of passport control. Apart from exceptional cases, there is no passport control on domestic flights. The probability of passport control increases to 50 % if the destination is in Eastern Europe and to approximately 55 % if the destination is in Northern Europe. On flights to Southern Europe, the probability does not significantly differ from that of domestic flights.

Hypothesis 6B cannot be confirmed. In contrast to H6A, the positive effect of *gate_agents* on *bt* is not significant.

### 4.2.2 Stepwise Regression

Finally, we derive a parsimonious linear regression model to predict boarding times. Backward stepwise regression is used for variable selection. Variance inflation factors for all predictor variables in the initial model are small enough to exclude multicollinearity and hence omitted correlated variable bias when dropping variables. The result is presented in Table 5. In each step, the variable leading to the lowest Akaike Information Criterion (AIC) is dropped because the least information is lost by removing it. $\bar{R}^2$ and RMSE are cross-validated (ten-fold cross-validation with set.seed(1)). For clarity and comprehensibility, both values are for *bt* rather than $ln(bt)$ (Wooldridge, 2013, p. 204 ff.); therefore, the RMSE is given in seconds.

The stepwise regression leads to the final model, which is summarized in Table 6. The final model contains only the two significant predictor variables of the SEM in Figure 3: *pax* and *capacity*. This result is surprising, as it shows that the boarding time can be predicted fairly accurately based on only these two variables. The other variables do not improve the estimate of the boarding time. Consequently, the boarding time can be predicted as $bt = 1.0146 \cdot e^{6.3327+0.0090 \cdot pax - 0.0040 \cdot capacity}$, where 1.0146 is a consistent estimator correcting for transformation bias, i. e., for the fact that simply exponentiating the predicted value of $ln(bt)$ systematically underestimates the expected value of *bt*. It is the coefficient obtained by simple regression through the origin of the observed values for *bt* on the exponentiated values predicted for $ln(bt)$ by the model (Wooldridge, 2013, p. 205).

Table 5: Backward stepwise regression of ln(bt).

| independent variables in current model | model fit if variable is dropped: AIC | RMSE | $\bar{R}^2$ | current model fit | |
|---|---|---|---|---|---|
| *gate_agents* | −209.75 | 124.67 | 0.8372 | | |
| *carry_pp* | −209.73 | 124.53 | 0.8367 | | |
| *SouthernEurope* | −209.70 | 126.60 | 0.8240 | AIC = | −207.76 |
| *domestic* | −208.81 | 130.64 | 0.8191 | RMSE = | 130.49 |
| *doc_check* | −208.79 | 130.44 | 0.8122 | $\bar{R}^2$ = | 0.8150 |
| *capacity* | −196.23 | 150.44 | 0.7123 | | |
| *pax* | −128.02 | 294.40 | 0.2423 | | |
| *carry_pp* | −211.72 | 119.56 | 0.8537 | | |
| *SouthernEurope* | −211.70 | 121.76 | 0.8444 | AIC = | −209.75 |
| *domestic* | −210.79 | 125.54 | 0.8381 | RMSE = | 124.67 |
| *doc_check* | −210.77 | 124.92 | 0.8334 | $\bar{R}^2$ = | 0.8372 |
| *capacity* | −197.55 | 150.11 | 0.7252 | | |
| *pax* | −123.84 | 313.52 | 0.0995 | | |
| *SouthernEurope* | −213.68 | 116.82 | 0.8602 | | |
| *domestic* | −212.72 | 120.85 | 0.8532 | AIC = | −211.72 |
| *doc_check* | −212.69 | 120.07 | 0.8478 | RMSE = | 119.56 |
| *capacity* | −199.55 | 143.51 | 0.7479 | $\bar{R}^2$ = | 0.8537 |
| *pax* | −124.79 | 300.24 | 0.1385 | | |
| *doc_check* | −214.69 | 116.48 | 0.8552 | AIC = | −213.68 |
| *domestic* | −214.63 | 117.75 | 0.8596 | RMSE = | 116.82 |
| *capacity* | −201.19 | 139.69 | 0.7638 | $\bar{R}^2$= | 0.8602 |
| *pax* | −126.79 | 293.80 | 0.1568 | | |
| *domestic* | −216.34 | 115.82 | 0.8592 | AIC = | −214.69 |
| *capacity* | −202.51 | 136.09 | 0.7677 | RMSE = | 116.48 |
| *pax* | −128.78 | 289.08 | 0.1739 | $\bar{R}^2$= | 0.8552 |
| | | | | AIC = | −216.34 |
| *capacity* | −204.28 | 134.43 | 0.7767 | RMSE = | 115.82 |
| *pax* | −128.19 | 287.05 | 0.2692 | $\bar{R}^2$= | 0.8592 |

### 4.2.3 Goodness of Fit

The regression model in Table 6 explains 85.92 % of the variance in the boarding time. The cross-validated RMSE of 115.82 seconds indicates that the average difference between the boarding time predicted by the model and the observed value is approximately 1.9 minutes.

Table 6: Final regression model of ln(bt).

| independent variable | parameter estimate | unadjusted p-value | Holm-Bonferroni adjusted p-value | model RMSE (in sec) | $\bar{R}^2$ |
|---|---|---|---|---|---|
| intercept | 6.3327 | | | | |
| *pax* | 0.0090 | 0.0000 | 0.0000 | 115.82 | 0.8592 |
| *capacity* | −0.0040 | 0.0003 | 0.0042 | | |

The partial residual plots in Figure 4 suggest that the assumption of a linear relationship between the logarithmized boarding time and the predictor variables is valid.

