Relative Performance Evaluation and Strategic Competition

Li He, Toni M. Whited, and Ran Guo*

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ABSTRACT

We examine how relative performance evaluation (RPE) affects industry competition—a question relevant for corporate boards interested in incentivizing executives. Using U.S. airline data, we estimate a dynamic game of competition with heterogenous firms in an oligopolistic market with RPE contracts. RPE naturally makes CEO compensation less sensitive to market demand. However, because RPE amplifies a firm's cost efficiency relative to its peers, RPE does not always induce aggressive product market competition, often weakening competition from inefficient firms. While RPE induces endogenous selection of efficient firms into large, high entry-cost markets, and vice versa, RPE has little effect in uncompetitive markets.

*He is from Rotterdam School of Management, Erasmus University Rotterdam, Burgemeester Oudlaan 50, 3062 PA Rotterdam, The Netherlands. he@rsm.nl. Whited is from Ross School of Business and the NBER, University of Michigan, 701 Tappan St., Ann Arbor, MI 48109. twhited@umich.edu. Guo is from the China-ASEAN Institute of Financial Cooperation, Guangxi University. rguo@thecaifc.cn. We would like to thank seminar participants at Erasmus University, the University of Michigan, Oxford University, the University of Zurich, and the European Finance Association meetings for helpful comments. This work was carried out on the Dutch national e-infrastructure with the support of SURF Cooperative.

1. Introduction

Relative performance evaluation (RPE) is the use of peer performance to set individual compensation. It efficiently incentivizes CEO effort because comparisons between competing CEOs filter out common shocks and thus extract information about individual effort (Holmström 1979, 1982). While RPE reduces CEOs' exposure to economy-wide events, it can induce them to take actions that hurt peer performance because they receive higher compensation if industry peers perform worse (Aggarwal and Samwick 1999). Yet this intuitive relation between RPE and competition has received scarce empirical attention (e.g., Aggarwal and Samwick 1999; Vrettos 2013). This lack of evidence is puzzling given the secular decline in the competitiveness of many U.S. industries (Grullon, Larkin, and Michaely 2019) and given policy makers' natural interest in factors that either inhibit or enhance competition.

In this paper, we quantify the strategic implications of the incentives induced by RPE in executive compensation contracts, focusing on the effects of RPE provisions on market entry and exit. This question is challenging. Board compensation decisions are endogenous, thus generating endogenous patterns in firm actions. There are no obvious instruments. Moreover, RPE is likely difficult to measure (Edmans, Gabaix, and Jenter 2017).

Therefore, we study the interaction between RPE and competition in a new way by estimating a dynamic game of competition in an oligopoly market where CEOs of heterogeneous firms, under given contracts, make entry–exit decisions in heterogeneous markets to maximize their utility. Using data on airline routes and CEO compensation, we infer the use of RPE and its impact on strategic interactions by viewing observed market entry–exit decisions and CEO compensation through the lens of the model. This approach allows us to identify competitive effects by modeling any strategic interactions explicitly and then imposing this structure on the data. Moreover, the theoretical framework allows us to conduct counterfactual experiments that provide quantitative conclusions regarding the effects of RPE on strategic interactions.

Our main message is that RPE does not always induce overly aggressive product market strategies. First proposed by Aggarwal and Samwick (1999), this idea that RPE intensifies competition has dominated the thinking on RPE. Instead, we extend the framework of Aggarwal and Samwick (1999) by allowing for heterogeneous competitors. We show that RPE also makes competition depend heavily on firm and and market characteristics such as firm efficiency, market entry costs, and market size. Our empirical and quantitative analyses show that these attributes matter at least as much for CEO competitive actions as the risk-lowering properties of RPE contracts, with the result that RPE produces heterogeneous effects on competition. This general principle manifests itself in three ways.

First, RPE encourages the selection of different firms into markets of different sizes. RPE has little effect on efficient firms with low fixed costs, as the likelihood they operate in a market is already high without RPE. In contrast, RPE implies that less efficient firms shy away from all markets to avoid comparisons with their more efficient peers, with this effect being more pronounced in large markets.

Second, even in a world without RPE contracts, markets with high entry costs are more likely to contain efficient firms with low fixed costs, and markets with low entry costs are more likely to contain inefficient firms with high fixed costs (Asplund and Nocke 2006). Intuitively, RPE naturally amplifies the competitive advantage of firms with low fixed costs, as their peer groups contain firms with heterogeneous fixed costs. The converse naturally holds for firms with high fixed costs, so there is more endogenous selection of firms into high- and low-entry-cost markets. These two findings imply that efficient firms are more aggressive in entering high-demand markets with high fixed entry costs, leaving less efficient firms to compete in low-demand markets with lower entry costs. For example, we estimate that Southwest has high fixed operating costs, and its well-known strategy of entering smaller markets like Providence or Baltimore is a clear example of this selection effect.

Third, we find that RPE has little effect on entry–exit decisions when markets exhibit two features that inhibit competition: high entry costs and small effects of new entrants on the revenues of incumbents. High entry costs mechanically make entry–exit decisions depend less heavily on nearly any aspect of the firm's environment, including RPE. The effect of competition is more subtle. If new entrants do not siphon off much revenue from competitors, and the number of possible players is finite, then firms have high variable revenues. In this case, differences in fixed costs across competitors induce little variation in profits, so RPE has a small effect.

To deepen the intuition behind these results, we elaborate on the model, which is a parsimonious dynamic game of competition with heterogenous firms in an oligopoly market, based on Aguirregabiria and Mira (2010). All firms have identical technologies, except along the dimension of fixed operating costs, and all CEOs are given the same contracts that contain RPE provisions. They maximize the expected present value of their utility by deciding each period whether to enter or exit specific markets in the economy, which are characterized by different levels of demand and entry costs. The firms make these decisions while taking as given their expectations about competitor actions. Although these firms make simultaneous moves, each CEO's market entry–exit decisions are forward looking. These decisions in turn affect other firms' profits through their effect on equilibrium variable profits.

Several features of the model directly influence the interaction between RPE and competition. First, RPE makes CEO compensation less sensitive to market demand, mitigating managers' punishment in bad times, but also dampening rewards in good times. Second, firms are heterogeneous in the dimension of their fixed operating costs, so RPE makes CEO compensation depend heavily on the firm's cost advantage relative to its peers. Third, RPE means that one firm's entry lowers other managers' compensation, as competitors' profits fall.

