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Shopping or dining? On passenger dwell time and non-aeronautical revenues

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ABSTRACT

Data reveal that passengers spend more time at airports. Does this translate to enhanced commercial revenue, and if so which revenue types—food and beverage, retail, and other terminal services—are impacted? Leveraging a unique panel data of passenger dwell time at 89 U.S. airports, this study explores its influence on non-aeronautical revenues. We find that dwell time positively influences non-aeronautical revenues (10% increase in dwell time implies a 5% increase in revenues) with varying impacts on the revenue components. Specifically, we find that a 10% increase in dwell time is associated with an increase of 8% and 6%, respectively, in food and beverage as well as retail revenues, but with no significant impact on other terminal services revenues. Importantly, these impacts further vary with the airport terminal design, which we categorize as either linear, finger pier, or concourse. Our findings suggest that non-aeronautical revenues increase in dwell time at both linear and finger pier airports, with no such impact at concourse airports. Further, dwell time elasticities for food and beverage are roughly double at linear-design airports than at finger pier design airports. These are instrumental insights for further airport development and of merit for the discourse on airport privatization and regulation.

1. Introduction

Airports generate two main streams of revenues: aeronautical and non-aeronautical. Aeronautical revenues include all the financial operations strictly related to the air transport sector, such as passenger charges and airline landing fees. Non-aeronautical revenues capture diverse commercial activities offered by the airports, such as duty-free shopping and parking fees. Over the years, airports have managed to increase the revenue generation from non-aeronautical activities (Graham, 2009; Frank, 2011). Worldwide, the total amount of non-aeronautical revenues has increased from $42.7 billion in 2008 (ACI, 2009), to $61.8 billion in 2015 (ACI, 2018), and ultimately to about $70 billion in 2019 (ACI, 2021). All-in-all, non-aeronautical revenues account for roughly 40% of the overall revenues of airports, reflecting the importance of this stream of revenues.

Accordingly, airports have started to diversify their portfolios, dedicating growing attention to non-aeronautical revenues (Fuerst and Gross, 2018; Chen et al., 2020), which are often used to cross-subsidize aeronautical operations (Choo, 2014; Zuidberg, 2017). This is a lucrative strategy for airports as, compared to traditional aeronautical revenues, non-aeronautical revenues tend to generate higher margins (Lucas, 2022) thereby guaranteeing competitiveness for airport business and higher efficiency (Adler and Liebert, 2014).

As non-aeronautical revenues become a critical strategic component of airports, it is instrumental to explore the dynamics associated with the growth of this type of revenues. Naturally, the consistent growth in airborne travel, which has been increasing at a pace of close to 4% (except for the period during the COVID-19 pandemic), has played a major contributing role to the increase in non-aeronautical revenues. However, the focal interest of this paper is beyond the impact of travel demand on non-aeronautical revenues. In essence, we seek to assess whether the time passengers spend at airports impacts the generation of non-aeronautical revenues, and if so, whether it contributes positively or negatively to them, and whether this effect varies by type of revenue, which can be classified into food and beverage, retail, and other terminal services. We recognize that spending more time at airports is a double-edged sword: it can enhance revenue generated from passengers and their diverse activities at the airport; however, extending passengers' footprint time at airports may backfire as passengers may use alternative airports or may avoid flying altogether. Our interest is in the former, short-term positive impact, as we seek to quantify the magnitude of longer stays at airports.

Insights derived from our study could feed into future development of airports and determine the composition of services offered at their

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terminals. Furthermore, we seek to explore whether the design of the airport's terminals, which we classify as belonging to either linear, finger pier, or concourse, plays a role in the capacity of airports to generate non-aeronautical revenues. Understanding the limits and opportunities associated with the various designs can support the design of future layouts and possibly contribute to the development of airport regulatory schemes.[1]

The literature has dedicated considerable attention to exploring airport financial performance and further understanding the determinants of non-aeronautical revenues. These determinants can be divided into two broad categories: airport-related features, such as the airport size, layout and mix of offered outlets (e.g., Fuerst and Gross, 2018; Silva et al., 2023), and passenger-related characteristics, such as demographic, social, and economic features (Torres et al., 2005; Fuerst et al., 2011; Graham, 2018; Silva et al., 2023). Airport managers can leverage this information to plan and design the airport layout, as well as to develop efficient marketing strategies in daily decision-making process (Volkova, 2009; Mwesiumo et al., 2023). One of the critical factors demonstrated to impact revenues is passengers' dwell time. An argument could be made that more time passengers spend in terminal facilities would induce greater economic activity. This theory is supported by a few studies (Castillo-Manzano, 2010; Liu et al., 2014; Torres et al., 2005; Tseng and Wu, 2019), showing a positive relationship between dwell time and a part of non-aeronautical revenues, such as those related to retail and food and beverage purchases. However, these papers are based on surveys with self-reported waiting times and activities at airports, which can be subjective (as they rely on passengers' recall, which may be several months past their airport visit) and likely biased (as only certain passenger types might participate in the survey), and were conducted at a rather limited number of airports.

Different from the above-mentioned studies, our work is based on a unique dataset that relies on large-scale mobile-based tracking of foot-traffic at airports, which was collected at numerous airports in the U.S. across several years. As such, our paper expands the current literature by analyzing a multi-source database which includes dwell time data of travelers at 89 U.S. airports in the period 2017–2019. The impact of dwell time on non-aeronautical revenues is assessed by means of fixed-effect panel regressions. Our results reveal that dwell time, defined as the time passengers spend at the airport, has varying impacts on different components of non-aeronautical revenues (we focus on terminal-related revenues, *that is* food and beverage, retail, and other terminal services), and that the effect varies with airport terminal design.

The rest of the paper is organized as follows. Section 2 provides a literature review on the main determinants of non-aeronautical revenues. In Sections 3 and 4, we present the data and the methodology employed in this study, respectively. Section 5 reports the descriptive statistics, whereas Section 6 provides the empirical analyses. Finally, Section 7 summarizes our conclusions, providing avenues for future research.

2. Literature review

The literature on the determinants of airports' non-aeronautical revenues distinguishes between airport- and passenger-related features (Chen et al., 2020). Below, we review these two streams of features and provide more context on passengers dwell time at airports.

