Gender Differences within the Firm: Evidence from Two Million Travelers

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Abstract

We document gender differences in the behavior of similar workers within a firm when they book business air travel. We show that women pay consistently less per ticket than men, after accounting for a large set of covariates that include the characteristics of the traveler, the routes and class they travel on, the firms that employ them, and the position that the traveler holds in the firm. A large proportion of the lower fares paid by women is explained by women booking flights earlier than men. We find significant variation in gender differences across the regions of the world. Using country-level data on preference differences, we show that gender differences in both positive and negative *reciprocity* are an important factor associated with the documented gender differences. In particular, *negative reciprocity* alone is able to explain the gender difference in paid fare: women (men) are less (more) willing to trade the firms' money for their own utility when they feel they have been treated unfairly. The documented gender differences have both important monetary implications for firms and implications for the role of morale within the firm.

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Keywords: Gender differences; worker gender differences.

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1 Introduction

Despite there being robust evidence about fundamental differences in the preferences of men and women, less is understood about how these differences manifest in the behavior of workers within firms. Measuring and comparing the behavior of individual workers within a firm is challenging. For many firms, data is only available at the plant or firm level. One approach to understanding individual differences involves estimating a production function using plant-level or firm-level output, and using the structure to identify gender differences.[1] Alternatively, it is possible to directly measure the behavior of individual workers in the small fraction of occupations where output is directly recorded, such as lawyers, real estate agents, and salespeople.[2]

This paper takes a complementary approach by studying gender differences in the performance of a specific task: the booking of business air travel. By studying a single task, we directly observe individual behavior and include workers from many different occupations, firms, and countries. Our dataset contains information about the business travel behavior of around two million unique travelers working in over 8,000 unique firms, in over 60 countries, for the year 2014. It allows us to account for a large set of covariates (over 43 thousand fixed effects in our preferred specification) that includes the characteristics of the traveler, the routes and class they travel on, the firms that employ them, and the position that the traveler holds in the firm, among others. About 25 percent of the workers in our dataset are women.

We document significant gender differences in the performance of similar workers within a firm. Women pay consistently less per ticket than men, after accounting for these rich set of covariates. The covariates explain over 90 percent of the variation in the price paid of an airline booking. We find that approximately 70 percent of the estimated gender difference is explained by women booking flights earlier than men. Woman are five percent more likely to book at least two weeks in advance compared to men after accounting for our set of covariates. The observed gender difference results in a savings of 15.48 U.S. dollars per trip.

[1] See, *e.g.*, Hellerstein, Neumark, and Troske (2002) and Gallen (2018).

[2] See, *e.g.*, Azmat and Ferrer (2017) and Cook, Diamond, Hall, List, and Oyer (2018) for studies using data on lawyers and Uber drivers, respectively.

This represents a savings of about 3.1 (1.9) percent of the median (mean) price of a plane ticket.

We find significant heterogeneity in the estimated gender differences. We estimate models that include gender interactions with age, length of stay, traveler type, and region. We find significant variation by region of the world. Workers in the United States and Europe exhibit the largest gender differences. Differences are smaller in South America, non-significant in Australia, and inverted in Asia. Women book tickets that are on average \$10 more expensive in Asia compared to men. This heterogeneity suggests that cultural influences may play an important role in understanding gender differences.[3] We also find that gender differences increase with age, where the difference is \$11.75 for workers less than 25 years old, and \$18.89 for workers between 55 and 64 years old. Interestingly, we do not find any deviation from this trend during the childbearing years. Finally, we do not observe heterogeneity in gender differences by traveler or trip type. Gender differences do not substantively change when considering travelers who fly few or many trips in a year. With the exception of trips that last less than 24 hours, gender differences do not vary with length of the trip.

Next we investigate potential mechanisms that could explain the observed gender differences in both fare paid and advanced booking. To do that, we complement the business travel data with information about economic preferences in each country.[4] Preference data is obtained from the Global Preference Survey documented in Falk, Becker, Dohmen, Enke, Huffman, and Sunde (2018). We consider gender differences in patience, risk taking, altruism, positive reciprocity, negative reciprocity, and trust. We show that gender differences in both negative and positive reciprocity are important factors associated with gender differences in both fare paid and advanced booking. In particular, *negative reciprocity* alone is able to explain the observed gender difference in paid fare. The main insight of this result is that women (men) are less (more) willing to trade the firms' money for their own utility when they feel they have been treated unfairly. This is exacerbated in a context of incomplete con-

[3] Falk, Becker, Dohmen, Enke, Huffman, and Sunde (2018) report considerable gender differences in preferences using an experimentally validated survey dataset from 80,000 individuals across 76 countries. They show that positive reciprocity and altruism are more pronounced among women, while negative reciprocity is weaker among women (see table 5 in FBDEHS).

[4] See Pope and Sydnor (2010) for another example where geographic variation in cultural attitudes and gender stereotypes is used to understand gender disparities in standardized test scores in the United States.

tracts, whereby the firm cannot specify every possible contingency regarding the air bookings performed by its workers. This increases the scope to spend firms' money by the employee.

The literature on gender differences in economic experiments has studied several traits for which the documented gender differences may help explain our results.[5] Women have been documented to be more risk averse than men in the vast majority of environments and tasks for studies selecting members of the general population (as in, *e.g.*, Sunden and Surette 1998; Finucane, Slovic, Mertz, Flynn, and Satterfield 2000; Bernasek and Shwiff 2001).[6] If women are more risk adverse about a price increase they may book earlier. For managers and professional populations like ours, however, gender differences in risk aversion have been found to be small or nonexistent (*e.g.* Masters and Meier 1988; Birley 1989; Johnson and Powell 1994; Atkinson, Baird, and Frye 2003). There are a number of papers documenting that women are more generous than men at least in certain contexts. Women have been shown to be more altruistic (*e.g.* Eckel and Grossman 1998; Güth, Schmidt, and Sutter 2007) and more cooperative (*e.g.* Frank, Gilovich, and Regan 1993; Seguino, Stevens, and Lutz 1996; Ortmann and Tichy 1999; Chermak and Krause 2002) than men.[7] Women may be booking earlier flights to save the firm money, even if they do not receive a direct benefit or recognition for doing so.