These three features imply that managers under RPE contracts make entry–exit decisions that differ sharply from those made by managers unaffected by RPE. Most importantly, the effects of RPE on competition hinge on cost heterogeneity across competitors. Managers with high operating costs always lose when compared with competing peers. As such, they are reluctant to enter a market, especially under high demand. Although they are not punished for the common component of their bad performance, and although their entry lowers their competitors' profits, our estimates show that their relative cost disadvantage dominates and thus reduces their propensity to enter. Conversely, for firms with low fixed operating costs, although RPE implies they benefit little from high demand, they benefit more from being compared to peers with heterogeneous fixed costs, so they are motivated to operate, especially in high-demand markets where profit opportunities are by definition more abundant.

At first glance, studying the interaction between competition and RPE appears puzzling, when evidence on the mere existence of RPE appears weak, with most studies finding little relation between CEO compensation and other firm performance (Edmans et al. 2017). Moreover, Jenter and Kanaan (2015) find that CEOs are fired after bad firm performance caused by factors beyond their control. This evidence clearly contradicts the hypothesis that boards filter out common shocks.

However, Albuquerque (2009) and Jayaraman, Milbourn, Peters, and Seo (2018) show that careful classification of the peer group leads to a significant negative correlation between compensation and peer performance. In addition, studies that postdate the 2006 Security and Exchange Commsion (SEC) executive compensation disclosure rules find direct evidence of RPE, with RPE provisions in 25% to over 80% of contracts (Gong, Li, and Shin 2011; De Angelis and Grinstein 2019). The implicit use of RPE may be even higher, as mandatory disclosures of RPE may omit any implicit use. For example, firms occasionally comment favorably on the principle of RPE as part of their compensation philosophies without disclosing any details (Gong et al. 2011). Similarly, while all the U.K. directors interviewed in Ferri (2009) claim to consider peer performance in the design of executive pay, only 42% of the FTSE 350 firms explicitly disclose the use of RPE in performance-vested equity grants (Carter, Ittner, and Zechman 2009).

Much of the extant empirical work on the relation between competition and RPE focuses on the association between measures of competitiveness and the sensitivity of compensation to other-firm performance. For example, Aggarwal and Samwick (1999) examine the theoretical optimality of RPE under Bertrand and Cournot competition. They note that incentives to stifle competition in competitive industries can lead to a positive relation between compensation and peer performance. Using data on U.S. industries, they find that the correlation between compensation and rival firm performance is positive and increases with the level of industry competitiveness, as measured by the usual Herfindahl index. Vrettos (2013) argues that the relation between compensation and peer performance is negative when firms compete as strategic substitutes but positive when they compete as strategic complements. He additionally argues that network and regional U.S. airlines compete in strategic substitutes within their respective groups, but they compete as strategic complements between the two groups. Within each group, he finds evidence of a negative association between compensation and peer performance; across groups, he finds a positive association. In contrast to these papers, Bloomfield, Marvão, and Spagnolo (2020) find that firms participating in illegal cartels decrease their use of RPE after cartels are discovered, suggesting that these firms only use RPE when the potential for competition is low.

We build on this evidence by showing how RPE shapes a specific competitive action: entry–exit decisions. This focus is preferable to reliance on a noisy measure of competition, such as a Herfindahl index. We also expand the conceptual framework used in previous work by allowing for both heterogeneous markets and heterogeneous competitors, both of which are likely featured in many markets, not just the airline industry that we study. We show that the effect of RPE on competition and profits hinges strongly on the dimensions of heterogeneity that we study: individual airline efficiency, market demand, and market entry costs. This type of evidence is useful for theories of optimal RPE, as it provides guidance as to the firm and market characteristics that matter for competitive actions under RPE.

2. Model

In this section, we present a parsimonious dynamic game of competition with heterogenous airlines in an oligopoly market. The players are the airline CEOs, who, under given contracts, make entry–exit decisions to maximize the expected present value of their utilities. These decisions are forward looking and thus incorporate the implications of any decision on future profits and future competitor reactions.

2.1 Competition

The industry is characterized by N airlines and M markets. A market is defined as a non-directional city-pair; that is, if an airline operates flights from city A to city B, then it operates return flights as well. This definition is useful for two reasons. First, potential entrants are observable. Second, treating routes as markets and characterizing market competition at the route level allows us to capture heterogeneity across different routes.

At each time t, airline i in market m earns profits, π_{imt}, which depend on two state variables and one choice variable. The two state variables, market size and airline incumbency status, are common knowledge among all airlines. Incumbency status, $x_{imt} \in \{0, 1\}$, is an endogenous state variable, with $x_{imt} = 1$ indicating an incumbent airline that currently operates in market m at time t, and $x_{imt} = 0$ indicating a potential entrant. We assume that the size of market m at time t, s_{mt}, is exogenous and evolves according to a Markov process. In what follows, we refer to s_{mt} as either market size, market demand, or market conditions.

The first component of airline profits are the variable profits that accrue from operating in a market. Specifically, if airline i operates in market m at time t, i.e., $x_{imt} = 1$, it competes with other incumbent airlines and earns equilibrium variable profits y_{mt} that are determined by market size and the number of incumbents in market m at time t, as follows:

$$y_{mt}(s_{mt}, \boldsymbol{x}_{mt}) = \gamma_s s_{mt} - \gamma_n \ln(n_{mt}), \quad \text{where} \quad n_{mt}(\boldsymbol{x}_{mt}) = \sum_{j=1}^{N} x_{jmt}. \tag{1}$$

In equation (1), the vector $\boldsymbol{x}_{mt} = \{x_{imt} : i = 1, 2, \ldots, N\}$ summarizes the incumbency status of the N airlines, with the number of incumbents denoted as n_{mt}. Note that all airlines operating in a market earn the same variable profits, which are strictly decreasing in the number of competitors. The two terms in the revenue function (1) represent the impact of market size and competition, respectively. We interpret market size as reflecting demand. The sensitivity of revenue to market size is captured by the parameter $\gamma_s > 0$. The impact of competition is captured by the parameter γ_n, with a large γ_n leading to more intense strategic interaction, as in this case, any single market entrant has a large impact on industry revenue. Note that in the model, the intensity of competition is characterized by the number of airlines present in the market. This general feature of our model is shared by Aguirregabiria and Mira (2007), who show that it can arise from static Cournot competition with linear demand. While their functional form is different from the second term in equation (1), our functional form is simpler, and both share the notion that competition depends only on the number of competitors. A computationally more intensive alternative is in Aguirregabiria and Ho (2012), who model variable profits as the outcome of equilibrium price competition and estimate the resulting demand system using a nested logit model. We opt for our simpler approach because it provides us with the tractability to focus on the effects of compensation contracts on the dynamics of competition.