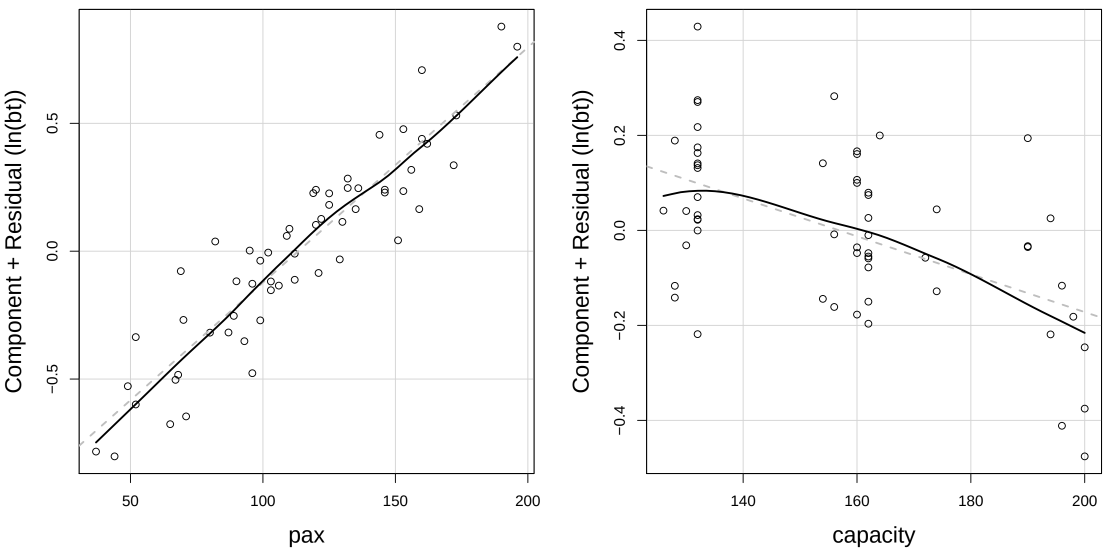


Figure 4: Partial residual plots for the final regression model of $ln(bt)$ on *pax* and *capacity*.

In the quantile-comparison plot on the left of Figure 5, the studentized residuals are plotted against a t-distribution with 55 degrees of freedom. With some exceptions, the points fall close to the straight 45-degree line and are all within the 95 % confidence envelope, suggesting that the normality assumption of the dependent variable, and consequently the residual values, is satisfied. Additionally, the Shapiro-Wilk (p-value = 0.8299), Kolmogorov-Smirnov (p-value = 0.9396), and Jarque-Bera (p-value = 0.9103) tests of normality of the residuals confirm this conclusion. The spread-level

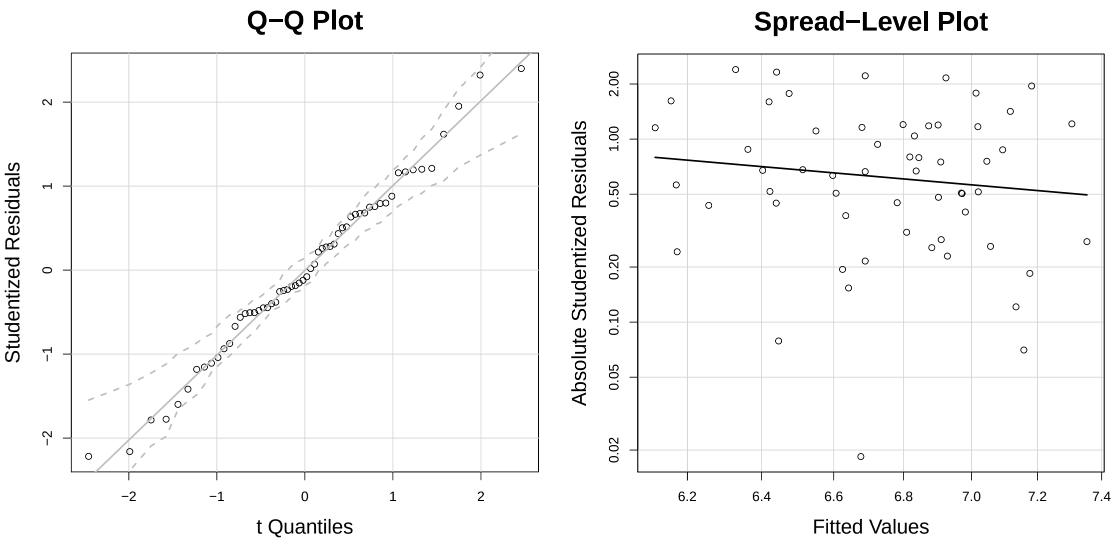


Figure 5: Diagnostic plots for the final regression model of $ln(bt)$ on *pax* and *capacity*.

plot on the right side of Figure 5 shows no evidence of heteroscedasticity, as the error variance is constant around an almost horizontal line of best fit. This result is confirmed by the Goldfeld-Quandt (p-value = 0.2709) and studentized Breusch-Pagan (p-value = 0.4368) tests of homoscedasticity.

As in the initial model, for the two predictor variables *pax* and *capacity*, variance inflation factors of 1.47 and 1.21, respectively, indicate that multicollinearity is not a problem in the final regression model.

## 4.3 Interpretation

In Section 4.1 and Section 3.2, we presented our data and conducted various analyses. In the following, we evaluate and discuss the results. Several findings support our assumptions and are perspicuous, but there are also some rather surprising results.