Our paper is also related to the literature on gender performance gaps in real world labor markets. This literature is quite small due to the difficulties of measuring the output of individual workers within firms. There are two papers (Hellerstein, Neumark, and Troske, 2002; and Gallen, 2018) that study gender productivity gaps by estimating production functions using data on value added and the labor force of firms. These papers estimate the

[5] See Eckel and Grossman (2008), Croson and Gneezy (2009), and Niederle (2014) for comprehensive reviews of the literature examining gender differences in economics experiments. See Bertrand (2011) and Azmat and Petrongolo (2014) for comprehensive reviews of the literature examining the role of experimental findings on gender differences for labor economics.

[6] This can sometimes be attributed to women experiencing emotions more strongly than men (*e.g.* Harshman and Paivio 1987; Loewenstein, Weber, Hsee, and Welch 2001), or to overconfidence of men relative to women about their relative performance in a task (*e.g.* Niederle and Vesterlund 2007). Cite Dohmen, Falk, Huffman, Sunde, Schupp, and Wagner (2011).

[7] These findings, however, do not hold universally (*e.g.* Brown-Kruse and Hummels 1993; Sell and Wilson 1991; Solow and Kirkwood 2002; Ben-Ner, Kong, and Putterman 2004; Bolton and Katok 1995; Ortmann and Tichy 1999). Croson and Gneezy (2009, section 3) attribute the variation in the findings in these studies to a "differential sensitivity of men and women to the social conditions in the experiment." They show evidence that women are more sensitive to the social context of the experiment, by looking within and between a large number of studies investigating gender differences in social preferences.

labor input as the sum of different types of labor, including among other things gender, race, age/experience, education, and occupation. Hellerstein, Neumark, and Troske (2002) use U.S. survey data on firms from the manufacturing sector. They find a gender productivity gap, where men are more productive than women. Most of the difference is driven by non-managerial, non-professional, and younger workers. These results may be specific to the manufacturing sector. Gallen (2018) uses data on the full Danish economy and finds that, on one hand, women with children are less productive than men. On the other hand, women without children are more productive than men. An alternative approach is to focus on a particular occupation/industry, where individual output can be directly measured. Azmat and Ferrer (2017) study the performance of young lawyers in the U.S. They find that male lawyers bill 10 percent more hours and bring in more than twice as much client revenue as female lawyers. Matsa and Miller (2013) study the behavior of firms that are affected by a change in gender quotas for corporate board seats in Norway. They find that affected firms undertake fewer workforce reductions, leading to increased labor costs and reduced short-term profits. Cook, Diamond, Hall, List, and Oyer (2018) study the performance of Uber drivers in the U.S. They document a roughly 7% gender earnings gap that can be explained by experience on the platform, location preference, and preference for driving speed. The goal of most of these studies is to measure the full output of workers and compare the gender productivity gap to the gender wage gap. While this paper does not attempt to explain the gender wage gap, it provides new insights about gender behavior differences within a firm. We observe the output of our task directly for a variety of firms, occupations, industries, and countries. In addition, we document an association in the behavioral differences to differences in economic preferences. Studying business travel bookings is also of interest as it is likely not sensitive to biological explanations (*e.g.* physical strength and bearing children) and more sensitive to differences in preferences.

In summary, we make two main contributions: (1) We document robust gender differences in the behavior of working professionals, using a large dataset spanning a wide variety of industries, firms, and countries. Women pay consistently less per ticket and book flights earlier than men. A large proportion of the lower fares paid by women are explained by women booking flights earlier than men. (2) We show that cross-country gender differences in *reciprocity* are an important factor associated with the documented gender differences. In addition, *negative reciprocity* explains the gender difference in paid fare: women (men) are less (more) willing to trade the firms' money for their own utility when they feel they have been treated unfairly. The documented gender differences have important monetary implications for firms, and implications for the role of morale within the firm.

The rest of the paper is organized as follows. In section 2 we describe the data. Section 3 presents the empirical results. Section 4 discusses potential mechanisms. Finally, section 5 concludes. Details about the computational implementation, and additional robustness analysis are the appendix.

2 Data Description

We combine data from two sources. The main data contains information about business travel bookings of workers. Business travel data is an administrative dataset obtained from a large multinational travel management company. We complement these data with information about economic preferences in each country. Preference data is obtained from the Global Preference Survey as presented by Falk, Becker, Dohmen, Enke, Huffman, and Sunde (2018, henceforth FBDEHS). Below we describe these sources. We devote more space to business travel data, which is novel. Details about the preference data are in FBDEHS.

2.1 Business Travel Data

We collected business travel data from a large multinational travel management company. This company fulfills the business travel needs of corporate clients in North America, South America, Europe, Africa, Asia, and Australia. In a given year, this company fulfills tens of millions of transactions across all travel categories (air, hotel, rental car, rail, *etc.*). The geographical scope comprises over 45 countries in which this company has wholly-owned operations, joint ventures, and minority holdings, plus over 15 countries in their partner network.

For the analysis, we use a unique administrative dataset, which includes information on travelers and their business air bookings in 2014. We observe detailed information about the bookings: price of the ticket, dates of travel, origin and destination airports, ticket class, whether or not the flight is direct, date booked, location of the booking. The information on travelers is anonymous, and is based on the information provided by the travelers to the airlines needed to perform the booking. This includes the gender and age of the traveler. We also have anonymous identifiers of the firms where the employee works and the division within the firm in which the employee works. In our dataset there are over $8,000$ unique firms, and over $25,000$ unique division-firm pairs. We also have information about the position of the employee within the division-firm for some firms.

To obtain the final sample used in our analysis, we applied the following selection criterion:

- Only original transactions are included; refunds or ticket modifications are not taken into account.
- Only round-trip tickets are selected.
- Only routes with 100 tickets or more are included.
- The top 1 percent of the tickets with highest fares are excluded.

The resulting panel dataset has approximately 7.4 million airline transactions corresponding to around 2 million unique travelers. Based on the information in the dataset we constructed the following variables: length of the trip in days, number of trips per traveler per year, and the number of days in advance that the trip was booked.