The incumbent airline i also pays fixed operating costs, f_{im}, that are airline- and market-specific. These costs capture time invariant airline heterogeneity across markets.

Finally, profits depend on the entry decision. Airline i can decide whether to operate, either as an incumbent or an entrant, in the market at time $t + 1$. The decision whether to enter or exit market m next period is denoted by a_{imt}, which equals one if the airline operates in the market, and zero otherwise. By definition, $x_{im,t+1} = a_{imt}$, that is, we use different notation to distinguish state and choice variables. This timing also implies that a new entrant is not active until the next period.

Once airline i decides to enter, it has to pay an entry cost, k_m, that is market-specific, but homogeneous across airlines and time. Following Aguirregabiria and Ho (2012), we assume that one year is needed to build up the inputs required for operating in a market, so the entry cost is paid at t, but entry–exit decisions are not effective until $t + 1$. Equivalently, the entry cost, k_m, is paid in period t only when the airline transitions from being inactive in period t to being active in period $t+1$, that is, if $x_{imt} = 0$ and $a_{imt} = 1$. In contrast, an exiting airline that is operative during time t incurs no exit costs. Although barriers to exit are likely high in the airline industry as a whole, this assumption about costless exit refers to one route, not the entire business.

On the other hand, if airline i stays out of a market m at time t, i.e., $x_{imt} = 0$, it gets zero profits. If airline i does not operate in market m, it is not prohibited from operating in any of the other M markets. In equilibrium, the profits of airline i are equal to the value of its best outside option. However, because this outside option is airline- and market-specific, it cannot be identified separately from the average fixed cost, f_{im}. Therefore, we normalize the outside option to zero following, for example, Aguirregabiria and Mira (2007). As such, the fixed cost, f_{im}, should be interpreted as net of the opportunity cost of operating elsewhere.

These assumptions imply the following expressions for airline profits, which we denote formally as $\pi_{imt}(\boldsymbol{x}_{mt}, s_{mt}, a_{imt})$.

$$\pi_{imt}(\boldsymbol{x}_{mt}, s_{mt}, a_{imt}) = \begin{cases} x_{imt}\,(y_{mt} - f_i) - (1 - x_{imt})k_m & \text{if } a_{imt} = 1, \\ x_{imt}\,(y_{mt} - f_i) & \text{if } a_{imt} = 0. \end{cases} \tag{2}$$

Equation (2) summarizes all four incumbency–action pairs: incumbent who stays, incumbent who exits, potential entrant who remains out of the market, and potential entrant who enters. The interaction between the terms x_{imt} and $(y_{mt} - f_{im})$ captures the notion that only active firms earn profits. The presence of the fixed cost term, $(1 - x_{imt})k_m$, only in the case of $a_{imt} = 1$ indicates that only inactive firms that enter pay the entry cost.

2.2 Manager's Compensation and Utility

An airline CEO receives an exogenously specified representative compensation contract. We do not derive the form of an optimal contract but instead approximate observed contracts, so the representative contract is inferred from data, and we do not take a stand on whether the contract is optimal or not. We view this assumption as sensible for two reasons. First, (Dittmann and Maug 2007) find that observed contracts do not approximate theoretical optimal contracts. Second, and alternatively, observed contracts in the data might very well be optimal, given incentives and constraints that are unobservable to outsiders.[1]

The contract consists of two parts: a profit share and RPE, so the CEO is rewarded on the basis of absolute performance and peer performance. Formally, let $\boldsymbol{x}_t = \{x_{imt} : i = 1, 2, \ldots, N; m = 1, 2, \ldots, M\}$, $\boldsymbol{a}_t = \{a_{imt} : m = 1, 2, \ldots, M; n = 1, 2, \ldots, N\}$, and $\boldsymbol{s}_t = \{s_{imt} : i = 1, 2, \ldots, N; m = 1, 2, \ldots, M\}$. Then we can express the CEO compensation contract at time t as a function of $(\boldsymbol{x}_t, \boldsymbol{s}_t, \boldsymbol{a}_t)$ as follows:

$$c_{it}(\boldsymbol{x}_t, \boldsymbol{s}_t, \boldsymbol{a}_t) = \lambda_o \pi_{it} - \lambda_p \pi_{-it}, \tag{3}$$

where π_{it} represents profits of airline i at time t, aggregated over markets, i.e., $\pi_{it} = \sum_{m=1}^{M} \pi_{imt}$. Peer performance of airline i at time t is denoted by π_{-it}, which is the average profits of all airlines other than i:

$$\pi_{-it} = \frac{1}{N-1} \sum_{j \neq i} \pi_{jt}. \tag{4}$$

In equation (3), $\lambda_o > 0$ and $\lambda_p \geq 0$ are parameters representing the contract loadings on an airline's own and peer performance respectively, so the contract indicates that the CEO utility of airline i increases with that airline's own performance but decreases with peer performance.

Finally, CEO utility depends on information revealed to airline i about market m before the CEO makes an entry–exit decision. Let ϵ_{imt} denote this information for a single market-CEO-time triplet. This information is choice-specific and is an independent and identically distributed (i.i.d.) extreme value type-I random variable, with zero mean and unit dispersion. We denote the associated transition probability as $G(\epsilon_{imt})$. This distributional assumption

[1] Glover and Levine (2015), Glover and Levine (2017), and Nikolov and Whited (2014) also fit data to models with possibly suboptimal contracts.

is standard in dynamic discrete choice frameworks.[2] Next, letting $\epsilon_{it} \equiv \sum_{m=1}^{M} \epsilon_{imt}$ be the private information aggregated over markets, CEO utility is given by:

$$u_{it}(\boldsymbol{x}_t, \boldsymbol{s}_t, \boldsymbol{a}_t, \epsilon_{it}) = c_{it}(\boldsymbol{x}_t, \boldsymbol{s}_t, \boldsymbol{a}_t) + \epsilon_{it}. \tag{5}$$

2.3 Optimization and Equilibrium

The timeline of events is as follows. At time t, airlines are characterized by their own incumbency status in market m. After the realization of the demand shock s_{mt}, which is common knowledge among all airlines, and the private shock ϵ_{imt}, which is both airline- and market-specific, airlines earn variable profits and pay operating costs depending on their incumbency status. CEOs then decide simultaneously whether to operate in the market at time $t+1$, taking as given their expectations about peer actions.