Airport-related characteristics significantly affect non-areonautical revenues. In a recent literature review on determinants of retail revenues, Chen et al. (2020) find that the following five airport characteristics are frequently demonstrated as having an impact: (i) ownership (i.e., public vs private airports), (ii) the area dedicated to retail activities, (iii) the airport comfort and environment, (iv) the offered brand image, and (v) the traffic volume and the shop location. Accordingly, Fuerst and Gross (2018) demonstrate that private airports generally exhibit higher yields than public ones, corroborating previous literature engaging theoretical discussions on the subject (Freathy, 2004; Freestone, 2011). Furthermore, traffic volume is generally found to have a positive impact on revenues (e.g., Appold and Kasarda, 2006; Fuerst et al., 2011; Fuerst and Gross, 2018; Volkova, 2009; Churchill et al., 2008). Features (ii)–(v) from the above-mentioned literature review (Chen et al., 2020) are often studied together: several papers jointly focus on the role of airport layout and traffic volume as key determinants (Fuerst et al., 2011; Fuerst and Gross, 2018; Volkova, 2009), accompanied by additional airport-related features. Fuerst and Gross (2018) explore the extent to which the layout and size of both airport and commercial areas affect airport financial performance, demonstrating that a higher share of food and beverage outlets is negatively associated with commercial revenue per passenger due to the low profit margin incurred by the restaurant business. Volkova (2009) finds that the number of short stay parking places, check-in facilities and employees improve retail income. Additionally, he observes that the volume of intercontinental passengers increases retail revenue per square meter at hub airports but not in regional airports.

The second stream of features that play a role as drivers of airport revenues relate to passengers' characteristics. In their study, Fuerst et al. (2011) reveal that revenues per passenger depend on national income level in the airport region and the proportion of leisure passengers. Fuerst and Gross (2018) find that the share of international passengers is positively correlated with the level of commercial income. In his study, Castillo-Manzano (2010) observes that business passengers are not likely to make last-minute purchases, and elderly passengers spend less on food and beverage activities. He also demonstrates that passengers from outside the Eurozone tend to spend more on food and beverage and that LCC passengers spend less on food and beverage. Lei and Papatheodorou (2010) and Fasone et al. (2016) provide evidence of a lower contribution to commercial revenues of LCC passengers compared with passengers of full service carriers. Yokomi et al. (2017) show that the extent to which LCC passengers contribute more on revenues strongly depends on the capacity of airports (constrained vs unconstrained). A survey conducted by Lu (2014) reveals that male passengers have less pre-planned shopping intentions and that older passengers have stronger pre-planned shopping intentions. Similarly, Tseng and Wu (2019) demonstrate that males spend more on entertainment and less on retail compared to females, while income positively affects retail shopping and dining purchases. Liu et al. (2014) point out that the socio-demographic characteristics as well as travel related information have impact on passengers' activity patterns at airports. For instance, frequent travelers are less likely to shop at airports, and travelers with higher incomes are more likely to dine and shop. Based on a study of 75 U.S. airports, Appold and Kasarda (2006) show that the average passengers' travel distance positively correlates with both food and beverage sales and non-food sales.

Ultimately, dwell time is largely considered as a determinant of non-aeronautical revenues, even if there is not a common agreement on the role it plays. In their survey conducted on passengers of five Spanish airports, Castillo-Manzano (2010) find that the dwell time prior to embarking positively correlates with passengers' decisions of buying food and beverage and purchasing goods. Assessing passengers' preferences via a web-based survey, Liu et al. (2014) point out that with more available time at the airport, passengers are more likely to spend on dining, shopping, and entertainment. Similarly, Tseng and Wu (2019) base their research on an internet survey to illustrate a

[1] Since this paper relies on U.S. data, privatization and, hence, regulation of airports is beyond the scope of this paper. Nevertheless, our analysis sheds light on the refinement of the regulation of privatized airports. We return to this point in Section 7.

positive impact of the amount of free time at terminal and retail, dining, and entertainment purchases. While the above studies demonstrate the positive link between longer dwell time and higher spend at the airport, some studies do not find support to the notion that more dwell time contributes positively to airports' revenues. Appold and Kasarda (2006) estimate dwell time based on security point waiting time and survey reports, finding a weak relationship between dwell time and commercial sales. In his survey conducted on more than 400 passengers, Lu (2014) demonstrates that the reported shopping time is not significantly correlated with passengers' buying tendency, including both pre-planned and impulsive buying. Thus, this paper implies that passengers have a set "budget" for airport spend and greater dwell time will not affect their shopping at the airport.

The challenge of understanding the impacts of dwell time on passengers' activities at airports stems from the lack of available data on passenger dwell time at airports. The literature to date relies on self-reported surveys, which can lead to imprecise estimates (this is particularly true for web-based surveys as they rely on passengers' recall of their time spent during their last airport visit) and potentially present selection-bias issues (for instance, passengers in a hurry will not bother to respond to the survey). In this work, we explore the impacts of dwell time on airport non-aeronautical revenues based on passengers' footprint data and study whether the impacts of dwell time vary with airport terminal designs. Another feature of our data is its availability over several years. Existing studies have a single time observation, and thus can only suggest what passengers might do at airports in case they had more time at their disposal. By contrast, our study, as it tracks the evolution of dwell time over the years, can demonstrate the link between longer (or shorter) dwell time and increased (or decreased) non-aeronautical activity at airports. In the next section, we describe the data and the methodology employed in this research.

3. Data and sources

This study relies on an extensive joint dataset that comprises airport revenues, airport characteristics, and passenger dwell time. Dwell time data are retrieved from Placer.ai, a company that tracks mobile users' footprint via a dedicated application (to which the users consent). The primary scope of Placer.ai is foot traffic at retail outlets. Recently, they started providing data on dwell time spent at different point of interest located in the U.S., among which there are airports. Placer.ai performs data cleaning from their mobile-tracked information, separating visitors from employee and resident counts. At airports, the algorithm examines patterns in length to stay to distinguish short-stay visitors (like meet and greet), employees of the airport facilities, as well as taxi drivers (including hailing services, such as UBER and Lyft). Given Placer.ai's methodology, our definition of dwell time encapsulates the entire time passengers spend at airports.[2] In this study, our focus is to analyze the top 100 airports in the U.S. (in terms of annual passengers transported according to the Department of Transportation (DOT) annual ranking in 2019) in the period 2017–2019. Of the top 100 airports, only 89 are included in the Placer.ai database.[3] The median tracked duration of stay of users is used as a proxy of passengers' dwell time. Placer.ai also provides information regarding the hourly distribution of stays as well as socio-economic characteristics, such as income and age profile. Such data, unfortunately, are available only for a subgroup of 55 airports.[4]

Airport revenues are gathered from the Federal Aviation Administration's (FAA) Form 5100-127. This form summarizes annual operating and financial statistics for U.S. commercial airports. Airports' revenues in this report are broken down into several categories, including passenger airline aeronautical revenues, non-passenger aeronautical revenues, and non-aeronautical revenues. The latter consists of eight sub-categories: (i) Land and non-terminal facility leases and revenues, (ii) Terminal food & beverage, (iii) Terminal retail stores & duty free, (iv) Terminal services and other (which relates to various services offered at the airport such as telecommunications, internet access, and spas), (v) Rental cars, (vi) Parking and ground transportation, (vii) Hotel, and (viii) Other. Relevant to our study are those related to terminal activities, *that is*, categories (ii)–(iv).