Table A1 displays summary statistics for selected variables in our dataset. The fare paid varies considerably as expected, given the heterogeneity in destinations, ticket class, and the number of days booked in advanced. The mean paid fare is \$791.49 and the standard deviation is \$1,021.32. There is also substantial variation in the number of days booked in advance, with a mean of 18.70 days and a standard deviation of 21.49 days. Table A1 shows that 25 percent of the trips are booked by female travelers. Although there is considerable variation in the age of the traveler performing the booking, 65 percent of the trips are booked by travelers in the age range between 35 and 54 years old. There is also considerable variation in the number of trips per year performed by the travelers. The majority of the trips (89 percent) are booked without connection (*i.e.* "direct" flights) and are booked in the "economy" ticket class (89 percent). In terms of the length of the stay, 13 percent of the trips are performed in the same day (less than 24 hours), 58 percent last more than one day and less than four days, and the remaining 29 percent last 5 days or more. In terms of the destinations, 63 percent of the trips are domestic (*i.e.* origin and destination airports within same the country), 25 percent are continental (*i.e.* origin and destination airports within same the continent), and 13 percent intercontinental. Finally, the trips originating from North America or the European Union encompass 85 percent of the booked flights.

2.2 Preference Data

We complement the previous data with information about economic preferences in each country. Preference data is obtained from the Global Preference Survey (GPS) as presented by FBDEHS. The GPS is an experimentally validated survey dataset of time preference (patience), risk preference (risk taking), positive and negative reciprocity, altruism, and trust from 80,000 individuals in 76 countries. Table A2, obtained from FBDEHS, summarizes the survey items for each preference. See FBDEHS for a thorough discussion.

For each preference item in table A2, we obtain the gender difference at the country level reported by FBDEHS (online appendix EB). Then we merge the gender difference preferences to the business travel data using the country where the traveler works. The country-level gender preference differences are measured in standard deviations of the respective country. They represents the mean gender difference by country in the original preference. See appendix A for details. Table A3 displays summary statistics of the preference data. See FBDEHS for a detailed description and interpretation.

3 Empirical Results

We begin analyzing business travel purchasing behavior by gender. We find that on average women pay 104.07 U.S. dollars less per ticket than men (column 1 of table 1). The difference in fare paid by women and men is endogenous to a number of factors that include the characteristics of the traveler, the routes and class they travel on, the firms that employ them, and the position that the traveler holds in the firm. We take advantage of our rich dataset to develop multiple covariates for each of these factors. Table 1 displays the results for several specifications of the difference in fare paid by women compared to men. First, we condition on basic characteristics of the traveler and flight: age of the traveler, the number of trips the traveler made that year, whether the flight was direct, and the length of the stay (the difference, in days, between the day of departure and the day of return). Column 2 in table 1 shows that conditioning for these basic characteristics explains about 30 percent of the raw mean difference ($^{-104.065+72.095}/_{-104.065} = 0.307$). In column 3, we add $18,172$ fixed effects for origin-destination route and ticket class interactions (route-class fixed effects henceforth). Adding route-class fixed effects reduces the gender difference in fare paid to 21.92 U.S. dollars. Men are more likely to travel on more expensive routes and in a higher ticket classes. In column 4, conditioning on week of the year and the country where the flight originates, do not change the difference in the fare paid by gender nor the goodness of the fit. Conditioning on employee type in the firm (*i.e.* position of the employees within the division-firm) reduces the difference to 16.37 U.S. dollars. Finally, in column 6 we add $25,167$ fixed effects for the division and firm interactions (*i.e.* unique division-firm combination) where the employee works. This reduces the coefficient to 15.48 U.S. dollars. Over 85 percent of the raw gender difference in fare paid is explained by the characteristics of the traveler, the flight, and the division-firm combination where the traveler works ($^{-104.065+15.482}/_{-104.065} = 0.851$). A back of the envelope calculation shows that a saving of 15.48 U.S. dollars per trip for all the trips done by the men in each firm, represents a mean (median) saving across firms of 1.90 percent of the total annual expenditure of the firm in air tickets, or 10,601 U.S. dollars per year for the mean (median) firm. This represents a savings of about 3.1 (1.9) percent of the median (mean) price of a plane ticket.[8]

In the final specification we seek to understand why women pay 15.48 US dollars per ticket less than men after conditioning for these factors. We show that a major factor explaining why women pay lower fares is because they book flights earlier than men. In our data, we have the date of the booking, in addition to the dates of departure and return of the flights. In column 7, we include 26 fixed effects for how many days the traveler booked in advanced: a set of 15 dummy variables, one for each of the first 15 days prior to a flight;

[8]Similar results are obtained when using a log specification for fare paid.

a set of 10 dummy variables, one for each of the 10 weeks following the first 15 days prior to a flight; and an additional dummy variable for a booking that took place more than 85 days ($85 = 15 + 10 \times 7$) before the flight.[9] We find that accounting for the advanced booking behavior explains approximately 70 percent of the difference in the fare paid by women not explained by the covariates in column 6 ($^{-15.482+4.460}/_{-15.482} = 0.711$). As regards the overall goodness of the fit, the adjusted R^2 in column 7 is 90.7 percent.

We also report the gender differences for days booked in advance, female interactions, and a linear probability model for advance booking of female travelers. Column 6 in table A4 in the appendix, which has a similar structure to table 1, shows that women book on average 1.81 days earlier than men, after accounting for the characteristics of the traveler, the flight, route-class fixed effects, week and country fixed effects, employee type, and the division-firm combination where the traveler works. Table 2 reports additional fare paid models that include interactions between female and other characteristics using the specification in column 6 of table 1. The difference in the fare paid by gender increases with age. Again, this is mainly explained because the gender difference in days booked in advance increases with age.[10] Tables 2 and 3 show that gender differences do not depend on the length of stay and the number of trips per year. Table 3 also shows that gender differences vary considerably by the region where the worker is based. The specification in column 6 of table A5, which has a similar structure to table 1, shows that women are 5.3 percent more likely than men to book a flight two or more weeks in advance. The probability of men of booking a flight two or more weeks in advance is 44.2 percent. Thus, it represents a substantial increase.[11]

We also find that using the same set of covariates as in the specification in column 6 of table 1 (with the obvious modifications) women are less likely to: (i) book a flight in first class, business class, or premium economy; (ii) book a flight that spans over a weekend; and (iii) book a direct flight. Finally, for robustness, we repeated all tables and specifications

[9]We obtained almost identical results using other specifications for the "days booked in advanced fixed effects," including a set of 91 dummy variables, one for each day booked in advance before the departure for the first 90 days and 1 additional dummy variable for more than 90 days. See also footnote 12.