The entry and exit decisions are dynamic, that is, they depend on expectations about future competition. Upon entry, however, equation (1) implies that competition is static. We justify this assumption given the argument in Aguirregabiria and Ho (2012) that pricing of tickets is short-run and at the level of individual flights. We capture these effects in a reduced-form way in the second term of equation (1).

After signing the contract, the CEO chooses a set of market entry–exit decisions $\boldsymbol{a}_{it} = \{a_{imt} : m = 1, 2, \ldots, M\}$. We assume that CEOs' strategies depend only on payoff-relevant state variables, that is, we assume a Markov perfect equilibrium. To describe this equilibrium, let an airline's payoff-relevant information at time t be $\{\boldsymbol{x}_t, \boldsymbol{s}_t, \boldsymbol{\epsilon}_{it}\}$, with $\boldsymbol{\epsilon}_{it} = \{\epsilon_{imt} : m = 1, 2, \ldots, M\}$. Let $\boldsymbol{\sigma} = \{\sigma_i(\boldsymbol{x}_t, \boldsymbol{s}_t, \boldsymbol{\epsilon}_{it}) : i = 1, 2, \ldots, N\}$ be a vector of strategy functions, one for each airline. A Markov perfect equilibrium (MPE) in this game is a vector of strategy functions $\boldsymbol{\sigma}$ such that each airline's strategy maximizes the expected present value of the

[2] Permitting serial correlation in the privately observed shock would give rise to models of learning in which players form beliefs about other players' states based on past actions. To model these beliefs consistently, the state space would need to be amplified to include the set of all possible past actions. As such, serial correlation is likely to render the method computationally infeasible. See, for example, Pesendorfer and Schmidt-Dengler (2008), for a detailed discussion.

utility of the airline's manager for each possible state $(\boldsymbol{x}_t, \boldsymbol{s}_t, \boldsymbol{\epsilon}_{it})$, taking as given other airlines' strategies.

We can express the decision problem of player i as a standard single-agent dynamic programming problem as in Rust (1994). Letting the superscript $\boldsymbol{\sigma}$ indicate dependence on all players' strategy functions, the Bellman equation for an individual CEO is:

$$\tilde{U}^{\boldsymbol{\sigma}}_{it}(\boldsymbol{x}_t, \boldsymbol{s}_t, \boldsymbol{\epsilon}_{it}) = \max_{\boldsymbol{a}_{it}} \left\{ u^{\boldsymbol{\sigma}}_{it}(\boldsymbol{x}_t, \boldsymbol{s}_t, \boldsymbol{a}_{it}, \boldsymbol{\epsilon}_{it}) + \frac{1}{1+r}\mathbb{E}\left[\tilde{U}^{\boldsymbol{\sigma}}_{i,t+1}(\boldsymbol{x}_{t+1}, \boldsymbol{s}_{t+1}, \boldsymbol{\epsilon}_{i,t+1}) \middle| \, \boldsymbol{x}_t, \boldsymbol{s}_t, \boldsymbol{a}_{it}, \boldsymbol{\epsilon}_{it} \right] \right\}, \tag{6}$$

where $u^{\boldsymbol{\sigma}}_{it}(\boldsymbol{x}_t, \boldsymbol{s}_t, \boldsymbol{a}_{it}, \boldsymbol{\epsilon}_{it})$ denotes player i's current utility if it chooses a_{it} and the other players behave according to their respective strategies in $\boldsymbol{\sigma}$. Similarly, $\tilde{U}^{\boldsymbol{\sigma}}_{it}(\boldsymbol{x}_t, \boldsymbol{s}_t, \boldsymbol{\epsilon}_{it})$ denotes the value for player i when it behaves optimally now and in the future, given that the other players follow their strategies in $\boldsymbol{\sigma}$.

It is extremely challenging to solve and estimate the dynamic game of competition described above. This intractability arises because the equilibrium of this dynamic game of competition, an MPE, is based on information covering the space of all state variables $(\boldsymbol{x}_t, \boldsymbol{s}_t)$. For example, the dimension of the space $\boldsymbol{x}_t$, is 2^{NM}, as it contains all possible combinations of binary entry–exit decisions for all airlines in all markets. Given the number of markets and airlines in our empirical analysis, solving a dynamic game with this state space is not feasible.

To deal with this computational complexity, we follow Aguirregabiria and Ho (2012) and reduce the dimension of the state space by assuming that an airline's entry–exit decisions are decentralized to local managers. That is, every airline has M local managers, one for each market. While we assume that the local managers and the CEO have perfectly aligned interests, we also assume that each local manager solves her own decision problem irrespective of the other managers. Each local manager, indexed by (i, m), chooses $a_{imt} \in (0, 1)$ to maximize the expected present value of her future utility. Thus, the optimization problem in (3) and (6) can be rewritten as:

$$\tilde{U}^{\boldsymbol{\sigma}}_{imt}(\boldsymbol{x}_{mt}, s_{mt}, \epsilon_{imt}) = \max_{a_{imt}} \Big\{ u^{\boldsymbol{\sigma}}_{imt}(\boldsymbol{x}_{mt}, \boldsymbol{s}_{mt}, a_{imt}, \epsilon_{imt}) + \frac{1}{1+r}\mathbb{E}\left[\tilde{U}^{\boldsymbol{\sigma}}_{im,t+1}(\boldsymbol{x}_{m,t+1}, \boldsymbol{s}_{m,t+1}, \epsilon_{im,t+1}) \Big| \, \boldsymbol{x}_{mt}, \boldsymbol{s}_{mt}, a_{imt}, \epsilon_{imt} \right] \Big\}, \tag{7}$$

in which the one-period utility of the local manager (i, m) is given by:

$$u_{imt} = \lambda_o \pi_{imt} - \lambda_p x_{imt} \pi_{-imt} + \epsilon_{imt} \tag{8}$$

$$\equiv c_{imt} + \epsilon_{imt}. \tag{9}$$

Here, $\boldsymbol{x}_{mt}$ and $\boldsymbol{s}_{mt}$ are defined analogously as $\boldsymbol{x}_t$ and $\boldsymbol{s}_t$.