Importantly, Form 5100-127 provides airports' direct revenues from the various activities and services offered at the airport. As such, it does not reveal the actual revenues experienced by the service providers. Nevertheless, we use these reported revenues as a proxy for the actual revenues of the service providers. There are two reasons for the use of this proxy. First, airports regularly (normally on an annual basis) adjust the fee that service providers need to pay based on various factors. Specifically, they often engage in a variable payment scheme that consists of the variable component and a MAG (Minimum Annual Guarantees) (Serrano and Kazda, 2020). Second, numerous airports transition to full revenue sharing contracts with service providers (e.g., Dallas Fort Worth International Airport, TheMoodieDavittReport, 2020). Both contract types ensure that actual sales are reflected, to varying degrees, in the reported airport revenues.

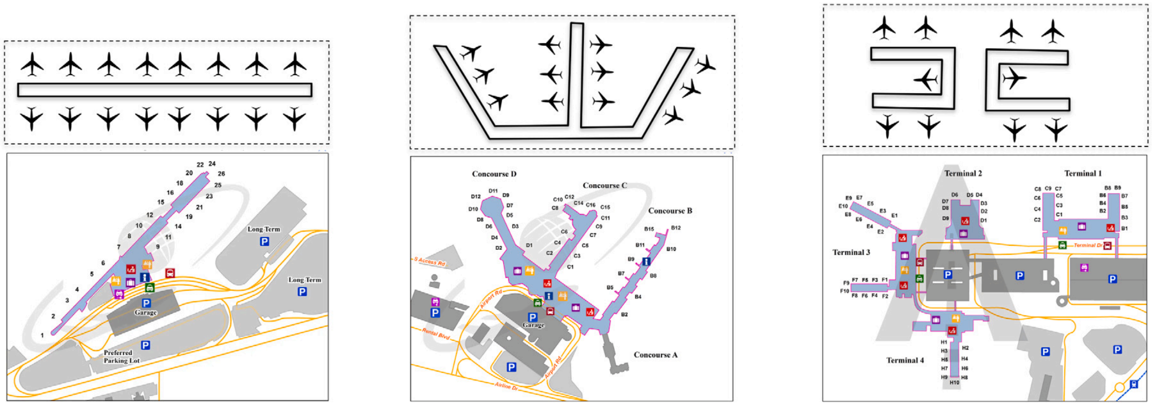
Additional airport features are obtained from the Official Airline Guide (OAG) database. These measures include the number of flights offered, the percentage of domestic flights, the proportion of seats offered by LCC, and airport congestion, which was developed *ad hoc* for this paper; further details on its construction are available in Section 4.1. These four airport-related metrics help us profile flights and passengers at airports, serving as control variables with impacts on revenues. Airport layout data is gathered from *AirportGuide.com*, which provides detailed layout design information for a large number of airports. Instead of focusing on interior designs, we look at the overall structure of airport terminals and explore whether passengers behave differently. We follow the method proposed by Chen et al. (2020) to create different groups of airports.[5] (Chen et al., 2020)'s classification primarily accounts for two factors that are relevant in our context: the walking distance to the departure gates and the placement of shops within the terminal. Both factors can significantly affect passengers' purchasing behavior. For example, shorter walking distances to gates reduce passengers' travel time within the terminal, providing more opportunities for shopping (De Neufville et al., 2002; Chen et al., 2020). Our sample presents three major categories of airport design, namely linear (L), finger pier (F), and (midfield) concourse (C). Fig. 1 illustrates the three layouts with sample airports.

[2] As Placer.ai is not able to distinguish between different airport areas, data do not provide the resolution to differentiate between time spent before and after security.

[3] Placer.ai did not have enough subscribers in 11 airports out of 100 to provide sufficient confidence on the data reliability. Indeed, they provide data only if the number of observations they record is above a predetermined confidence threshold (i.e., at least 3000 monthly data points).

[4] For this subset of 55 airports, we have dwell time on a monthly bases, which, in essence, allows us to match dwell time on a 12-month basis to the airports' fiscal year-end. Performing the analysis on this reduced panel, we obtain consistent results that, for the sake of parsimoniousness, are not reported in the paper.

[5] No airport adopts transporter design and the three airports with satellite design can be also considered as concourse (TPA, MCO) or finger pier (SEA). A complete list of the airports in this study and their respective layout is available in Table B.3 in Appendix B.



(a) Linear design (L): *Buffalo Niagara International Airport (BUF)*

(b) Finger pier design (F): *Louis Armstrong International Airport (MSY)*

(c) Concourse design (C): *Fort Lauderdale/Hollywood International Airport (FLL)*

Fig. 1. Examples of the three identified airport terminal layouts.
Source: Airportguide.com

4. Methodology

The impact of dwell time on airport non-aeronautical revenues is assessed by means of a fixed-effect panel regression, capturing the airport-level heterogeneity. Specifically, the model is formulated as follows:

$$\ln Y_{it} = \beta_0 + \beta_1 \ln DwellTime_{it} + \beta_2 \ln Movements_{it} + \beta_3 Z_{it} + \omega_i + \epsilon_{it}, \quad (1)$$

where Y_{it} refers to the amount of yearly non-aeronautical revenues, $DwellTime_{it}$ is the median time spent by passengers at the airport, $Movements_{it}$ is the airport size measured in terms of departing flights, and Z_{it} is a vector of airport-level time-varying characteristics. Y_{it} accounts for revenues both in absolute terms and relative to the airport size (i.e., revenues per passenger—RPP).[6] Along with the total amount of non-aeronautical revenues, Y_{it} considers the non-aeronautical revenues potentially affected by dwell time, namely food and beverage, retail, and other services revenues. As time-varying airport characteristics, Z_{it} considers airport congestion (on which we elaborate in Section 4.1), the percentage of domestic departing flights $Domestic_{it}$ and the portion of departing seats offered by low-cost carriers LCC_{it}. Finally ω_i represents airport fixed effects, and ϵ_{it} is the error term.[7]

Two additional analyses are included in this study. First, aiming to evaluate how dwell time affects non-aeronautical revenues in differently-designed airport, we replicate the analysis for various groups of airports, categorized based on their layout. Second, acknowledging the potential correlation among the tested dependent variables, we conduct seemingly unrelated regression (SUR) analysis with airport fixed effects. Results are reported in Section 6.

4.1. Airport congestion

Airport congestion is commonly defined as the utilization of airport capacity and it is mainly explored in the literature dealing with airport congestion pricing and slot allocation (e.g., Brueckner, 2002; Jacquillat and Odoni, 2015; Pels and Verhoef, 2004). However, these investigations typically delve into micro-detailed assessments of congestion. In our study, we adopt a broader perspective, utilizing a yearly measure of congestion.