[10]This can be seen, *e.g.*, in unreported results, where we repeated tables 2 and 3 using "Days Booked in Advanced" as dependent variable with the specification in column 6 of table A4. See also footnote 12.

[11]We obtained similar results to the ones in table A5 using linear probability models for booking: one week or more in advance, three weeks or more in advance, and four weeks or more in advance. We have also obtained similar interaction results to the ones in tables 2 and 3 using these linear probability models. See also footnote 12.

using the subset of the 25 percent most popular routes, and obtained similar results.[12]

4 Potential Mechanisms

Why do women book earlier than men in the firm? Although the evidence we presented is correlational, we now discuss potential mechanisms that could explain the observed gender differences. To do that, we analyze the preference data presented in subsection 2.2.

Tables 4 and 5 display female interactions with gender differences in preferences. Table 4 displays the interactions with paid fare using specification 6 from table 1. Likewise, table 5 displays the interactions in a linear probability model of whether the traveler booked at least 14 days in advance, using specification 6 from table A5. Column 1 in tables 4 and 5 repeat specification 6 in tables 1 and A5 (respectively) with the sample of countries that have preference data.[13] Similar results to tables 1 and A5 are obtained. Column 1 shows the base gender difference in fare paid and advanced booking behavior without accounting for gender differences in preferences. Columns 2 to 7 add interactions between female and each preference item from table A2. We include both the variable *female* and the interaction between *female* and the *preference*, because we are interested in both the gender difference in fare paid and advance booking behavior in a country with no gender difference in a preference, *i.e.* the *female* coefficient, and how the gender difference in fare paid (advance booking behavior) varies with gender differences in preferences, *i.e.* the *female* × *preference* coefficient.

Columns 2 to 4 in tables 4 and 5 show that there is no evidence that *patience*, *risk taking*, and *altruism* play a role explaining lower fares paid or the advance booking behavior by women. Column 2 shows that the interaction between *female* and *patience* is not statistically different from zero.

Regarding *risk taking*, one potential explanation of women paying lower fares (booking earlier), is that women may be more risk adverse about a price increase than men. Although women have been documented to be more risk averse than men in the vast majority of

[12]Results reported in this paragraph, footnotes 9, 10, and 11 are available to be include in the paper.
[13]See appendix A for details about the countries without preference data.

environments (*e.g.* Sunden and Surette 1998; Finucane, Slovic, Mertz, Flynn, and Satterfield 2000; Bernasek and Shwiff 2001; Croson and Gneezy 2009; Niederle 2014), column 3 in tables 4 and 5 show that the interaction between *female* and *risk taking* is not statistically different from zero.

Under the *altruism* hypothesis, women may be more altruistic or generous towards the firm. For example, women may value the firm more than men, or, thought as a public good, women may be more willing to contribute more than men to the public good as in, *e.g.*, Vesterlund, Babcock, and Weingart (2014). However, in column 4 in tables 4 and 5 the interaction between *female* and *altruism* is not statistically different from zero. This indicates that altruism or generosity towards the firm are not the primary driver of the gender difference either. This is consistent with the results in the economics experimental literature, where there are not robust differences in average contributions in public good games between men and women (*e.g.* Ledyard 1995; Eckel and Grossman 2008; Croson and Gneezy 2009; Niederle 2014).

We now consider *Positive reciprocity*, where someone who has higher reciprocity is someone who is more likely to give a “gift in exchange for help” and “to return a favor.” Column 5 in tables 4 and 5 show that the interaction between *female* and *positive reciprocity* is statistically different from zero. It is negatively correlated with paid fare and positively correlated with advance booking behavior as might be expected. However, the coefficient on *female* is similar in magnitude to the one in column 1, and is statistically different from zero. This indicates that although gender differences in positive reciprocity are associated with gender differences in the fare paid and also the advanced booking behavior, it does not explain the average behavior differences for both fare paid or advanced booking.

As regards *negative reciprocity*, we refer to its definition in table A2. A positive interaction term means that women (men) are less (more) “willing to take revenge and to punish unfair behavior towards self/others.” In the context of the firm in our empirical setting, the main insight of *negative reciprocity*, is that women (men) are less (more) willing to trade the firms’ money for their own utility if they feel that they have been treated unfairly. This is exacerbated in a context of incomplete contracts, whereby the firm cannot specify every possible contingency regarding the air bookings performed by its workers. This increases the scope to spend firms' money by the employee. FBDEHS show that negative reciprocity is weaker among women (table 5). Consistent with that, column 6 in table 4 shows that the interaction between *female* and *negative reciprocity* is positive, statistically different from zero at the 5 percent level, and large in magnitude. Interestingly, the coefficient on *female* in column 6 in table 4 is the only one that is not statistically different from zero. Taken together, these results indicate that women being less willing to trade the firms' money for their own utility than men, explains most of the gender difference in paid fare. Also consistent with this interpretation, while we find that women pay approximately $30 more than men in Asia compared to the United States ($9.288 + 18.935 = 28.22$ in table 3), FBDEHS find that negative reciprocity is less pronounced for women in Asia relative to the United States.[14] The results for advanced booking (table 5) are similar. The interaction between *female* and *negative reciprocity* is statistically different from zero, indicating that *negative reciprocity* can explain some of gender differences in advanced booking. The advanced booking coefficient on *female* is smaller, but still statistically significant though, indicating that *negative reciprocity* does not fully explain the overall behavioral differences.

Finally, column 7 in tables 4 and 5 investigates the interaction with *trust*, in that "people have only the best intentions," according to table A2. The results are mixed. On the one hand, the interaction between *female* and *trust* is statistically different from zero in both tables. On the other, although the magnitude of the *female* coefficient is reduced, it is still large in magnitude and statistically different from zero. So *trust* explains part of the gender difference in paid fare and advance booking behavior, but not all of it. Gender difference in *trust* is highly correlated with *negative reciprocity* (coefficient of correlation of -0.68). Due to this collinearity, when both coefficients interactions are included, neither is statistically significant. The null hypothesis that both are zero is rejected. So one explanation for the mixed results could be that *trust* is partially capturing the effect of *negative reciprocity*, which have a more clear interpretation in our empirical context. However, we cannot accept or reject this hypothesis with our data. This is an avenue of further research.