In equation (8), peer performance is defined as in equation (3), except at the market level. Note that at the market level, RPE enters the utility of a local manager under two conditions. First, only local managers of incumbent airlines ($x_{imt} = 1$) get evaluated relative to their peers. Second, the market must have at least one incumbent airline other than i, i.e., $n_{mt} > 1$. Thus, the state space of the optimization problem of a local manager is reduced to 2^N.

Because the private shocks, ϵ_{imt}, are assumed to be additive and i.i.d. over players and over time, we can define value functions integrated over private information as $U^{\boldsymbol{\sigma}}_{imt}(\boldsymbol{x}_{mt}, \boldsymbol{s}_{mt}) = \int \tilde{U}^{\boldsymbol{\sigma}}_{imt}(\boldsymbol{x}_{mt}, \boldsymbol{s}_{mt}, \epsilon_{imt}) dG(\epsilon_{imt})$ and re-express the Bellman equation as:

$$U^{\boldsymbol{\sigma}}_{imt}(\boldsymbol{x}_{mt}, \boldsymbol{s}_{mt}) = \int \max_{a_{imt}} \{ v^{\boldsymbol{\sigma}}_{imt}(\boldsymbol{x}_{mt}, \boldsymbol{s}_{mt}, a_{imt}) + \epsilon_{imt} \} dG(\epsilon_{imt}), \tag{10}$$

with

$$v^{\boldsymbol{\sigma}}_{imt}(\boldsymbol{x}_{mt}, \boldsymbol{s}_{mt}, a_{imt}) = c^{\boldsymbol{\sigma}}_{imt}(\boldsymbol{x}_{mt}, \boldsymbol{s}_{mt}, a_{imt}) + \frac{1}{1+r}\mathbb{E}[\tilde{U}^{\boldsymbol{\sigma}}_{im,t+1}(\boldsymbol{x}_{m,t+1}, \boldsymbol{s}_{m,t+1}, \epsilon_{im,t+1}) | \boldsymbol{x}_{mt}, \boldsymbol{s}_{mt}, a_{imt}].$$

Next, after converting the dynamic game into a standard single-agent dynamic programming problem, we can express the best response function of player i in market m, σ^*_{imt}, as:

$$\sigma^*_{imt}(\boldsymbol{x}_{mt}, \boldsymbol{s}_{mt}, \epsilon_{imt}) = \arg\max_{a_{imt}} \left\{ v_{imt}(\boldsymbol{x}_{mt}, \boldsymbol{s}_{mt}, a_{imt}) + \epsilon_{imt} \right\}.$$

This best response function gives the optimal strategy of player i if the other players behave according to their respective strategies in $\boldsymbol{\sigma}^*$. The set of optimal strategy function $\boldsymbol{\sigma}^*$ characterizes a Markov perfect equilibrium in this game.

Following Milgrom and Weber (1985), the MPE can be described as a fixed point of a mapping in probability space. Specifically, we can define a set of conditional choice probabilities (CCPs) associated with this set of optimal strategy functions, $\boldsymbol{\sigma}^*$, as $\boldsymbol{p}^* \equiv \{p^*_{it}(a_{it}|\boldsymbol{x}_t, \boldsymbol{s}_t)\}$, such that:

$$p^*_{imt}(a_{imt}|\boldsymbol{x}_{mt}, \boldsymbol{s}_{mt}) = \int \mathbb{1}\{a_{imt} = \boldsymbol{\sigma}^*_{imt}(\boldsymbol{x}_{mt}, \boldsymbol{s}_{mt}, \epsilon_{imt})\} dG(\epsilon_{imt}),$$

where $\mathbb{1}\{\cdot\}$ is the indicator function. The probabilities $p^*_{imt}(a_{imt}|\boldsymbol{x}_{mt}, \boldsymbol{s}_{mt})$ represent the expected behavior of player i from the point of view of the rest of the players when player i follows its strategy in $\boldsymbol{\sigma}^*$. The value functions $v_{imt}(\boldsymbol{x}_{mt}, \boldsymbol{s}_{mt}, a_{imt})$ depend on other players' strategies only through other players' choice probabilities. As such, it is straightforward that $\boldsymbol{p}^*$ is a fixed point of $\boldsymbol{p}^* = \boldsymbol{\Psi}(\boldsymbol{p}^*)$, where $\boldsymbol{\Psi}(\boldsymbol{p}) = \{\Psi_{imt}(a_{imt}|\boldsymbol{x}_{mt}, \boldsymbol{s}_{mt}; p_{-imt})\}$ and

$$\Psi_{imt}(a_{imt}|\boldsymbol{x}_{mt}, \boldsymbol{s}_{mt}; p_{-imt}) = \int \mathbb{1} \left(a_{imt} = \arg\max_{a_{imt}} \left\{ v^{\boldsymbol{p}^*}_{imt}(\boldsymbol{x}_{mt}, \boldsymbol{s}_{mt}, a_{imt}) + \epsilon_{imt}) \right\} \right) dG(\epsilon_{imt}). \tag{11}$$

2.4 Effects of Relative Performance Evaluation

In this subsection, we discuss the two effects generated by the use of RPE. On the one hand, as noted in the introduction, RPE can be used as an efficient tool to incentivize CEO effort because comparisons between competing agents can serve as a device to filter out common shocks and thus extract information about effort. We term this first effect the incentive effect. On the other hand, the use of RPE also provides incentives for CEOs to take actions that influence peer performance, as CEOs receive higher compensation if peers perform worse. We term this second effect the competition effect.