### 4.3.1 Number of Passengers

A correlation greater than 80 % was measured between *pax* and *bt*. This positive relation was expected, but its strength is worth noting. The first hypothesis test (H1A) matches this result: *pax* significantly influences *bt* and alone explains 77.67 % of the variance in *bt*. This result is impressive, as it indicates that it is possible to make relatively accurate boarding time predictions based on only the number of passengers in the airplane.

### 4.3.2 Capacity

The quality of the prediction improves if the total capacity of the airplane is also considered. Although H2A could not be confirmed after controlling the FWER with the Holm-Bonferroni correction, the influence of *capacity* on *bt* was positive in the sample when the variable was observed separately. The different directions of the effects of *capacity* on *bt* in the A and B hypotheses (positive in H2A and negative in H2B) can be explained by the correlation of *capacity* with *pax* ($0.56^{***}$). The higher the capacity of an airplane, the more passengers there are on the flight, and because the positive effect of *pax* on *bt* is stronger than the direct negative effect of *capacity* on *bt*, there is a positive effect of *capacity* on *bt* when the variable is observed separately in H2A. When considering the other variables, *capacity* has a negative influence on *bt*, as assumed in H2B. The more seats on an airplane, the lower *bt* for fixed values of all other variables, especially the number of passengers. Hypothesis H2B could be confirmed, as the influence is significant in the SEM. This result is in accordance with the result of the stepwise regression leading to the final regression model consisting of *pax* and *capacity*, which explains nearly 86 % of the variance in *bt*.

### 4.3.3 Occupancy Level

As mentioned in the descriptive section, the lowest mean *occupancy* appeared on domestic flights, which can be explained by the frequency of flights to certain destinations. Some routes are offered several times a day, resulting in lower occupancy levels on particular flights. The variable *occupancy* also appears to be a good indicator for *bt*, as the two are highly correlated. However, to mitigate multicollinearity, we neglected this variable and only considered *pax* and *capacity*, which incorporate this effect, in our analyses.

### 4.3.4 Total Amount of Carry-on Baggage

The variable *carry* is highly correlated with *bt*. However, *carry_pp* is barely or even slightly negatively correlated with *bt*, which is shown in the scatterplot in Figure 2. Therefore, the high correlation of *carry* and *bt* can be attributed to the variable *pax*, with which *carry* is highly correlated. Like *occupancy*, *carry* was not analyzed further, as its influence is assumed to be covered by the variables *carry_pp* and *pax*.

### 4.3.5 Average Amount of Carry-on Baggage per Passenger

The negative correlation of *carry_pp* and *bt* is surprising; the opposite effect was assumed (see Hypothesis 3A). It was expected that high *carry_pp* would lead to long *bt* due to the time required by passengers to stow their baggage and the consequential aisle interferences. However, as high values of *carry_pp* were often observed on flights with small *pax*, which significantly reduces the boarding time according to H1B, this negative effect on *bt* in the sample might actually be caused by the low values of *pax*. Moreover, high values of *carry_pp* often occurred on flights to domestic destinations, which reduced boarding times in the sample. On these flights, the ratio of passengers who fly on business and do not have checked baggage but do have more carry-on baggage is assumed to be high. These passengers are familiar with the boarding procedure and are usually in good physical condition, enabling them to board fast. As these factors could lead to this opposing effect, it seems comprehensible that H3A could not be confirmed. Even in the SEM, where the separate influence of *carry_pp* on *bt* (H3B) was tested, no significant results were observed. *Carry_pp*, which also represents *carry* controlled for the influence of *pax*, consequently does not have as strong of an influence on *bt* as assumed in most of the related literature. However, we assumed that *carry_pp* has a stronger impact on *bt* when *occupancy* is higher. Consequently, we tested the influence of *carry_pp* on *bt* for flights with occupancy levels of at least 94 %. The positive influence on *bt* was significant for these flights, but as the analysis relies on only nine flights, it can only suggest a tendency. The lowest mean *carry_pp* was observed on flights to destinations in Southern Europe, where the highest *pax* occurred in the sample and for which the percentage of passengers flying on business is assumed to be low. These characteristics are also a possible explanation for the negative correlations of *carry_pp* with *pax* and *occupancy*: domestic flights, for which *carry_pp* was high, had low values of *pax* and *occupancy* in the sample. By contrast, on flights to Southern Europe, which featured low *carry_pp*, high values of *pax* and *occupancy* were observed.

### 4.3.6 Destination

Hypotheses 4.1 and 4.2 could not be confirmed, but the directions of the influence of the two variables are in accordance with the hypotheses: flights to Southern Europe in the sample tended to have longer boarding times, and domestic flights tended to have shorter boarding times. As mentioned in Section 4.1, flights to destinations in Southern Europe had the highest *pax*. By contrast, domestic flights tended to have lower *pax* than flights to other destinations, which might at least partly explain the effect of the destination on *bt* in the sample. Nevertheless, the analysis of the influence of the single variables, such as *domestic*, on *bt* without considering the other variables is justified because the insight that certain flights, e. g., flights to domestic destinations, tend to have shorter boarding times is valuable irrespective of the source of the effect. However, neither the influence in the separate considerations

(H4.1A and H4.2A) nor the effect in the SEM (H4.1B and H4.2B) is significant. Contrary to our expectations, flights to Eastern Europe, not flights to Southern Europe, had the longest average boarding time in the sample. The most likely reason for this result is that the occupancy level of flights to Eastern Europe (87 %), not of flights to Southern Europe (81 %), had the highest mean in the sample. *Occupancy* was significantly higher for flights to Eastern Europe than for flights to Northern Europe (71 %) or domestic destinations (66 %).