[14]Obtained by comparing the coefficients (reported next in parenthesis) on negative reciprocity, 1 if female, from tables 15 and 16 in online appendix EB, for the Asian countries included in those tables, China (-0.195^{***}), Japan (-0.284^{***}), South Korea (-0.023), and Vietnam (0.007), relative to the United States (-0.329^{***}).

5 Concluding Remarks

We documented gender differences in the behavior of similar workers within a firm when they book business air travel. Women pay consistently less per ticket and book flights earlier than men. The results are robust after accounting for a large set of covariates that include the characteristics of the traveler, the routes and class they travel on, the firms that employ them, and the position that the traveler holds in the firm. A large proportion of the lower fares paid by women are explained by women booking flights earlier than men. The observed gender differences in advance booking for business travel results in substantial monetary savings for the firms.

We complemented the analysis with country-level information on economic preferences to discuss potential mechanisms that could explain the observed gender differences. We found that *reciprocity* is an important factor associated with gender differences in paid fare and advanced booking behavior. In addition, we showed that gender differences in *negative reciprocity* is able explain the observed gender difference in paid fare. The main insight of this result is that women (men) are less (more) willing to trade the firms' money for their own utility when they feel they have been treated unfairly. This is exacerbated in a context of incomplete contracts, whereby the firm cannot specify every possible contingency regarding the air bookings performed by its workers. This increases the scope to spend firms' money by the employee. The documented gender differences have important monetary implications for firms as worker behavior can lead to increased costs for the firm. Our findings also demonstrate the importance of morale within a firm. We have shown that variation in worker's preferences for reciprocity are also associated with both extra savings and extra costs to the firm.

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Table 1: Paid fare by gender.

Dependent variable: paid fare	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-104.065***	-72.095***	-21.923***	-21.952***	-16.365***	-15.482***	-4.460***
	(0.866)	(0.821)	(0.289)	(0.287)	(0.293)	(0.293)	(0.285)
Controls F.E. (13)	No	Yes	Yes	Yes	Yes	Yes	Yes
O-D route $\times$ ticket class F.E. (18,172)	No	No	Yes	Yes	Yes	Yes	Yes
Week and country F.E. (118)	No	No	No	Yes	Yes	Yes	Yes
Employee type F.E. (6)	No	No	No	No	Yes	Yes	Yes
Division $\times$ firm F.E. (25,167)	No	No	No	No	No	Yes	Yes
Days booked in advance F.E. (26)	No	No	No	No	No	No	Yes
Number of F.E. included	0	13	18,185	18,303	18,309	43,476	43,502
Adjusted R^2	0.0019	0.1240	0.8958	0.8973	0.9013	0.9015	0.9069
Number of observations	7,430,331	7,430,331	7,430,331	7,430,331	7,430,331	7,430,331	7,430,331

Notes: Dependent variable is the paid fare, which is measured in U.S. dollars. "Controls" include the following variables: direct flight, age dummy variables, length of stay dummy variables, and number of trips per traveler dummy variables. "F.E." stands for "Fixed Effects." The parenthesis in the initial column, next to the labels, summarizes the number of fixed effects included in each line. See appendix D for definitions of the variables, and fixed effects. All regressions are OLS regressions. Standard errors are in parentheses.

* significant at $p < .05$; $^{**}p < .01$; $^{***}p < .001$.

Table 2: Paid fare: female interactions (part I).

Dependent variable: paid fare	(1)	(2)
Female ×		
($age \leq 24$)	-11.752***	
	(2.931)	
($25 \leq age \leq 34$)	-13.420***	
	(0.640)	
($35 \leq age \leq 44$)	-14.253***	
	(0.489)	
($45 \leq age \leq 54$)	-16.285***	
	(0.505)	
($55 \leq age \leq 64$)	-18.888***	
	(0.757)	
($age \geq 65$)	-26.386***	
	(2.422)	
(length of stay $<$ 1 day)		-10.596***
		(0.763)
($1 <$ length of stay ≤ 2 days)		-14.537***
		(0.598)
($2 <$ length of stay ≤ 3 days)		-16.949***
		(0.619)
($3 <$ length of stay ≤ 4 days)		-18.395***
		(0.677)
(length of stay ≥ 5 days)		-15.719***
Controls F.E. (13)	Yes	Yes
O-D route × ticket class F.E. (18,172)	Yes	Yes
Week and country F.E.(118)	Yes	Yes
Employee type F.E. (6)	Yes	Yes
Division × firm F.E. (25,167)	Yes	Yes
Number of F.E. included	43,476	43,476
Adjusted R^2	0.9015	0.9015
Number of observations	7,430,331	7,430,331

Notes: Dependent variable is the paid fare, which is measured in U.S. dollars. The table displays female interactions using specification (6) from table 1. "Controls" include the following variables: direct flight, age dummy variables, length of stay dummy variables, and number of trips per traveler dummy variables. "F.E." stands for "Fixed Effects." The parenthesis in the bottom of the initial column, next to the labels, summarizes the number of fixed effects included in each line. See appendix D for definitions of the variables and fixed effects. All regressions are OLS regressions. Standard errors are in parentheses.
* significant at $p < .05$; $^{**}p < .01$; $^{***}p < .001$.

Table 3: Paid fare: female interactions (part II).

Dependent variable: paid fare	(3)	(4)
Female ×		
(trips per year ≤ 5)	-15.564***	
	(0.419)	
(6 ≤ trips per year ≤ 10)	-14.089***	
	(0.596)	
(11 ≤ trips per year ≤ 15)	-16.293***	
	(0.792)	
(trips per year ≥ 16)	-16.391***	
	(0.653)	
Africa		-7.812
		(4.593)
Australia		2.020
		(1.356)
Europe		-16.149***
		(0.512)
Asia		9.288***
		(1.457)
Middle East		13.669
		(9.441)
North America		-18.935***
		(0.397)
South America		-10.292***
		(1.307)
Controls F.E. (13)	Yes	Yes
O-D route × ticket class F.E. (18,172)	Yes	Yes
Week and country F.E.(118)	Yes	Yes
Employee type F.E. (6)	Yes	Yes
Division × firm F.E. (25,167)	Yes	Yes
Number of F.E. included	43,476	43,476
Adjusted R^2	0.9015	0.9015
Number of observations	7,430,331	7,430,331

Notes: Dependent variable is the paid fare, which is measured in U.S. dollars. The table displays female interactions using specification (6) from table 1. "Controls" include the following variables: direct flight, age dummy variables, length of stay dummy variables, and number of trips per traveler dummy variables. "F.E." stands for "Fixed Effects." The parenthesis in the bottom of the initial column, next to the labels, summarizes the number of fixed effects included in each line. See appendix D for definitions of the variables and fixed effects. All regressions are OLS regressions. Standard errors are in parentheses.
* significant at $p < .05$; $^{**}p < .01$; $^{***}p < .001$.