We illustrate these two effects by substituting the expressions for profit given by equations (2) and (4) into the compensation contract in equation (8) as follows:

$$c_{imt} = \lambda_o(y_{mt} - f_{im}) - \lambda_p \frac{1}{n_{mt} - 1} \sum_{j \neq i} (y_{mt} - f_{jm}). \tag{12}$$

Because all incumbent airlines earn the same variable profits, $y_{mt}(s_{mt}, \boldsymbol{x}_{mt})$, in market m at time t but are heterogenous in their fixed operating costs, f_{im}, we can rewrite the compensation contract in equation (12) as:

$$c_{imt} = (\lambda_o - \lambda_p)y_{mt} - (\lambda_o - \lambda_p)f_{im} + \lambda_p(f_{-im} - f_{im}) \tag{13}$$

The first term reflects the incentive effect discussed in the theoretical literature. The presence of RPE ($\lambda_p > 0$) reduces the weight on variable profits, y_{mt}, that are outside the manager's control, making CEO compensation less sensitive to exogenous market conditions. The second term demonstrates that RPE exacerbates the effects of fixed costs on firm profits. The third term demonstrates the effect of competition. The use of RPE adds extra rewards to the local manager if he has lower fixed operating costs (and thus higher profit margins) than the peer average. In other words, RPE provides higher incentives to the manager whose fixed costs of operating in a given market are lower. Of course, the magnitude and sign of the effect of RPE on CEO utility and competition depends on the relative magnitudes of the various parameters. We turn to this problem next.

3. Data

Our main source of data is the Airline Origin and Destination Survey (DB1B) of the U.S. Bureau of Transportation Statistics (BTS). The DB1B survey is a sample of 10% of all airline tickets from the large U.S. certified carriers. It contains information on quantities, prices, and route entry and exit decisions for every airline company operating in the routes between the 50 largest U.S. metropolitan statistical areas (MSAs). The data set is ideal for three reasons. First, the detail allows us to treat a route as a market. Second, we are able to observe the entry–exit decisions for all players in the airline industry. Observations on the entry–exit decisions at the market level are crucial for us to infer information about strategic interactions. Finally, by focusing on a single industry, we can conduct the analysis without considering possible industry misclassifications (see, for example, Jayaraman et al. 2018).

We construct the airline entry and exit data following Ciliberto and Tamer (2009), with details explained in Appendix A. We define a market as a trip between a pair of MSAs, irrespective of intermediate stops and of the direction of the flight. This definition is in line with the previous literature. For example, Ciliberto and Tamer (2009) consider airport-pairs and Aguirregabiria and Ho (2012) considers city-pairs. We end up with seven airlines in the final sample: Southwest, American, Delta, United, US Airways, Northwest, and Continental. We also restrict our sample to the 1993–2008 time period to avoid airline mergers, as our model does not incorporate these extreme entry–exit decisions. Table 1 in Appendix A describes the annual number of passengers and the number of operating markets for these airlines. Southwest is the airline that flies the most passengers (about 2.5 million in the 10% sample), while American, United, and Delta follow in the ranking. These seven carriers in total serve 80.49% of passengers and generate 82.14% of revenues in the markets among the top 50 MSAs.

We collect airline managerial compensation information from ExecuComp and stock returns from CRSP. Because ExecuComp covers S&P 1500 firms starting only in 1994, we supplement these data with hand-collected compensation information from SEC filings on EDGAR.

Finally, as documented in Appendix D, we obtain narrative evidence of the use of RPE during our sample for all of our airlines, except Southwest and United. United eventually started using RPE in 2011, so the possibility of implicit RPE use is likely.

Our final sample consists of two annual-frequency panels from 1993 to 2008: a panel of managerial compensation and stock returns for seven airlines and a panel of entry–exit data for 8,575 airline-market pairs: seven airlines times 1,225 markets).

3.1 Descriptive statistics

Figure 1 presents the distribution of the 1,225 markets we examine over our sample period, twelve of which have never been served by any of the airlines over the years. Approximately 75% of the markets have at least three airlines operating, and one-third of the markets on average have six incumbent airlines providing service. The average number of airlines operating per market is 4.69, guaranteeing the existence of comparable peers.[3]

In Table 2, we report statistics related to market dynamics. In Panel A, we report the fraction of market-year observations with a specified number of entries or exist. The frequency of entry and exit per market-year is low, with no entry or exit in over 80% of market-year observations. Similar to Aguirregabiria and Ho (2012), the average numbers of entries and exits per market-year are 0.13 and 0.18, respectively. These low frequencies suggest a high barrier to entry.

At the same time, as seen in Panel B of Table 2 the frequency of entry and exit per market over the length of the panel is high, where we calculate this statistic by summing either entries or exits over the panel for each market, and then dividing by the number of markets. Among the 1,225 markets over the sample period, 82.19% (84.42%) experienced at least one entry (exit). This large turnover provides us with enough variation to identify the parameters that quantify fixed operating and entry costs.

Panel C of Table 2 presents statistics describing the considerable heterogeneity in our sample of airlines. First, we report the number of monopoly markets for each airline over

[3] Aguirregabiria and Ho (2012) reports the average number of airlines with non-stop flights per market is only 1.4. We have a much larger number for two reasons. First, we define a market as the trip between a pair of MSAs, irrespective of intermediate stops or the direction of the flight. Second, we aggregate quarterly data into yearly data.

sample period. Delta and US Airways are the largest monopoly carriers, serving 32% and 29% of the monopoly markets, with on average 12 and 16 monopoly markets per year, respectively. Southwest, at 14%, is a distant second. Second, we report the average conditional probabilities of an airline remaining in a market, which we calculate as follows. We discretize market size, and then form bins defined by size and the number of competitors. For each bin, we count the number of airline entry–exit decisions, and then average these counts for each airline over the bins. This measure allows us to capture heterogeneous airline characteristics while controlling for market size, the level of competition, and the heterogeneity of peers, all of which are important determinants of survival in a market. Delta, with 87%, has the highest probability of staying in a market once it has entered, while Continental, with 68%, has the lowest probability of staying.

4. Estimation

This section describes our approach to estimating the parameters of our model. To reduce the computational burden, we use a two-step strategy. First, we estimate directly the process describing the dynamics of market size. Second, we estimate the rest of parameters using a method of moments estimator, with moments derived using our dynamic game of competition.

For all estimations, the real risk-free interest rate, r, is set to 0.97% (quarterly) to match the average difference between three-month T-bill rate and the growth rate of the Consumer Price Index over our sample period.

4.1 Market Size

To estimate the process governing the size of market m, s_{mt}, we refine our assumption of an exogenous Markov process for s_{mt} by further assuming that s_{mt} follows an AR(1) process in logs with drift:

$$\ln(s_{m,t+1}) = \mu + \rho \ln(s_{mt}) + \sigma \omega_{m,t+1}, \tag{14}$$

where μ is the drift, ρ is the autoregressive coefficient, ω is a standard normal i.i.d. innovation with standard deviation σ. We obtain values of the drift, persistence, and volatility of market size by directly estimating the regression in (14) using the dynamic panel method in Han and Phillips (2010) that accounts for fixed effects.