### 4.3.7 Gate Operations

Although the effect of *doc_check* on *bt* was slightly positive in the sample, H5A and H5B could not be confirmed. However, the relationship might partly explain why domestic flights, which usually do not require *doc_check*, had shorter *bt* in the sample (H4.2A).

Another surprising result is the effect of *gate_agents* on *bt*. We could not confirm H6A; moreover, contrary to our expectations, the effect in the sample was positive. Employing two or three gate agents instead of one increases *bt* by $(e^{0.2364} - 1) \cdot 100\,\% \approx 26.67\,\%$. This relationship might be due to the fact that more gate agents are employed on flights with more passengers. Similar to the seemingly negative effect of *carry_pp* on *bt* in the sample, the positive effect of *gate_agents* could actually be caused by *pax*. In the joint model, this effect is not significant, even before the Holm-Bonferroni adjustment, but it was negative in the sample, which supports the assumption that the tendency toward a positive effect on *bt* in the separate consideration of *gate_agents* can be derived from *pax*. In Section 1.4, we showed that gate agents can reduce the inter-arrival times of passengers and hence also the boarding time; however, if the inter-arrival time drops below a critical value, it no longer influences the boarding time. Few flights in our sample had passenger inter-arrival times at the airplane door that were sufficiently long to allow them to directly enter the airplane. The passengers were usually forced to queue in front of the door. Consequently, the critical value apparently was already exceeded, and thus, employing more gate agents could not reduce the boarding time, in accordance with the results of our analyses.

### 4.4 Validation Against Other Models

#### 4.4.1 Simulation Models

In this section, we compare the results of various simulation studies that use random boarding to the boarding times predicted by our final regression model for the corresponding values of *pax* and *capacity* (Table 6). Note that in our sample, the mean value of *carry_pp* was 0.75, which is in accordance with the empirical results of Steiner and Philipp (2009), whereas most authors conducting simulations assume *carry_pp* to be at least 1, often referring to Van Landeghem and Beuselinck (2002).

Boeing developed a computer simulation model to compare boarding times for different airplane configurations (Marelli et al., 1998). For a Boeing 757-200 with 201 passengers and a Boeing 757-300 with 240 passengers, this model predicts that boarding will take 22 and 26 minutes, respectively. These results for 'traditional methods', which were not specified more precisely, were confirmed by previous observations. Assuming that the airplanes were configured for the maximum number of seats (239 and 295, respectively), our final model predicts boarding times of 23.3 and 26.7 minutes, respectively, which corresponds to an RMSE of one minute.

Van Landeghem and Beuselinck (2002) ran simulations for an airplane with 132 seats, occupancy levels of 100 % and 62.5 %, and 1.5 carry-on baggage items per passenger. On average, the simulation results are underestimated by our predicted values by approximately 4.2 minutes, which can be at least partly attributed to the high value of *carry_pp* and its strong effect on the boarding time assumed in the simulation.

Ferrari and Nagel (2005) conducted simulations with the same assumptions as Van Landeghem and Beuselinck (2002), but they included robustness tests with additional occupancy levels. The boarding times of their simulation model are overestimated by our final model for low occupancy levels and underestimated for high occupancy levels, which might again be due to the effect of carry-on baggage assumed in the simulation, leading to an RMSE of approximately 3.2 minutes.

Schultz (2010), who also assumed 1.5 carry-on baggage items per passenger, ran simulations for different occupancy levels of an airplane with 174 seats. On average, the values predicted by our final model differ from the simulated boarding times by approximately 1.2 minutes.

Milne and Kelly (2014) considered different values of *carry_pp* in their simulation model. For an average of 0.8 carry-on baggage items per passenger, which is consistent with our *carry_pp* mean of 0.75, random boarding takes 17.9 minutes in the simulation model, which is only approximately six seconds more than predicted by our final model for the values of *pax* and *capacity* used by Milne and Kelly (2014).

In the simulation model of Qiang et al. (2014), random boarding takes substantially longer than predicted by our final model for a fully loaded airplane with 150 seats. Again, this difference may be due to the fact that even under normal conditions, Qiang et al. (2014) assume 1.5 carry-on baggage items per passenger, which increases the boarding time in the simulation and leads to an estimation error of almost 10 minutes. Qiang et al. (2016b) ran similar simulations but reduced the value of *carry_pp* to one item. The simulated boarding time is still underestimated by our final model, but the RMSE decreases to 6.5 minutes.

Kierzkowski (2016), who used empirically determined parameters in his simulation model, reported a median boarding time of 20 minutes for random boarding. Our final model overestimates this value by approximately 4.3 minutes, which is still within the range of Kierzkowski's (2016) results for single simulation runs.

Overall, applying our model to the input data used in different simulation studies and comparing the relevant results indicate only minor deviations in most cases. However, if carry-on baggage is assumed to have a strong effect on the boarding time in a simulation model, the boarding times are generally higher than those predicted by our model, which was derived from observations of actual flights. This suggests that explicitly including carry-on baggage as an influencing factor in simulation models is not necessary and might result in overestimated boarding times.