As such, based on OAG Schedule data, we build a yearly measure of airport congestion for each airport-year pair in our sample. The procedure is as follows:

– For each airport i in year t, we divide each day of operations (from 6 am to 10 pm) into 15-minute intervals, resulting in 64 daily blocks or 23,360 blocks per year. We define b_{it} as the block counter for each airport-year pair, with discrete values ranging from 1 to 23,360.
– For each time block b_{it}, we generate $\text{Flights}_{b_{it}}$, which counts the total number of scheduled departing flights during that time block.
– For each airport-year pair, we define MaxFlights_{it} to capture as maximum number of flights departing within a single time block for airport i in year t, computed as $max(\text{Flights}_{b_{it}})$. We use MaxFlights_{it} as a proxy of airport capacity.
– For each time block of an airport-year pair, we calculate the ratio of scheduled departing flights to its corresponding MaxFlights_{it}.
– We define a congested block as one with a ratio exceeding a threshold ψ. This threshold can take any value between 0 and 1.
– Ultimately, $Congestion(\psi)_{it}$ for airport i in year t is the count of congested blocks (given threshold ψ) divided by the total number of time blocks in a year.

$Congestion(\psi)_{it}$ represents the proportion of time during which the airport's scheduled operations exceed a fraction ψ of the maximum number of scheduled operations. As mentioned, $\psi \in (0, 1)$. Fig. 2 shows the distribution of $Congestion(\psi)$ at various threshold levels for the airports in our sample in 2019. For this paper, we take $\psi = 75\%$.[8]

5. Descriptive analysis

In our sample, non-aeronautical revenues account for around 45% of the total airport revenues. By focusing on the revenues that may

[6] To ensure consistency in analyzing both revenues and revenues per passenger, we have opted to employ aircraft movements as a metric for airport size. Aircraft movements and passengers volume are correlated at 96%.

[7] Additional analysis testing the potential endogeneity of dwell time is provided in Appendix A. Although results are overall consistent with those shown in Section 6 and the selected instrumental variables are significant and not weak, the endogeneity test suggests that the fixed-effect panel regression and 2SLS fixed-effect panel regression are not systematically different, thereby confirming that the dwell time is not endogenous.

[8] In our analysis, we tested for different ψ values and $\psi = 75\%$ emerged as the threshold providing the highest significance to the model.

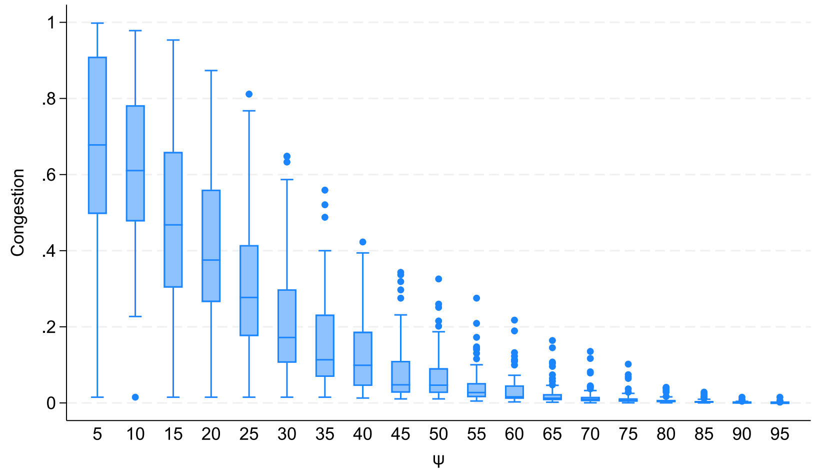


Fig. 2. The distribution of $Congestion(\psi)$ in 2019 for varying levels of the threshold ψ.

Table 1
Change in average values of key variables over time with respect to 2017.

Variable	2018	2019
Dwell time	4.9%	8.8%
Aircraft movements	22.0%	25.1%
Revenues		
Total non-aeronautical	2.9%	8.8%
Food and beverage	6.7%	15.2%
Retail	7.1%	14.1%
Other services	3.0%	5.8%
Revenues per passenger		
Total non-aeronautical	−1.5%	0.7%
Food and beverage	2.5%	14.1%
Retail	1.6%	4.2%
Other services	−2.7%	1.5%

potentially be affected by dwell time, the largest portion (around 9% of total non-aeronautical revenues in 2019) refers to food and beverage. Retail revenues rank second (around 8.5% of total non-aeronautical revenues in 2019), followed by other terminal services (around 5% of total non-aeronautical revenues in 2019). Table 1 shows the variation in revenues, revenue per passenger, dwell time, and aircraft movements in 2018 and 2019 compared to 2017. Overall, there is an increase in airport revenues. Food and beverage revenues register the highest variation (+15.2% and +14.1% in revenues and RPP in 2019, respectively). While total non-aeronautical revenues increase of 2.9% from 2017 to 2018, total non-aeronautical RPP slightly decrease (−1.5%), suggesting that the increase in the offered flights, and therefore passengers, did not result in such a consistent rise in revenues. The dwell time also increased over time, gaining +4.9% in 2018 and +8.8% in 2019.

Table 2 reports the descriptive statistics of our sample in 2019. Airports report a high heterogeneity in terms of non-aeronautical revenues and the related breakdown. Total non-aeronautical revenues range from $12.2 million for the Myrtle Beach International Airport (MYR) in South Carolina to $571 million for the Los Angeles International Airport (LAX). By considering non-aeronautical RPP, the average value is equal to $13.50, with the minimum value being equal to $5.22 for LaGuardia Airport in New York (LGA) and the maximum equal to $23.40 for Indianapolis International Airport (IND). These large differences also emerge while analyzing the non-aeronautical revenues breakdown. LAX is the first airport in terms of retail revenues and RPP. Chicago O'Hare International Airport (ORD) and Des Moines International Airport (DSM) are the airports registering the highest values of food and beverage revenues and RPP, respectively.[9]

Aircraft movements, congestion, the proportion of domestic flights, and the percentage of low-cost seats offered confirm the high heterogeneity of the airports in the sample. On average, airports offer 78 thousand flights per year, with the busiest airport being Hartsfield-Jackson Atlanta International Airport (ATL), while the smallest one is the St. Pete-Clearwater International Airport (PIE). PIE, classified as a low-cost airport, is also the airport with the highest percentage of seats offered by LCC (99%), far exceeding the average of 25% and the minimum value of 2% for Ted Stevens Anchorage International Airport (ANC). Additionally, PIE records the lowest congestion levels, with only 0.3% of the annual capacity utilized when considering the threshold 75% of maximum capacity, well below the average of 1.1%. Notably, 60 airports in our sample have a *Congestion* value below 1%. In contrast, Dallas Fort Worth International Airport (DFW) experiences the highest congestion levels in 2019, with 10.2% of blocks utilized close to maximum capacity. Following closely behind is Charlotte Douglas International Airport (CLT), with a congestion rate of 7.4%. 24 out of 89 airports offer only U.S. domestic flights, while at the John F. Kennedy International Airport (JFK) in New York, 57% of the flights have an international destination.

The average value of median dwell time is around 80 min and it ranges from 39 for the Cleveland Hopkins International Airport (CLE) to 113 min for ATL. Although 39 min might appear to be a relatively short duration, it has to be considered that this value includes the time spent by all passengers, also those arriving.