This estimation requires a measure of market size, which is challenging to measure because of heterogeneity in local economies, airport network structures, and consumer preferences. However, the number of passengers served provides a useful measure of market size if we assume that realized demand is an equilibrium outcome of competition. In our own data, this assumption gives rise to a further problem. Because we only observe a 10% sample, we occasionally observe no passengers in a market and therefore must conclude that there is no demand in the market. In these cases, we replace zeros with imputed values from the following regression:

$$\begin{aligned} \ln(\text{Passenger}_{mt}) &= \beta_0 + \beta_1 \ln(\text{Population}_{mt}) + \beta_2 \ln(\text{Income Per Capita}_{mt}) \\ &+ \beta_3(\text{Income Growth}_{mt}) + \beta_{4m} + \beta_{5t} + \epsilon_{mt}, \end{aligned} \tag{15}$$

where Passenger_{mt} is the number of passengers carried in market m at time t. We include three demographic variables. Population_{mt} is the sum of the metropolitan populations of the route endpoints; $\text{Income Per Capita}_{mt}$ is the average of the metropolitan personal income per capita; and $\text{Income Growth}_{mt}$ is the average rate of income growth, which we use to measure the strength of the local economy. Data on MSA per capita income are from the Regional Economic Accounts of the Bureau of Economic Analysis. Other measures, such as GDP, are not reported for all years of our sample. In addition, we include market fixed effects, β_{4m}, that capture within-market differences such as geographic location that are constant over time. We also include year fixed effects, β_{5t}, to account for year-specific differences that are common to all markets, for example, the impact of September 11, 2001.

With the estimates of the parameters of (14) in hand, we then use the method in

Rouwenhorst (1995) to discretize this AR(1) process into a transition matrix with five points of support. We choose this method because Galindev and Lkhagvasuren (2010) and Kopecky and Suen (2010) find that it is more accurate than other alternatives when persistence is high. Moreover, Kopecky and Suen (2010) show that the Rouwenhorst method produces highly accurate approximations even when $N = 5$.

4.2 Estimation of the Dynamic Game

The estimation of the dynamic game is based on a representation of Markov perfect equilibria as fixed points of a best response mapping in the space of players' choice probabilities. We interpret these choice probabilities as players' beliefs about the behavior of their opponents. Given these beliefs, each player's problem can be interpreted as a game against nature with a unique optimal decision rule (the players' best response) in probability space.[4] The best response mapping is always a unique function of structural parameters and players' beliefs about the behavior of other players.

Model estimation requires that we assume that the data have been generated by only one Markov perfect equilibrium. In this case, even if the model has multiple equilibria, we do not need to specify an equilibrium selection mechanism because the equilibrium that has been selected will be identified from the conditional choice probabilities in the data (Aguirregabiria and Mira 2007).

4.2.1. Estimator

Because the model implies a probability distribution over the possible outcomes, a natural starting point would be to use airline entry–exit data to construct a nested maximum-likelihood algorithm that, in each iteration, would solve the fixed-point problem given the current estimate of the parameter values. However, this strategy is inapplicable to our model

[4] We consider only pure-strategy equilibria because of the result in Harsanyi (1973) that they are observationally equivalent to mixed-strategy equilibria. Harsanyi (1973) shows that a mixed-strategy equilibrium in a game of complete information can be interpreted as a pure-strategy equilibrium of a game of incomplete information. That is, the probability distribution of players' actions is the same under the two equilibria.

because of the following identification problem. In the utility function (8), the sets of contract- and profit-related parameters enter multiplied with one another. Thus, a maximum likelihood estimation that only uses market-level entry–exit data would not contain enough information to disentangle and therefore separately identify these parameters.

To overcome this identification problem, we use a two-step of moments estimator in the spirit of Pesendorfer and Schmidt-Dengler (2008). In the first step, computation of a fixed-point problem delivers the equilibrium choice probabilities for a given set of parameter values. In the second step, we estimate the parameters by matching the equilibrium choice probabilities as well as some other auxiliary moments with their data counterparts.[5] This approach allows for identification of the contract-related parameters in the model by allowing for the incorporation of airline-level compensation data.

Specifically, let $\boldsymbol{\theta}$ denote the vector of parameters to be estimated. In the first step, we solve the following fixed-point problem to obtain the conditional choice probabilities $\boldsymbol{p}$:

$$\boldsymbol{p}(\boldsymbol{\theta}) = \boldsymbol{\Psi}(\boldsymbol{p}(\boldsymbol{\theta})), \tag{16}$$

where $\boldsymbol{\Psi}$ is given by (11) and denotes the best response mapping.

In the second step, the parameters of interest are inferred by matching a set of data moments with an analogous set of model moments. Specifically, we choose our parameter vector, $\boldsymbol{\theta}$, to minimize the following quadratic form:

$$\boldsymbol{\theta} = \arg\min_{\boldsymbol{\theta}} \boldsymbol{g}(\boldsymbol{\theta})'\boldsymbol{W}\boldsymbol{g}(\boldsymbol{\theta}),$$

where $\boldsymbol{W}$ denotes a positive-definite weight matrix, and $\boldsymbol{g}(\boldsymbol{\theta})$ is the vector of differences between the model and data moments. We describe the weight matrix in Appendix C.

[5] Pesendorfer and Schmidt-Dengler (2008) show that structural estimators for dynamic models proposed by Rust (1994), Hotz and Miller (1993), and Aguirregabiria and Mira (2002) are asymptotic least squares estimators defined by a set of equilibrium conditions. The estimators differ in the weights they assign to individual equilibrium conditions.