### 4.4.2 Analytical Model

Bachmat et al. (2006) and Bachmat et al. (2009) propose the following formula for boarding times with random boarding: $B(k) = 2\sqrt{k} + \frac{2(1-ln(2))}{\sqrt{k}}$. $k$, which is a central parameter in their work, is a measure of congestion in an airplane. It is the ratio of the total queue length of passengers to the aisle length of the airplane. According to the authors, a reasonable value for $k$ is 4. As they assume an occupancy level of 100 %, $k$ must be replaced by $k \cdot occupancy$ if the airplane is not fully loaded. $B(k) \cdot \sqrt{capacity}$ is an asymptotic estimate of *bt* (Bachmat et al., 2009, p. 508), and similar to $k$ above, *capacity* must be multiplied by *occupancy* for occupancy levels other than 100 %. These adjustments result in $bt_{Bachmat} = \left(2\sqrt{4 \cdot occupancy} + \frac{2(1-ln(2))}{\sqrt{4 \cdot occupancy}}\right) \cdot \sqrt{capacity \cdot occupancy}$, which can be reduced to $bt_{Bachmat} = (4 \cdot occupancy + 1 - ln(2)) \cdot \sqrt{capacity}$. Bachmat et al. (2006) and Bachmat et al. (2009) used a completely different approach, and thus, their values do not match our predictions in absolute value and have to be adjusted to compare the relative deviation. A regression of our predicted values on the times predicted by the authors' analytical model shows that without an intercept, which corresponds to regression through the origin, the values predicted by our model are on average 22.71 times larger than the values predicted by the analytical model. After multiplying $bt_{Bachmat}$ by this factor, we obtain an RMSE of less than one minute, which indicates that their predictions fit ours relatively well.

Regressing the boarding times measured in our empirical study on the boarding times estimated by the analytical model results in $bt = -78.89 + 24.52 \cdot bt_{Bachmat}$. This model explains 84.93 % of the variance in *bt* (ten-fold cross-validation with set.seed(1)), which is slightly less than the variance explained by our simpler model (Table 6). Moreover, the cross-validated RMSE is 150.03 seconds, which means that the values predicted by the adjusted analytical model are on average approximately half a minute farther from the actual boarding times than those predicted by our model in Table 6.

### 4.4.3 Other Empirical Data

The empirical data published by other authors can also be used for out-of-sample testing of our final regression model.

Steiner and Philipp (2009) provided data on the number of passengers, airplane type, airplane capacity, destination airport, and the boarding time for eight flights observed at Zurich Airport. Applying our final regression model in Table 6 to these observations to predict boarding times produces an RMSE of approximately 2.4 minutes, which is not much worse than the original RMSE of our final model (1.9 minutes). Thus, our final model tests fairly well out of sample and does not overfit the collected data.

Using the data provided by Steiner and Philipp (2009) to perform an OLS regression of $ln(bt)$ on *pax* and *capacity* results in the following model: $ln(bt) = 6.2255 + 0.0069 \cdot pax - 0.0013 \cdot capacity$. This model's RMSE of approximately 2.3 minutes is only slightly better than the RMSE obtained by applying our final model to this sample, even though the observations of Steiner and Philipp (2009) only contain flights with high occupancy levels. Furthermore, the intercept of this regression model is similar to that of our final model (Table 6). Moreover, the effects of *pax* and *capacity* (although insignificant in this model) have the same directions.

As in our sample, boarding flights to destinations in Southern Europe tended to take longer than boarding flights to Northern Europe in Steiner and Philipp's (2009) sample.

In addition, the effect of the airplane type on *capacity* is significant and similar to the effect in our sample (Figure 3).

# 5 Managerial Implications

In the following, we use the observations and analyses to derive recommendations that can be of direct value when operating flights.

First, our collected data can be used as a database on which existing models (analytical models or simulation models) can be calibrated and validated. Using optimization tools is an important aspect in the airline industry (Barnhart and Cohn, 2004). As a direct implication of our study, models used to predict boarding times or to evaluate boarding strategies can be adjusted, and careful considerations concerning input factors should be made. As our empirical analyses show, the total number of passengers and the capacity of an airplane are the most important factors influencing the boarding time and hence should be considered in simulation models – in contrast to factors such as the number of gate agents or the existence of an additional document check, whose consideration in a model is not expected to improve the boarding time estimate. Additionally, the influence of carry-on baggage per passenger seems to be overestimated in existing simulation models. Based on these adjustments, a re-evaluation of existing boarding strategies allows for further improvements in the boarding process and thus for corresponding cost savings.

Commonly, boarding is started once an airplane is ready to be boarded. However, if an airplane is considerably early, the start of the boarding process is regularly postponed. This comes with the risk of a flight delay, which induces additional costs and can affect other flights and passenger satisfaction (Anderson et al., 2009; Ball et al., 2010). To minimize this risk, the boarding procedure must start early enough. A good estimate of the boarding time can be obtained with our regression model; only the number of passengers and the capacity of the airplane have to be known. Therefore, gate agents can predict the boarding time of each flight and adjust the starting time as necessary, which is especially relevant for bottleneck flights, as described by Arıkan et al. (2013). This process could be simplified by providing a table with the most common combinations of the number of passengers and the capacity along with the resulting estimate of the boarding time and the standard deviation.

Another advantage of predicting and adjusting the boarding time is the avoidance of starting boarding too early, which would prevent unnecessarily long waiting times for passengers and the air crew in the boarded airplane before the airplane is pushed back from the gate.