6. Results

Tables 3 and 4 show the results of the fixed effect panel regression. Controlling for aircraft movements, dwell time is recognized to significantly affect total non-aeronautical revenues, along with food and beverage and retail revenues. Specifically, a 10% increase in dwell time leads to a 5% increase in total non-aeronautical revenues. This value increases up to 8% and 6% for food and beverage and retail revenues, respectively. Not surprisingly, aircraft movements have a positive impact on revenues (with the exception of retail revenues),

[9] Please note that values reported as 0 do not correspond to absent revenues. In case of revenues, it means that they are lower than $100 thousand, while RPP is below $0.01. Airports that do not report revenues for a specific revenue component are excluded from the analysis.

Table 2
Statistical summary of Year 2019.

Variable	No. of Obs	Mean	Std. dev.	Min	Max
Revenues (million $)					
Total non-aeronautical	89	111.00	126.00	12.20	571.00
Food and beverage	89	10.00	13.60	0.29	61.70
Retail	87	9.48	17.40	0	118.00
Other services	85	5.58	10.60	0	54.10
Revenues per passenger ($)					
Total non-aeronautical	89	13.50	3.79	5.22	23.40
Food and beverage	89	0.95	0.59	0.09	5.33
Retail	87	0.70	0.45	0.00	2.76
Other services	85	0.50	0.47	0.00	2.22
HTML]333333 $DwellTime$ (minutes)	89	80.26	9.45	39.00	113.00
$Movements$ (thousand)	89	72.69	78.38	7.73	395.01
$Congestion$ (%)	89	0.01	0.02	0.00	0.10
$Domestic$ (%)	89	0.93	0.11	0.43	1
LCC (%)	89	0.37	0.25	0.02	0.99

suggesting that a 10% increase in the offered flights would lead to an increase in revenues of 1%, 3%, and 5% for total non-aeronautical, food and beverage, and other services revenues. Of the additional control variables, only $Congestion$ and $Domestic$ are found to play a role in other services revenues. Generally speaking, at congested airports passengers experience prolonged wait times in queues and slower terminal navigation. Consequently, they have limited time to engage with additional amenities offered at the airport. Unlike food and retail options, which can be conveniently purchased and consumed elsewhere and are not significantly affected by our measure of congestion, the negative impact of congestion on other services may be caused by the greater difficulty in attracting passenger engagement under such circumstances. Regarding $Domestic$, consistently with previous literature (Volkova, 2009; Fuerst and Gross, 2018) showing that international passengers positively contribute to airport revenues, airports with a higher portion of domestic flights register lower additional services revenues (Column 4 in Table 3).

Slightly different outcomes are derived by focusing on non-aeronautical revenues per passenger (Table 4). Dwell time has a significant influence solely on food and beverage RPP—a 10% increase in dwell time leads to 5% increase in revenues per passenger. This indicates that spending more time in airport does not necessarily encourage retail shopping behaviors, but passengers likely purchase more food as time passes by. Interestingly, the amount of aircraft movements is no longer a determinant of revenues per passenger, thus suggesting that there is not a scale-effect. While the role of $Congestion$ and $Domestic$ are in line with that shown in Table 3, the percentage of seats offered by LCC negatively contributes to total non-aeronautical RPP. In the current literature, there is no common agreement on the effect of LCC passengers on revenues. Our outcomes are consistent with the belief that, given the typical lower willingness to pay, LCC passengers contribute less to non-aeronautical revenues with respect to full-service carriers' passengers, who are normally characterized by a higher proportion of business travelers (Martini et al., 2020; Castillo-Manzano, 2010; Lei and Papatheodorou, 2010; Fasone et al., 2016).

6.1. The importance of airport layout

Since our analysis is based on a fixed-effect panel regression, time invariant variables cannot be directly included into the model. Airport layout is one of the most investigated factors in the literature, affecting non-aeronautical revenues and potentially the impact of dwell time on revenues and RPP. To assess the impact of airport layout, we conduct panel regression with fixed effects by grouping airports according to their layout and summarize the results in Table 5.[10] The subsamples are as follows: 23 airports have a linear shape (L), 38 have a finger pier shape (F), and 28 are concourse-shaped airports (C). Results in Tables 5 and 6 reveal that dwell time does not have an impact on revenues and RPP in C-shaped airports. Contrarily, the effect it has on F- and L- shaped airports significantly vary according to the revenue components we are accounting for. Specifically, for F-shaped airports, dwell time positively influence total non-aeronautical revenues, food and beverage revenues, and food and beverage RPP. A 10% increase in dwell time contributes to food and beverage revenues and RPP for a value of +13% and +9%, respectively. The positive impact of a +10% in dwell time on total non-aeronautical revenues amounts to an increase of +6% for F-shaped airports, while for L-shaped airports, it is +10%. Finally, in L-shaped airports, dwell time significantly affects food and beverage revenues and RPP (an increase of 10% leads to an increase of +24% and +16%, respectively) and retail revenues (an increase of 10% leads to an increase of +9%).

These results confirm the important influence that airport design has on non-aeronautical revenues, corroborating previous literature insights (e.g., Fuerst and Gross, 2018). Linear designed airports have a shorter walking distance with a clear orientation (Chen et al., 2020) and generally provide the most efficient configuration to minimize passengers' walking distance (De Neufville et al., 2002). Under these circumstances, it is likely that, with more free time, passengers explore more purchase options (De Neufville et al., 2002), being able to come back to their boarding gates efficiently. In finger pier designed airports, which normally consists of multiple linear hallways, passengers likely walk for a longer distance compared to the linear design. Nevertheless, passengers still have a clear understanding of the terminal layout since F-designed airports concentrate flows in a single space. Hence, it is more likely that passengers opt for food and beverage consumption. By contrast to L- and F-designed airports, airports with concourse designs split flows into different concourses which function as independent but smaller scale terminals. It is shown that the dwell time of passengers in such airports does not have significant impacts on non-aeronautical revenues and RPP. This outcome responds to the debate on the impact of concourse design on revenues. On the one hand, footfall is generally believed to improve retail sales due to penetration rates (Chen et al., 2020). On the other hand, consistently with our analysis, the complexity of terminal design may not encourage passengers to explore food and beverage consumption as the perception of the risk of missing flights may be higher than that in a simple-designed airport.

[10] For the sake of conciseness, we report only the *Dwell Time* coefficient in both Tables 5 and 6. The set of variables included in the model is that described in Section 4 and the derived results are consistent with those reported in Tables 3 and 4.

Table 3
Panel fixed effects estimation results - revenues.