Table 4: Paid fare: female interactions with preference data.

Dependent variable: paid fare	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-15.782***	-14.988***	-9.688	-9.125*	-11.215***	-6.696	-8.294***
	(1.636)	(2.834)	(5.989)	(4.057)	(2.039)	(3.874)	(1.756)
Female ×							
Patience		9.965					
		(20.107)					
Risk Taking			19.156				
			(17.857)				
Altruism				-33.451			
				(23.608)			
Positive Reciprocity					-40.989**		
					(11.976)		
Negative Reciprocity						32.441*	
						(12.500)	
Trust							-25.619***
							(4.329)
Controls F.E. (13)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
O-D route × ticket class F.E. (16,066)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week and country F.E.(97)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employee type F.E. (6)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Division × firm F.E. (20,827)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of F.E. included	37,009	37,009	37,009	37,009	37,009	37,009	37,009
Adjusted R^2	0.899	0.899	0.899	0.899	0.899	0.899	0.899
Number of Observations	7,014,989	7,014,989	7,014,989	7,014,989	7,014,989	7,014,989	7,014,989

Notes: Dependent variable is the paid fare, which is measured in U.S. dollars. The table displays female interactions using specification (6) from table 1. "Controls" include the following variables: direct flight, age dummy variables, length of stay dummy variables, and number of trips per traveler dummy variables. "F.E." stands for "Fixed Effects." The parenthesis in the bottom of the initial column, next to the labels, summarizes the number of fixed effects included in each line. See appendix D for definitions of the variables and fixed effects. See table A2 for a summary of the survey items for each preference. All regressions are OLS regressions. Robust standard errors clustered at the country level are in parentheses.
* significant at $p < .05$; ** $p < .01$; *** $p < .001$.

Table 5: Probability model for booking two weeks or more in advance: female interactions with preference data.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	0.0526***	0.0549***	0.0378***	0.0442***	0.0446***	0.0413***	0.0382***
	(0.00325)	(0.00395)	(0.00901)	(0.00694)	(0.00367)	(0.00414)	(0.00359)
Female ×							
Patience		0.0284					
		(0.0278)					
Risk Taking			-0.0467				
			(0.0272)				
Altruism				0.0425			
				(0.0435)			
Positive Reciprocity					0.0724**		
					(0.0216)		
Negative Reciprocity						-0.0404*	
						(0.0173)	
Trust							0.0494***
							(0.00658)
Controls F.E. (13)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
O-D route × ticket class F.E. (16,066)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week and country F.E.(97)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employee type F.E. (6)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Division × firm F.E. (20,827)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of F.E. included	37,009	37,009	37,009	37,009	37,009	37,009	37,009
Adjusted R^2	0.189	0.189	0.189	0.189	0.189	0.189	0.189
Number of Observations	7,014,989	7,014,989	7,014,989	7,014,989	7,014,989	7,014,989	7,014,989

Notes: The table displays the estimates of a linear probability model. The dependent variable is a dummy variable equals to 1 if the traveler booked the flight with two weeks or more in advance (*i.e.* if the trip was booked 14 days or more prior to the day of departure), and 0 otherwise. The table displays female interactions using specification (6) from table A5. "Controls" include the following variables: direct flight, age dummy variables, length of stay dummy variables, and number of trips per traveler dummy variables. "F.E." stands for "Fixed Effects." The parenthesis in the bottom of the initial column, next to the labels, summarizes the number of fixed effects included in each line. See appendix D for definitions of the variables and fixed effects. See table A2 for a summary of the survey items for each preference. All regressions are OLS regressions. Robust standard errors clustered at the country level are in parentheses.
* significant at $p < .05$; **$p < .01$; ***$p < .001$.

Appendix (Not For Publication)

A Details about Preference Data

Preference data is obtained from the Global Preference Survey (GPS) as presented by Falk, Becker, Dohmen, Enke, Huffman, and Sunde (2018, henceforth FBDEHS). For each preference item in table A2, we obtain the gender difference at the country-level reported by FBDEHS (online appendix EB). Then we merge the gender difference preferences to the business travel data, using the country of the traveler.

The following countries have business travel data, but do not have preference data: Angola, Belgium, Bulgaria, Bahrain, Denmark, Dominican Republic, Ecuador, Hong Kong, Honduras, Kuwait, Luxembourg, Latvia, Malaysia, Norway, New Zealand, Oman, Panama, Qatar, Singapore, and Trinidad and Tobago. The number of observations from these countries in the business travel data is $415,342$. Thus, the number of observations drops from 7,430,331 in table A1, to 7,014,989 in table A3.

In online appendix EB (tables 15 and 16), FBDEHS report gender coefficients of several regressions by country. For each country, they regress the respective preference on a woman indicator (a dummy variable that equals one if the person is a woman and zero otherwise), age and its square, and subjective math skills. To make the countries comparable, they standardize (z-scores) each preference within each country before computing the coefficients. FBDEHS report the coefficients of the woman indicator for each country. Thus, each coefficient is in the same unit as the original preference measure from the GPS. The coefficient represents the mean gender difference by country in the original preference. In other words, a coefficient of 0.1 means that women in a given country report, on average, having 0.1 standard deviations higher in the respective preference compared to men.

B Computational Appendix

All regressions in subsection 3 are OLS regressions implemented using the numerical procedure from Gaure (2013). This is an iterative procedure that relies on the Frisch-Waugh-Lovell decomposition theorem[15] to avoid the inversion of the matrix of fixed effects. This procedure results in savings of computing time when the number of fixed effects is large as it is in our case. The statistical properties of this estimator are the same as the ones of standard OLS (Gaure 2013), whereby one inverts the matrix with all the fixed effects.