Our final regression model shows that, apart from the boarding strategy, passengers and airplane capacity are the main drivers of the boarding time. Most obviously, neither a reduction of the number of passengers nor an exchange of an airplane are reasonable options for reducing the boarding time. Yet, our observations during data collection and the discussions with airline managers revealed that a marginal change in the layout of the airplane can increase capacity. Most airplanes have some rows with six seats that can be used for either business or economy class. If these rows are used for business class passengers, only four seats per row are occupied (the window and the aisle seats); otherwise, all six seats are used. Consequently, if business class rows are unused, the capacity increases if these rows are used for economy class passengers (+2 seats for each row). The classes are simply separated by a curtain, which can easily be moved to a different row. By designating an unused business class row as an economy class row, boarding times can be reduced by 0.8 % (Table 6). The goal of increasing capacity is to create more space for passengers to stow their carry-on baggage and to reach their seats. This modification of the configuration depends on whether there are unoccupied seats in business class. In our sample, on average, eight seats in the business compartment were unoccupied. Using these two rows for economy class would result in a capacity increase of four seats, which would lead to a 1.6 % reduction in boarding time. Even with a conservative estimate of the cost of turn-around time of US$30 per minute, which is proposed by Nyquist and McFadden (2008), for a large airline with 5000 flights a day and a mean boarding time of 15 minutes, the possible cost savings are nearly US$14 million per year. Based on the estimated cost of US$250 for one minute of turn-around time (Horstmeier and de Haan, 2001), cost savings of US$114 million per year could be realized by adjusting the configuration of the airplane without sacrificing any revenue generated by business passengers.

## 6 Conclusion

This paper presented an empirical study on the factors influencing the airplane boarding time. To the best of our knowledge, no extensive empirical study has previously been conducted on this topic. We observed short- and medium-haul flights at a large airport and tested various hypotheses about the influence of certain variables such as the number of passengers, the capacity of the airplane, the amount of carry-on baggage, and the destination of a flight. The most surprising result was that the average amount of carry-on baggage per passenger did not have a significant influence on the boarding time. The destination of a flight, passport control, and the number of gate agents also did not have significant effects on the boarding time. Moreover, we developed a regression model to predict boarding times. In accordance with our hypothesis testing results, the number of passengers and the total capacity of the airplane in its selected configuration are the only variables that are required to obtain a good estimate of the boarding time. This means not only that focusing on these two variables is a reasonable way to decrease boarding times but also that only these two variables have to be known to predict the boarding time of a flight. Our final model predicts boarding times fairly well, with an $\bar{R}^2$ of nearly 86 % and an RMSE of less than 2 minutes. Validations against the data and models of other authors confirmed the explanatory power of our regression model.

For future research, we recommend conducting detailed empirical tests on the influence of different boarding strategies, e. g., outside-in or skipping halfrow (a variant of back-to-front and by halfrow), on boarding times. It could also be interesting to analyze the influence of the boarding strategy on customer satisfaction, which is an important aspect for most airlines. As mentioned in Section 1.4, the input parameters for the various models in the literature were either obtained only based on few observations or were adopted from other publications. Hence, data concerning these parameters, such as the time and space needed to walk in the aisle and stow carry-on baggage, should be collected in future research.

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# V Fazit und Ausblick

## 1 Zusammenfassung der zentralen Erkenntnisse und kritische Würdigung

Die drei in dieser Dissertation enthaltenen Beiträge befassen sich mit dem Boardingprozess bei Kurz- und Mittelstreckenflugzeugen und untersuchen sehr unterschiedliche, jedoch zusammenhängende Fragestellungen. Durch eine schrittweise Herangehensweise an das Boardingthema konnte dieser relativ junge Forschungsbereich strukturiert und für zukünftige Arbeiten eine Basis geschaffen werden.

Mit der Eingrenzung und Definition des Boardingproblems, einer Übersicht über bestehende Boardingmethoden und einem umfassenden Literaturüberblick sowie der Erörterung weiterer Forschungsbereiche wurde mit Beitrag 1 eine allgemeine Bestandsanalyse zum Boarden von Flugzeugen geschaffen. Diese umfasst sowohl den wissenschaftlichen Forschungsstand als auch anwendungsorientierte Gesichtspunkte, welche bei diesem Forschungsthema nicht außer Acht gelassen werden können. Es konnte festgehalten werden, dass es eine überschaubare Anzahl an wissenschaftlichen Arbeiten zum Thema Boarding gibt, wovon zwölf als Kernarbeiten identifiziert und ausführlicher vorgestellt wurden. Überwiegend verwenden die Autoren Computersimulationen, um den Boardingprozess abzubilden und Boardingzeiten verschiedener Boardingstrategien zu vergleichen. Jedoch existieren auch wenige analytische Modelle, welche überwiegend die Anzahl an Behinderungen, welche beim Einsteigen im Gang auftreten, zu minimieren versuchen sowie einzelne empirische Arbeiten, die für wenige Flüge Boardingzeiten erhoben und ausgewertet haben. Dabei zeigte sich durchweg, dass die weit verbreitete Boardingmethode back-to-front, bei der die Passagiere blockweise einsteigen, beginnend mit den hinteren Reihen im Flugzeug, schlechter performt als erwartet. Ein Boardingvorgang benötigt mehr Zeit, wenn die back-to-front-Methode angewendet wird, als wenn das Flugzeug random geboardet wird, d.h. keine Einsteigereihenfolge vorgegeben wird.

Zu Beitrag 1 ist anzumerken, dass der Stand des Übersichtsartikels aus dem Jahr 2014 ist, also neuere Literatur nicht berücksichtigt wurde. Wie im nächsten Kapitel ausgeführt, intensivierte sich die Forschung um das Thema Airplane Boarding seitdem jedoch und es existieren bereits zahlreiche neuere Arbeiten. Nichtsdestotrotz kann der Artikel *Airplane Boarding* als die einzige wissenschaftliche Arbeit gesehen werden, die das Boardingproblem von Grund auf betrachtet, indem auf relevante Begriffe, Boardingmethoden und Literatur eingegangen wird.