Revenues	(1) Total non-aeronautical (log)	(2) Food and beverage (log)	(3) Retail (log)	(4) Other services (log)
Dwell Time (log)	**0.4968***	**0.7683**	**0.5699*	−0.6476
	(0.1764)	(0.2937)	(0.3073)	(1.2551)
Movements (log)	**0.1443***	**0.2870***	0.0490	**0.4693*
	(0.0264)	(0.0937)	(0.1345)	(0.2678)
Congestion	0.1358	−0.2526	2.9909	**−3.8388*
	(0.4920)	(0.8473)	(3.9757)	(2.0138)
Domestic	−0.2150	−3.7496	−22.7027	**−14.8306**
	(3.3468)	(3.0837)	(16.8459)	(6.7346)
LCC	0.3302	−0.2715	4.5312	0.1925
	(0.3202)	(1.1554)	(4.0938)	(1.4030)
Constant	0.4991	−1.4645	17.4138	12.0559
	(3.4432)	(3.2578)	(16.0142)	(9.2459)
Observations	265	264	259	254
R-squared	0.3006	0.2989	0.0877	0.0356
Number of ids	89	89	87	85

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table 4
Panel fixed effects estimation results - revenues per passenger (RPP)

Revenues per passenger	(1) Total non-aeronautical (log)	(2) Food and beverage (log)	(3) Retail (log)	(4) Other services (log)
Dwell Time (log)	0.2015	**0.4753**	0.2834	−0.9306
	(0.1265)	(0.2326)	(0.3081)	(1.2756)
Movements (log)	−0.0277	0.1148	−0.1249	0.2992
	(0.0190)	(0.0898)	(0.1377)	(0.2727)
Congestion	−0.2295	−0.6166	2.6324	**−4.3297**
	(0.4539)	(0.5629)	(4.1452)	(2.1356)
Domestic	0.7895	−2.6816	−21.6777	**−13.3227**
	(2.9829)	(2.6286)	(17.2131)	(6.6920)
LCC	**−0.6911***	−1.2931	3.5253	−0.9001
	(0.2082)	(1.0300)	(4.2271)	(1.4449)
Constant	15.3027***	13.2664***	32.1493*	26.3053***
	(3.0668)	(2.7212)	(16.3643)	(9.2411)
Observations	265	264	259	254
R-squared	0.0376	0.1086	0.0603	0.0204
Number of ids	89	89	87	85

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table 5
Estimation results under three airport layouts for revenues.

Revenues	(1) Total non-aeronautical (log)	(2) Food and beverage (log)	(3) Retail (log)	(4) Other services (log)
C - 28 airports				
Dwell time (log)	0.2390	0.0899	0.6972	−2.1189
	(0.1833)	(0.3716)	(0.4270)	(2.1433)
F - 38 airports				
Dwell time (log)	**0.6257*	**1.2918***	1.1086	0.0479
	(0.3257)	(0.2757)	(0.8704)	(2.2819)
L - 23 airports				
Dwell time (log)	**1.0385***	**2.3747***	**0.8904**	1.9494
	(0.2523)	(0.5246)	(0.3659)	(1.2629)

Robust standard error in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

6.2. *Seemingly unrelated regressions (SUR)*

Lastly, we conduct the seemingly unrelated regression model with airport fixed effects. Seemingly unrelated regressions are particularly useful to deal with the potential contemporaneous correlation across equations and in our study. In our framework, the correlation across equations may be due to the substitution effect existing between expenses. Assuming a fixed passenger's budget, an increase in food expenditure may result, for example, in a decrease in available funds for retail expenditure.

Tables 7 and 8 show the results. Dwell time significantly impacts on non-aeronautical revenues. Food and beverage as well as retail revenues (and RPP) are positively affected by the time that passengers spend at airports. Consistently with what is reported in Tables 3 and 4, a 10% increase in dwell time leads to a 4% (5% in Table 3) increase in total non-aeronautical revenues. This value increases up to around 7% for both food and beverage and retail revenues (8% and 6% in Table 3). By focusing on RPP, the impact on food and beverage RPP is slightly lower than in Table 4 (i.e., 4.6% vs 4.8%). However, accounting for the correlation across components lets dwell time gain significance in influencing also retail RPP (with an elasticity equal to

Table 6
Estimation results under three airport layouts for revenues per passenger.

Revenues per passenger	(1) Total non-aeronautical (log)	(2) Food and beverage (log)	(3) Retail (log)	(4) Other services (log)
C - 28 airports				
Dwell time (log)	0.0955	−0.0536	0.5537	−2.2624
	(0.1144)	(0.2903)	(0.4542)	(2.1678)
F - 38 airports				
Dwell time (log)	0.2503	**0.9217*****	0.7497	−0.3271
	(0.2930)	(0.2519)	(0.8546)	(2.3571)
L-23 airports				
Dwell time (log)	0.2587	**1.5950*****	0.1106	1.1804
	(0.1802)	(0.4913)	(0.3029)	(1.1858)

Robust standard error in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table 7
Seemingly unrelated regression (SUR) model with airport fixed effects results - revenues.

Revenues	(1) Total non-aeronautical (log)	(2) Food and beverage (log)	(3) Retail (log)	(4) Other services (log)
Dwell Time (log)	**0.3941*****	**0.7383*****	**0.7235*****	−0.6576
	(0.1095)	(0.2733)	(0.2226)	(1.1217)
Movements (log)	**0.1473*****	**0.2871*****	**0.1724*****	**0.4638***
	(0.0248)	(0.0619)	(0.0504)	(0.2540)
Congestion	0.1864	−0.1122	−0.7225	−3.8965
	(0.5514)	(1.3758)	(1.1207)	(5.6469)
Domestic	**−3.0094*****	−4.1403	**−5.7881****	−14.6141
	(1.1433)	(2.8528)	(2.3238)	(11.7087)
LCC	0.3797	−0.1423	0.3778	0.2942
	(0.2996)	(0.7477)	(0.6090)	(3.0686)
Constant	2.7181**	−2.2833	0.0465	12.6983
	(1.2402)	(3.0945)	(2.5207)	(12.7010)
Observations	253	253	253	253
R-squared	0.9976	0.9919	0.9961	0.9012
Number of ids	89	89	87	85

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table 8
Seemingly unrelated regression (SUR) model with airport fixed effects results - revenues per passenger (RPP)

Revenues per passenger	(1) Total non-aeronautical (log)	(2) Food and beverage (log)	(3) Retail (log)	(4) Other services (log)
Dwell Time (log)	0.1125	**0.4566***	**0.4419****	−0.9392
	(0.0823)	(0.2577)	(0.2118)	(1.1233)
Movements (log)	−0.0222	**0.1176****	0.0030	0.2943
	(0.0186)	(0.0584)	(0.0480)	(0.2544)
Congestion	−0.2970	−0.5957	−1.2060	−4.3800
	(0.4145)	(1.2975)	(1.0662)	(5.6549)
Domestic	**−1.5295***	−2.6603	**−4.3082***	−13.1342
	(0.8594)	(2.6903)	(2.2108)	(11.7254)
LCC	−0.7260***	−1.2480*	−0.7279	−0.8115
	(0.2252)	(0.7051)	(0.5794)	(3.0730)
Constant	18.0222***	13.0207***	15.3506***	28.0024**
	(0.9322)	(2.9183)	(2.3982)	(12.7191)
Observations	253	253	253	253
R-squared	0.9852	0.9467	0.9862	0.8000
Number of ids	89	89	87	85

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

0.44). Among control variables, aircraft movements positively impact revenues, while the percentage of domestic flights and offered LCC seats significantly reduce RPP and $Congestion$ is no more significant. In summary, no relevant variations are found with respect to the general results provided.