C Additional Tables

[15] See Frisch and Waugh (1933), Lovell (1963), and Lovell (2008).

Table A1: Summary statistics of business travel data.

Panel A: Summary statistics of dependent variables

Statistic	Nmbr. Obs.	Mean	St. Dev.	Min.	Max.
Paid fare (in U.S. dollars)	7,430,331	791.49	1,021.32	78.58	7,344.00
Days booked in advance	7,430,331	18.70	21.49	0	102.00

Panel B: Summary statistics of independent variables

Variable	Categories	Nmbr. Obs.	Frequency
Female	0	5,580,934	0.75
	1	1,849,397	0.25
Direct flight	0	783,535	0.11
	1	6,646,796	0.89
Age (dummy variables)	$\leq$ 24 years old	51,978	0.01
	25-34	1,179,499	0.16
	35-44	2,389,990	0.32
	45-54	2,484,516	0.33
	55-64	1,194,603	0.16
	$\geq$ 65	129,745	0.02
Length of stay (dummy variables)	$\leq$ 1 day	993,459	0.13
	1-2	1,612,762	0.22
	2-3	1,452,302	0.20
	3-4	1,210,453	0.16
	$\geq$ 5	2,161,355	0.29
Number of trips per traveler (dummy variables)	$\leq$ 5 trips per year	2,989,860	0.40
	6-10	1,658,171	0.22
	11-15	1,018,922	0.14
	$\geq$ 16	1,763,378	0.24
Ticket class (dummy variables)	Economy Class	6,631,382	0.89
	Premium Economy	277,022	0.03
	Business Class	487,363	0.07
	First Class	34,564	0.01
Flight type (dummy variables)	Domestic	4,664,108	0.63
	Continental	1,910,481	0.25
	Intercontinental	855,742	0.12
Region	Africa	31,273	0.004
	Australia	343,427	0.046
	Europe	2,751,059	0.370
	Asia	345,982	0.047
	Middle East	13,097	0.002
	North America	3,568,806	0.480
	South America	376,687	0.051

Notes: Each observation represents one roundtrip flight. Panel A displays the summary statistics of the dependent variables used in tables 1 and A4. Panel B displays, for the independent variables used in those tables, the categories, number of observations, and frequency by category. In panel B, the total number of observations per variable is 7,430,331, which is the total number of observations in tables 1 and A4. Similarly, in panel B, the frequencies of the categories per variable sum to 100 percent. See appendix D for definitions of the variables, and fixed effects.

Table A2: Survey items of the GPS.

Preference	**Item Description**	Weight
Patience	Intertemporal choice sequence using staircase method	0.712
	Self-assessment: Willingness to wait	0.288
Risk taking	Lottery choice sequence using staircase method	0.473
	Self-assessment: Willingness to take risks in general	0.527
Positive reciprocity	Gift in exchange for help	0.515
	Self-assessment: Willingness to return a favor	0.485
Negative reciprocity	Self-assessment: Willingness to take revenge	0.374
	Self-assessment: Willingness to punish unfair behavior towards self	0.313
	Self-assessment: Willingness to punish unfair behavior towards others	0.313
Altruism	Donation decision	0.635
	Self-assessment: Willingness to give to good causes	0.365
Trust	Self-assessment: People have only the best intentions	1

Source: Obtained from Falk, Becker, Dohmen, Enke, Huffman, and Sunde (2018, table 1). See their online appendix AF for the wording of the questions, and online appendix AI for a details of the weights.

Table A3: Summary statistics of preference data.

Panel A: All Observations.

	Nmbr. Obs.	Mean	St. Dev.	Min.	Max.
Patience	7,014,989	-0.088	0.090	-0.288	0.085
Risk taking	7,014,989	-0.309	0.102	-0.395	0.028
Altruism	7,014,989	0.197	0.066	-0.161	0.406
Positive reciprocity	7,014,989	0.101	0.085	-0.207	0.270
Negative reciprocity	7,014,989	-0.272	0.117	-0.467	0.036
Trust	7,014,989	0.277	0.154	-0.143	0.418

Panel B: By Country.

	Nmbr. Countries	Mean	St. Dev.	Min.	Max.
Patience	46	-0.078	0.098	-0.288	0.085
Risk taking	46	-0.203	0.105	-0.395	0.028
Altruism	46	0.139	0.124	-0.161	0.406
Positive reciprocity	46	0.058	0.098	-0.207	0.270
Negative reciprocity	46	-0.161	0.110	-0.467	0.036
Trust	46	0.095	0.128	-0.143	0.418

Notes: Summary statistics from the merged preferences data obtained from the Global Preference Survey (GPS) as presented by Falk, Becker, Dohmen, Enke, Huffman, and Sunde (2018). For each preference item, the number represents the mean gender difference by country in the original preference. A positive coefficient means that women in that country have higher values in the respective preference. The preferences are in the same unit as the original preference measure from the GPS. See table A2 for a summary of the survey items for each preference. See subsection 2.2 and appendix A for details about the preference data.

Table A4: Days booked in advance by gender.

Dependent variable: Days Booked in Advance	(1)	(2)	(3)	(4)	(5)	(6)
Female	2.729***	3.009***	2.818***	2.800***	1.777***	1.809***
	(0.018)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Controls F.E. (13)	No	Yes	Yes	Yes	Yes	Yes
O-D route × ticket class F.E. (18,172)	No	No	Yes	Yes	Yes	Yes
Week and country F.E. (118)	No	No	No	Yes	Yes	Yes
Employee type F.E. (6)	No	No	No	No	Yes	Yes
Division × firm (25,167)	No	No	No	No	No	Yes
Number of F.E. included	0	13	18,185	18,303	18,309	43,476
Adjusted R^2	0.0031	0.0742	0.1595	0.1642	0.2275	0.2281
Number of observations	7,430,331	7,430,331	7,430,331	7,430,331	7,430,331	7,430,331

Notes: Dependent variable is the days booked in advance. "Controls" include the following variables: direct flight, age dummy variables, length of stay dummy variables, and number of trips per traveler dummy variables. "F.E." stands for "Fixed Effects." The parenthesis in the bottom of the initial column, next to the labels, summarizes the number of fixed effects included in each line. See appendix D for definitions of the variables and fixed effects. All regressions are OLS regressions. Standard errors are in parentheses. See appendix B for details about the computational implementation.