Aufbauend auf den im ersten Beitrag gewonnenen Erkenntnissen wurde in Beitrag 2 die Frage untersucht, ob sich der Boardingprozess auf dem kritischen Pfad des Flugzeug-Turnarounds befindet. Sollte dies der Fall sein, können durch eine Reduzierung der Boardingzeit enorme Einsparpotentiale realisiert werden. Die meisten wissenschaftlichen Arbeiten gehen von dieser Annahme aus, eine fundierte Analyse der Zusammenhänge gab es nach unserem Kenntnisstand bisher jedoch nicht. Um dies zu untersuchen, wurden an einem internationalen europäischen Flughafen alle den Boardingprozess betreffenden Zeiten von 54 Flügen erhoben und statistisch ausgewertet. Kritisch anzumerken ist hier, dass die Stichprobengröße von 54 Flügen zwar ausreichend ist, um die benötigten statistischen Tests durchzuführen und verlässliche Ergebnisse zu erhalten, ein größerer Stichprobenumfang aber dennoch mehr Aussagekraft besäße. Aufgrund der sehr zeit- und personalaufwändigen Datenerhebung, bei der pro Flug drei Personen circa eine Stunde eingebunden waren, kann der Umfang der Studie dennoch als beachtenswert gesehen werden. Auch wenn auf die Gewährleistung der Gütekriterien Objektivität, Reliabilität und Validität geachtet wurde, würde außerdem die Berücksichtigung von Flügen, welche von anderen Flughäfen ausgehen oder von anderen Fluggesellschaften durchgeführt werden, zu einer verbesserten Objektivität der Untersuchung führen. Hierzu müssten allerdings sowohl mehrere verschiedene Flughäfen als auch Fluggesellschaften in ausreichender Zahl berücksichtigt werden, was wiederum deutlich mehr Flüge und somit einen deutlich größeren Umfang der Studie erfordern würde.

Mit den erhobenen Daten wurden in Beitrag 2 vier Hypothesen aufgestellt, welche die Annahme stützen, dass der Boardingprozess auf dem kritischen Pfad des Turnarounds liegt. Nach Anwendung statistischer Tests zur Überprüfung der Normalverteilung der

Variablen, der Durchführung von Regressionsanalysen und 10-facher Kreuzvalidierung wurden die Hypothesen getestet. Alle vier Hypothesen konnten selbst nach Anwendung des Holm-Bonferroni-Verfahrens, welches für Fehler beim multiplen Testen korrigiert, bestätigt werden. Folglich kann davon ausgegangen werden, dass sich der Boardingprozess grundsätzlich auf dem kritischen Pfad des Turnarounds befindet. Hier muss jedoch beachtet werden, dass es immer Sonderfälle oder Verzögerungen beim Turnaround-Prozess geben kann, welche dafür sorgen, dass der Boardingprozess nicht mehr Teil des kritischen Pfads ist.

Dieses Ergebnis legitimiert weitere Untersuchungen zum Boardingprozess und zu Möglichkeiten, wie die dafür benötigte Zeit reduziert werden kann und dient somit als Motivation für Beitrag 3, in dem die Faktoren, welche den Boardingprozess beeinflussen, bestimmt werden. Der um vier Flüge erweiterte Datensatz aus Beitrag 2 dient auch hier als Grundlage für die statistischen Auswertungen. Als potentielle Einflussfaktoren auf die Boardingzeit wurden neben der Wahl der Boardingmethode, welche in diesem Beitrag nicht betrachtet wird, die Anzahl Passagiere, die Sitzplatzkapazität des Flugzeuges, die Anzahl Handgepäckstücke pro Passagier, die Destination des Fluges, die Anzahl Gate Agents und das Vorhandensein einer Passkontrolle identifiziert. Auch hier wurden mit Hilfe statistischer Tests und Regressionsanalysen die Hypothesen getestet, in welchen angenommen wurde, dass die zuvor identifizierten Variablen jeweils einen Einfluss auf die Boardingzeit haben. Nach Anwendung der Holm-Bonferroni-Korrektur konnten die ersten beiden Hypothesen bestätigt werden, das heißt, lediglich der Einfluss der Anzahl Passagiere und der Kapazität auf die Boardingzeit sind signifikant.

Die Art und der Umfang der Korrektur des $\alpha$-Fehlers beim multiplen Testen sorgt generell für Diskussionsbedarf. Ein Großteil der Forscher ignoriert diesen möglichen Fehler komplett und wendet kein Korrekturverfahren an, in Beitrag 2 und 3 dieser Dissertation wurden jedoch die p-Werte der Hypothesentests mit Hilfe des relativ konservativen Holm-Bonferroni-Verfahrens angepasst. Es könnte argumentiert werden, dass auch eine Korrektur der p-Werte für die Angabe von Signifikanzniveaus jeglicher berechneter Korrelationen nötig ist. Da dies allerdings eine sehr konservative

Vorgehensweise ist, wurde in dieser Arbeit ein Mittelweg gewählt, in dem lediglich die für die statistische Auswertung verwendeten p-Werte korrigiert wurden.