7. Conclusions

This paper explores whether and how passenger dwell time affects airport non-aeronautical revenues. We analyze data from users who grant a mobile app the access to their footprints and demographic information, focusing on 89 U.S. airports from 2017 to 2019. In addition to footprint data, we also collect airport financial data and airport flight information. To analyze the panel data, we apply fixed effects regression models to quantify the influence of dwell time on the various components of non-aeronautical revenues, while controlling for airport time-varying characteristics.

Our regressions show that dwell time positively contributes to total non-aeronautical revenue generation at airports with an elasticity of about 0.5, implying that a 10% increase in dwell time translates to a 5% increase in non-aeronautical revenues. In particular, we find that dwell time contributes to two of the relevant sub-categories—food and beverage as well as retail with elasticities of 0.8 and 0.6, respectively—but not to the sub-category of other terminal services.

We then shed light on the role of terminal design layouts. Such layouts can be categorized into three types: linear, finger pier, and concourse. By grouping airports according to their terminal design layouts, we find that dwell time significantly and positively increases total non-aeronautical revenues as well as the sub-category of food and beverage revenues for airports with logistical efficiency, namely, linear and finger pier designs. Importantly, the dwell time elasticities are roughly double at linear-design airports (1 for non-aeronautical and 2.4 for food and beverage) than at finger pier design airports (0.6 and 1.3, respectively). No significance emerges for multiple concourse airports. Overall, our findings validate the assumption that dwell time increases airport non-aeronautical revenues (and revenues per passenger) but the impacts vary dramatically with airport terminal design.

Our findings are important for understanding passenger behavior at airports and even more so relevant for airport planners for improving airport commercial activities. First, airport managers may leverage the positive contribution of dwell time to non-aeronautical revenues by seeking ways to increase the time passengers spend at airport, for instance, by changing the airport layout or by inducing passengers to arrive earlier and engage in commercial activities. Indeed, Mwesiumo et al. (2023) suggest that airports may extend promotional offers with passengers (who are willing to share information). This may incentivize them to arrive earlier at the airport to take advantage of the offers. Extending dwell time, however, may expose airports to a challenging trade-off. On the one hand, longer dwell times may lead passengers to spend more money on various activities at the airport. On the other hand, longer dwell times can backfire as they may induce some passengers to opt for alternative airports or, more in general, alternative transportation modes. This study focuses on the short-term effects of dwell time, paving the way for future research to explore the role of dwell time in airports in the short, medium, and long-term.

Second, as the impacts of dwell time vary with airport designs, managers may wish to organize the distribution of activities in ways that take into account passengers' spending behavior. For example, passengers may dine more at restaurants at linear design terminals than at finger or concourse terminals, as they have the confidence of being able to reach the gate for boarding on time. Accordingly, this can free up space next to the gate for other activities, such as retail, and locate restaurants elsewhere at the terminal. By contrast, for concourse layouts, restaurants shall be located closer to the gate to reduce perception of risk (from not being able to make it to the gate on time) and incentivize more passengers to dine there.

From a policy perspective, our paper sheds light on the strategies that airports may employ to induce passengers to spend more time at the facility and subsequently spend more money on different activities at the airport. Policy makers then need to carefully think about the objectives of airport privatization and regulation. Presumably, policy makers seek to maximize total welfare. Inherently, passenger time is one of the elements in social welfare that has been overlooked thus far. If airports artificially inflate the time passengers spend on site, this could hurt social welfare and shall be reviewed and taken into account when designing regulatory schemes. Indeed, our paper leverages data available for U.S. airports, which are all public entities. Nevertheless, it elucidates the link between regulation, airports' revenue streams of revenues—aeronautical and non-aeronautical revenues—and airport design. Airport regulation has sparked intense debate in the literature, in particular with respect to the role of non-aeronautical revenues (e.g., Kratzsch and Sieg, 2011; Littlechild, 2018; Malavolti, 2016), and whether regulation shall follow a single till or a dual till scheme.[11] These two approaches have evolved over time to more elaborate mechanisms such price-cap schemes and rate-of-return regulation (See Button, 2019, for a review on the trends of aviation economics and regulation policies). Our paper raises two critical points: (i) the degree to which dwell time can impact revenue generation and (ii) the role of airport design in facilitating, or limiting, such revenue generation. Future work shall capture such trade-offs both empirically, by looking at privatized airports from other geographies, and analytically, by developing guiding theories to support the development of more refined regulatory schemes.

CRediT authorship contribution statement

You Wu: Writing – original draft, Methodology, Formal analysis. **Chiara Morlotti:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Benny Mantin:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Declaration of competing interest

None

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Appendix A. 2SLS

The single-equation model employed in this study may lead to the concern of endogeneity. Although we control for airport fixed effects, it is of interest to test for the presence of endogeneity caused by omitted variables, such as retail areas and shop assortment. To this end, we apply a 2-stage least squares (2SLS) panel fixed-effect regression. We employ two instrumental variables (IV) of dwell time to correct for the potential omitted variable bias.

The first IV is the average delay (in minutes) ($\ln Delay$) of departure flights. As the average delay is about 12 min, it directly lengthens the amount of time passengers spend at the airport, but is not sufficient to facilitate major commercial activities. The second IV relies on data from Placer.ai, which is available only for a subset of 55 airports. Among others, Placer.ai provides statistics on locations visited right after they leave the premises of the airport (post-locations which, in the context of retail, provide retailers insights into how clients plan their shopping trips). This information is limited to the 5 primary post-locations. In our context, the most frequent destination is home, followed by work, then by airports, most of which are hub airports (but the order may vary for individual airports). For an instrument, we calculate the percentage of passengers whose next destination is an airport, out of the top five destinations. That is, we sum the percentages of (often three) post-destinations associated with airports. We term this IV $PostLocAP$.

The two-stage regression is formulated as follows.

First stage:

$$\ln DwellTime_{it} = \beta_0 + \beta_1 \ln Movements_{it} + \beta_2 IV_{it} + \beta_3 Z_{it} + \omega_i + \epsilon_{it}, \quad \text{(A.1)}$$

Second stage:

$$\ln Y_{it} = \beta_0 + \beta_1 \ln \widehat{DwellTime}_{it} + \beta_2 \ln Movements_{it} + \beta_3 Z_{it} + \omega_i + \epsilon_{it}, \quad \text{(A.2)}$$

[11] Under the former, a cap on aeronautical charges is determined by taking into account both streams of revenues (aeronautical and non-aeronautical). This approach is normally preferred by airlines and has been shown to lead to some valuable advantages for airports: lowering airport charges attracts airlines, thereby leading to higher demand and consequently maximizing airports' overall commercial revenues (Adler and Liebert, 2014). The latter approach, dual till, sets a cap on aeronautical charges based on the aeronautical revenues only.