* significant at $p < .05$; $^{**}p < .01$; $^{***}p < .001$.

Table A5: Probability model for booking two weeks or more in advance.

Linear probability model for booking two weeks or more in advance	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.087***	0.091***	0.079***	0.078***	0.053***	0.053***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Controls F.E. (13)	No	Yes	Yes	Yes	Yes	Yes
O-D route × ticket class F.E. (18,172)	No	No	Yes	Yes	Yes	Yes
Week and country F.E. (66)	No	No	No	Yes	Yes	Yes
Employee type F.E. (6)	No	No	No	No	Yes	Yes
Division × firm F. E. (25,167)	No	No	No	No	No	Yes
Number of F.E. included	0	13	18,185	18,303	18,309	43,476
Adjusted R^2	0.0057	0.0757	0.1301	0.1345	0.1904	0.1909
Number of observations	7,430,331	7,430,331	7,430,331	7,430,331	7,430,331	7,430,331

Notes: The table displays the estimates of a linear probability model. The dependent variable is a dummy variable equals to 1 if the traveler booked the flight with two weeks or more in advance (*i.e.* if the trip was booked 14 days or more prior to the day of departure), and 0 otherwise. "Controls" include the following variables: direct flight, age dummy variables, length of stay dummy variables, and number of trips per traveler dummy variables. "F.E." stands for "Fixed Effects." The parenthesis in the initial column, next to the labels, summarizes the number of fixed effects included in each line. See appendix D for definitions of the variables and fixed effects. All regressions are OLS regressions. Standard errors are in parentheses. The probability of a man booking two weeks or more in advance is: 0.442.

* significant at $p < .05$; ** $p < .01$; *** $p < .001$.

D Definitions of Variables and Fixed Effects

Below we present the definitions of the variables and fixed effects used in the regressions in subsection 3 and appendix C. See table A2 for a summary of the survey items for the preference data.

Paid fare: The price of the flight ticket in U.S. dollars.

Days booked in advance: The number of days booked in advanced, as measured by the difference between the day where the booking was done and the day of departure of the flight.

Female: A dummy variable that equals 1 if the traveler's gender is female, and 0 otherwise.

Direct flight: A dummy variable that equals 1 if the flight is a direct flight, and 0 otherwise. A direct flight is defined as a flight between two destinations with no change in flight numbers, nor stops.

Age: The age of the individual who performs the flight in years. In the regressions we use "age dummy variables" using the following 6 groups for age: 1) "24 or less," 2) "$(24, 34]$," 3) "$(34, 44]$," 4) "$(44, 54]$," 5) "$(54, 64]$," 6) "greater than 65." For each individual, each group represents a dummy variable equals to 1 if the age of the individual belongs to that group, and zero otherwise.

Length of stay: The length of the trip in days, as measured by the difference between the day of departure and the day of return. In the regressions we use "length of stay dummy variables" using the following 5 groups for length of stay: 1) "less than 1 day (*i.e.* less than 24 hours)," 2) "$(1, 2]$," 3) "$(2, 3]$," 4) "$(3, 4]$," 5) "5 days or more." For each individual, each group represents a dummy variable equals to 1 if the length of stay of the individual belongs to that group, and zero otherwise.

Number of trips per traveler: The number of trips per traveler per year. In the regressions we use "number of trips per traveler dummy variables" using the following 4 groups for the number of trips per traveler: 1) "5 trips or less," 2) "$(5, 10]$,", 3) "$(10, 15]$," 4) "$(10, 15]$," 5) "16 or more." For each individual, each group represents a dummy variable equals to 1 if the number of trips of the individual belongs to that group, and zero otherwise.

Ticket class: The fare basis code (typically referred to as a fare basis) used by the airlines. This is a categorical variable that belongs to one of the following 4 groups: 1) “First Class,” 2) “Business Class,” 3) “Premium Economy,” 4) “Economy Class.” In the regressions we use “ticket class dummy variables,” where for each individual, each group represents a dummy variable equals to 1 if the ticket class of the individual belongs to that group, and zero otherwise.

Flight type: This is a categorical variable that belongs to one of the following 3 groups: 1) “Continental,” 2) “Domestic,” 3) “International.” In the regressions we use “flight type dummy variables,” where for each trip, each group represents a dummy variable equals to 1 if the flight type belongs to that group, and zero otherwise.

Region: A categorical variable that records the region of the world where the flight originates. The possible regiones are: 1) “Africa,”, 2) “Australia,” 3) “Europe,” 4) “Asia,” 5) “Middle East,” 6) “North America,” 7) “South America.”

Origin-Destination route fixed effects: A set of 8,192 dummy variables, each corresponding to the unique origin-destination route in our sample (*e.g.* LAX-ORD is one origin-destination route). The round trip “from airport A to airport B” and “from airport B to airport A” are two different dummy variables.

(Origin-Destination route $\times$ ticket class) fixed effects: A set of 18,172 dummy variables, that result from the interaction of “Origin-Destination fixed effects” and the variable “ticket class.”

Week of the year fixed effects: A set of 52 dummy variables, each corresponding to the week of the year when the flight is scheduled.

Country fixed effects: A set of 66 dummy variables, each corresponding to the country of origin of the flight.

Firm fixed effects: A set of 8,067 dummy variables, each corresponding to the firm where the individual works when booking the flight.

Employee type: A set of 6 dummy variables, with the classification of the employees by their position within the firm where they work.

(Division $\times$ Firm) Fixed Effects: A set of 25,167 dummy variables, each corresponding to the unique division-firm combination (the classification of the divisions are unique to each firm) where the employee works when booking the flight.

Days booked in advance fixed effects: A set of 26 dummy variables, where each of the them equals 1 depending on how many days or weeks in advanced the booking was made, defined as follows. A set of 15 dummy variables, one for each of the first 15 days prior to a flight. A set of 10 dummy variables, one for each of the 10 weeks following the first 15 days prior to a flight. An additional dummy variable for a booking that took place 85 days ($85 = 15 + 10 \times 7$) before the flight.