Wie zu erwarten war, führt eine höhere Passagierzahl oder eine niedrigere Kapazität, ceteris paribus, zu einer längeren Boardingzeit. Etwas überraschend ist das Ergebnis, dass der Einfluss der Handgepäckmenge nicht signifikant ist. Dieser Faktor wird in bestehenden Modellen scheinbar etwas überschätzt. Eine mögliche Erklärung hierfür ist, dass die Anzahl Handgepäckstücke auf einem Flug stark mit der Anzahl Businesspassagiere korreliert, welche womöglich aufgrund ihrer Flugerfahrung ein zügiges Boardingverhalten an den Tag legen und somit dem Effekt von viel Handgepäck entgegenwirken. Zur Validierung unserer Ergebnisse und zur Überprüfung dieser Hypothese sind weitere Untersuchungen nötig. Als Ergebnis der Analysen konnte ein Regressionsmodell entwickelt werden, das mit Hilfe der Anzahl Passagiere und der Kapazität des Flugzeuges die Boardingzeit prognostiziert. Da damit über 80 Prozent der Varianz der Boardingzeit erklärt werden können, ist das Modell ein wertvolles Mittel für Fluggesellschaften, um die für einen anstehenden Flug benötigte Boardingzeit abzuschätzen.

Zusammenfassend kann festgehalten werden, dass eine Beschleunigung des Boardingprozesses prinzipiell auch zu einer Verkürzung der Turnaround-Zeit führt (Beitrag 2), wodurch enorme Kosteneinsparungen erzielt werden können (Beitrag 1). Außerdem wird der Boardingprozess, abgesehen von der Wahl der Boardingmethode, vor allem durch die beiden Variablen Anzahl Passagiere und Kapazität des Flugzeuges bestimmt. Die Anzahl der Handgepäckstücke hat unseren Analysen zufolge keinen signifikanten Einfluss auf die Boardingzeit (Beitrag 3).

## 2 Reaktionen und Entwicklungen nach Veröffentlichung von Beitrag 1

Nach Veröffentlichung des Beitrags 1 *Airplane Boarding* im Jahr 2015 im European Journal of Operational Research konnten verschiedene Entwicklungen in diesem

Forschungsbereich beobachtet werden. Gab es zu diesem Zeitpunkt lediglich wenige wissenschaftliche Arbeiten zum Boarden von Flugzeugen, so erschienen seitdem jährlich zahlreiche Artikel, die sich mit diesem Thema befassten. Neben einigen Studien, welche auf Computersimulationen zur Abbildung des Boardingprozesses basieren (Canzani und Lechner, 2014; Mota et al., 2014; Milne und Kelly, 2014; Shi und Mou, 2014; Qiang et al., 2014; Giitsidis und Sirakoulis, 2016; Kierzkowski, 2016; Notomista et al., 2016; Qiang et al., 2016; Ren et al., 2016; Schmidt et al., 2016; Utsunomiya et al., 2016; Schultz, 2017) und mehreren Artikeln mit analytischen Ansätzen (Carmona Budesca et al., 2014; Kuo, 2015; Milne und Salari, 2016; Miura und Nishinari, 2017; Zeineddine, 2017) entwickelte sich ein Forschungsstrang, der sich mit dem Design der Flugzeugkabine und neuartigen Technologien beschäftigt, die unter anderem auch den Boardingprozess beschleunigen sollen (Schultz, 2018; Yildiz et al., 2018). Ein Beispiel hierfür ist die Idee eines flexiblen Sitzes am Gang, welcher beim Boardingvorgang zunächst über den benachbarten Sitz geschoben wird und somit durch die Verbreiterung des Mittelgangs ein Überholen der Passagiere ermöglicht (Molon Labe Seating, 2018). Weitere Veröffentlichungen zum Airplane Boarding stammen beispielsweise von Qiang et al. (2017), die ein experimentelles Design entwickelt haben, um mit Hilfe von Bussen den Boardingprozess bei Flugzeugen nachzubilden oder von Sbrizzi et al. (2016), die aufgrund der Agilität eines Passagiers und seiner Handgepäckzahl dessen optimalen Sitzplatz bestimmen, um den Boardingprozess zu beschleunigen.

Des Weiteren bildete sich, motiviert durch das Erscheinen des Übersichtsartikels, eine internationale Gruppe führender Forscher in diesem Bereich, die jährlich einen interdisziplinären Workshop zum Thema Airplane Boarding abhält. Hier steht der gegenseitige Austausch über die aktuelle Forschung im Vordergrund, aber auch gemeinsame Forschungsprojekte werden verfolgt.

## 3 Zukünftiger Forschungsbedarf

Ergänzend zu den in Beitrag 1 ausführlich dargelegten möglichen Forschungsfeldern, welche bereits ein breites Spektrum für die weiterführende Forschung aufzeigen, bietet sich die Fortsetzung der im Rahmen der vorliegenden Dissertation durchgeführten Untersuchungen in folgende Richtung an: Um die Ergebnisse des Beitrags 3, vor allem bezüglich des nicht vorhandenen Einflusses der Anzahl Handgepäckstücke, zu bestätigen, sind weitere empirische Studien mit diesem Schwerpunkt nötig. Darüber hinaus ist die Durchführung detaillierter empirischer Tests zur Performance verschiedener Boardingmethoden sinnvoll. Hier ist vor allem die Auswirkung auf die Boardingzeit interessant, aber auch der Einfluss auf die Kundenzufriedenheit könnte untersucht werden, da diese wie eingangs beschrieben für Fluggesellschaften einen wichtigen Aspekt im Konkurrenzkampf um Passagiere darstellt. In Kombination mit den Ergebnissen zu Boardingmethoden könnten die Erkenntnisse zu einem in mehrerlei Hinsicht erfolgreichen Boardingprozess führen.

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