Table A.1
2SLS estimates - revenues.

Revenues	(1) Dwell time (First Stage)	(2) Total non-aeronautical (log)	(3) Food and beverage (log)	(4) Retail (log)	(5) Other services (log)
Dwell Time (log)		**0.5408****	**0.9400*****	0.5332	−1.1662
		(0.2198)	(0.3200)	(0.3932)	(2.8174)
Movements (log)	**0.0938*****	0.0718	0.0500	0.0769	0.2421
	(0.0209)	(0.0477)	(0.0642)	(0.0755)	(0.5146)
Congestion	−0.2172	−0.0162	−0.5760	−0.6673	**−6.3723*****
	(0.3116)	(0.5235)	(0.7406)	(0.7786)	(2.4727)
Income (log)	0.9064	**1.2184****	**2.2757****	1.0674	2.0567
	(0.5873)	(0.5041)	(1.1282)	(1.1501)	(4.8592)
Domestic	−0.7408	−3.8534	−4.6881	**−7.4035****	**−16.1593****
	(0.7761)	(2.3887)	(3.2703)	(3.0367)	(7.9638)
LCC	−0.3146	0.4485	−0.2488	0.3122	0.3418
	(0.2790)	(0.2982)	(0.6176)	(0.7004)	(1.6887)
Delay (log)	**0.1133*****				
	(0.0433)				
PostLocAP	**2.1516*****				
	(0.6444)				
Observations	165	165	165	164	162
R-squared	0.6023	0.4261	0.3366	0.2195	0.0153
Number of ids	55	55	55	55	54
Kleibergen–Paap Wald F-statistic	6.765**				
Hansen J statistic		0.559	3.299*	1.860	0.326
Endogeneity test of endogenous regressors		0.854	1.361	0.245	0.012

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table A.2
2SLS estimates - revenues per passenger.

Revenues per passenger	(1) Dwell time (First Stage)	(2) Total non-aeronautical (log)	(3) Food and beverage (log)	(4) Retail (log)	(5) Other services (log)
Dwell Time (log)		0.0693	**0.4684***	0.0741	−1.6294
		(0.1544)	(0.2451)	(0.3391)	(2.8444)
Movements (log)	**0.0938*****	−0.0152	−0.0370	−0.0071	0.1597
	(0.0209)	(0.0380)	(0.0541)	(0.0745)	(0.5209)
Congestion	−0.2172	−0.4919	**−1.0516***	−1.1356	**−6.8364*****
	(0.3116)	(0.4689)	(0.5828)	(0.7801)	(2.5593)
Income (log)	0.9064	0.1274	1.1848	−0.1219	0.9696
	(0.5873)	(0.3563)	(0.9832)	(1.0492)	(5.0587)
Domestic	−0.7408	−2.2567	−3.0914	**−5.8452****	**−14.5600***
	(0.7761)	(1.8478)	(2.7040)	(2.5674)	(7.8448)
LCC	−0.3146	−0.3375	**−1.0348***	−0.5117	−0.3252
	(0.2790)	(0.2642)	(0.5641)	(0.6270)	(1.7024)
Delay (log)	**0.1133*****				
	(0.0433)				
PostLocAP	**2.1516*****				
	(0.6444)				
Observations	165	165	165	164	162
R-squared	0.6023	0.0872	0.1554	0.0766	0.0127
Number of ids	55	55	55	55	54
Kleibergen–Paap Wald F-statistic	6.765**				
Hansen J statistic		0.006	2.166	0.813	0.261
Endogeneity test of endogenous regressors		0.326	0.061	0.056	0.020

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

where $\widehat{DwellTime}_{it}$ is the estimated dwell time derived by Eq. (A.1).

To assess the impact of additional variables and control for as many factors as possible, we tested different formulations (for instance, accounting for distribution of visits during the day, age of passengers, their education, etc.). The analyses reported in this section account, as part of Z_{it}, only for the control variables that significantly affect revenues, i.e. only the median passenger income ($\ln Income$).

Column 1 of Tables A.1 and A.2 shows the results of the first stage. The two IVs are positively and significantly affecting dwell time. Aircraft movements are found to play a role in influencing the time spent at the airports. Kleibergen–Paap Wald F-statistic is 6.765 (p-value 0.034) and suggests that the selected instruments are not weak. Additionally, the Hansen J statistic in almost all cases indicates no evidence of not-valid instruments. The results of the second stages are available in columns 2–5 of Tables A.1 and A.2.

Overall, the results are consistent with those reported in Tables 3 and 4: dwell time positively affects food and beverage revenues and RPP as well as non-aeronautical total revenues. Some important differences emerge. In the subsample analyzed, the amount of aircraft movements has no significant impact, and the proportion of domestic

Table B.3
Considered layout per airport - L: linear; F: finger pier; C: (midfield) concourse.

Airport code	Layout	Airport code	Layout	Airport code	Layout
ABQ	L	GSP	L	PBI	F
ALB	F	HNL	C	PDX	F
ANC	C	HOU	L	PHL	F
ATL	C	IAD	C	PHX	C
AUS	L	IAH	C	PIE	L
BDL	F	IND	F	PNS	L
BHM	F	JAX	L	PSP	F
BNA	F	JFK	C	PWM	L
BOI	L	KOA	C	RDU	C
BOS	C	LAS	C	RIC	C
BUF	L	LAX	C	RNO	F
BUR	F	LGA	C	ROC	F
BWI	F	LGB	L	RSW	F
CHS	F	LIT	L	SAN	F
CLE	C	MCI	C	SAT	F
CLT	F	MCO	C	SAV	L
CMH	F	MDW	F	SDF	F
CVG	C	MEM	F	SEA	F
DAL	L	MIA	C	SFB	F
DCA	F	MKE	F	SFO	F
DEN	C	MSN	L	SJC	L
DFW	C	MSP	C	SLC	F
DSM	L	MSY	F	SRQ	L
DTW	C	MYR	L	STL	F
ELP	L	OAK	F	TPA	C
EWR	C	OKC	L	TUL	F
FAT	L	OMA	L	TUS	F
FLL	C	ONT	C	TYS	F
GRR	F	ORD	C	XNA	F
GSO	F	ORF	F		

flights negatively affects both retail and other services revenues and RPP. Additionally, the percentage of seats offered by LCC negatively affects only food and beverage RPP. Finally, the *Congestion* variable negatively affects both other services RPP and food and beverage RPP. As for the additional control variable (*Income*), the analysis suggests that higher income leads to higher non-aeronautical total revenues and food and beverage revenues, while it does not affect RPP. We shall notice, however, that the endogeneity test for all different kinds of revenues is not significant, suggesting that we cannot reject the null hypothesis that 2SLS and the single-stage regressions are not systematically different with each other.

Appendix B. Airport layout

Table B.3 presents the layout considered for each airport in the analysis.

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