4.2.2. Identification

We estimate our set of six parameters $\boldsymbol{\theta} = (\gamma_s, \gamma_n, f_i, e, \lambda_e, \lambda_p)'$ by matching two sets of moments. The first set consists of regression coefficients that we obtain from the airline-level compensation data. The contract-related parameters, i.e., the loading on CEO compensation for the firm's own and peer performance are identified using the airline-level compensation data. Specifically, we use as moments the coefficients from the following regression:

$$u_{it} = \hat{\lambda}_1 + \hat{\lambda}_o \pi_{it} + \hat{\lambda}_p \pi_{-it} + e_{it}, \tag{17}$$

where π_{it} and π_{-it} denote separately the profits (Compustat item NI) of airline i and its peers $-i$ at time t. In the regression (17), peer performance is measured as the value-weighted average profits of all airlines other than airline i. We let u_{it} denote CEO compensation (ExecuComp item TDC1), adjusting for the other compensation (ExecuComp item OTHCOMP), of airline i at time t. We use this adjustment because focusing on total CEO compensation (ExecuComp item TDC1), an approach used in previous studies, can underestimate the extent to which total executive pay is correlated with performance. Other compensation received by the CEO (ExecuComp item OTHCOMP), such as severance payments and signing bonuses, is largely unrelated to the performance of the firm during the executive's tenure.

In the airline industry, the leading roles are long-tenured, and CEOs can switch companies within the industry. For example, there are two cases in which the same person served as CEO for different airlines during the sample period.[6] To this end, we include CEO times airline fixed effects to control for CEO-airline matches. This procedure gives $\hat{\lambda}_o = 1.356 \times 10^{-3}$, and $\hat{\lambda}_p = -0.196 \times 10^{-3}$. Interestingly, we find reduced-form evidence consistent with the presence of RPE in our relatively homogeneous set of competitors, as in Albuquerque (2009).

Note that the coefficients $\hat{\lambda}_o$ and $\hat{\lambda}_p$ do not correspond directly to the contract-related

[6] Stephen M. Wolf served as CEO of United from December 1987 to July 1994 and later as CEO of US Airways from January 1996 to November 1998. Richard H. Anderson served as CEO of Northwest from April 2001 to October 2004 and as CEO of Delta from September 2007 to May 2016.

parameters in the model because the airline-level compensation data omits information at the market level. Thus, the regression in equation (17) is not able to capture a given airline's heterogeneity, such as the operating status, across markets. Nevertheless, the regression coefficients are useful moments with which to identify contract-related parameters, as they are monotonically related to the underlying contract parameters, λ_o and λ_p. In addition, because we hold these contract-related moments fixed across markets for a given airline and then solve for profit-related parameters, heterogeneity across competitors is attributed to profit-related parameters, such fixed operating costs. This approach also is consistent with our model assumption that local managers are subject to the same contract as the CEO.

Our second set of identifying moments consists of the state-specific entry probabilities from the market-level entry–exit data. The profit-related parameters are then identified using the market-level entry–exit data. Before we discuss identification, we outline the estimation of these probabilities. Recall that the game has a Markov structure, that is, if $\{\boldsymbol{x}_k, s_k\} = \{\boldsymbol{x}_l, s_l\}$, then airline i's decisions at periods k and l are the same. To calculate the probability distribution of the Markov structure, we aggregate observations by state for each player and calculate the sample frequency of airline entry–exit decisions for each state-player pair. Specifically, let $p(a_i|\boldsymbol{x}, s)$ denote the probability that airline i selects entry–exit action a in state $\{\boldsymbol{x}, s\}$ for any given market. The sample frequency is calculated as

$$\hat{p}(a_i|\boldsymbol{x}, s) = \frac{\sum_t \mathbb{1}(a_{it} = 1, \boldsymbol{x} = \boldsymbol{x}_t, s = s_t)}{\sum_t \mathbb{1}(\boldsymbol{x} = \boldsymbol{x}_t, s = s_t)}.$$

As a result, the total number of $N \times M \times 2^N$ sample frequencies are obtained as moments that are used to match the equilibrium choice probabilities $\boldsymbol{p}$ from the model. The number $N \times M \times 2^N$ comes from multiplying the number of players N and the number of states $M \times 2^N$. The number of states is all possible combinations of market size M and the choices of the players 2^N.

The model is identified if there exists a unique set of model primitives that can be inferred from a sufficiently rich data set characterizing choice and state transition probabilities. From a technical standpoint, Magnac and Thesmar (2002) show that in a dynamic discrete choice framework, utility functions and their associated parameters can be identified for a given set of values of the discount rate, the distribution function of any unobserved private information, ϵ, and the agent's outside option. Our specification satisfies these identification conditions. Both the discount rate β and the distribution of ϵ are specified outside of the model estimation, and the expected value of the outside option if the firm is not active is normalized to zero.

From an intuitive standpoint, given all the state-specific entry probabilities as the moments, we use variation in the choice probability across players and states to identify separately the profit-related parameters for each CEO contract. The revenue-related parameters, γ_s and γ_n, are identified through variation in choice probabilities in response to the market size and the number of incumbents. The vector of airline-specific fixed operating costs f is identified through variation in the probability of being active by incumbents. The entry cost, k, is identified from the differences in the probability of being active between incumbents and potential entrants.

4.3 Market Heterogeneity

Note that our model characterizes the dynamic game in a single market, yet our data consist of 1,225 heterogeneous markets. To address this tension between our simulated data and our actual data, we consider two approaches.

Our first approach involves estimating the dynamic game using data pooled across markets, implying that we calculate empirical choice probabilities as if the entire data set comprises a single market. As such, we assume that the observed state-action profiles are generated from an identical data-generating process in all markets. More importantly, we assume a single and identical equilibrium of the game is played across all markets. This pooling affects the estimation of the parameters that are identified by traditional regression coefficients. In particular, heterogeneity stems from a specific property of the decentralized optimization problem in Section 2, which keeps the key features of the original optimization problem but adds a restriction that requires that decisions of local market managers are made independently. However, the data are generated by airlines that mostly operate in a hub-spoke network. Nonetheless, to the extent that this network structure mostly affects time-invariant market- and airline-specific operating costs, we can absorb this heterogeneity by including market times airline fixed effects in our regressions. In this way, we absorb all time invariant correlation among local markets for the same airline, making the set of local market decisions for the same airline independent of each other.

Using the estimated model, we use the model solution to simulate data, generating 1,225 markets over 15 periods. We start by finding the steady-state distribution of the states using the equilibrium choice probabilities and the transition probabilities for market size. The initial state values for each market $(s_{mt}, \boldsymbol{x}_{mt})$ are subsequently randomly drawn from the steady-state distribution of these variables. The entry–exit decision a_{imt} is calculated for a given state from the equilibrium choice probabilities. We simulate data conditioning on the initial observed states for each individual market group. We do so because the sample of each market group is small and therefore is initial-state dependent. We repeat the procedure 10 times to alleviate simulation bias following Michaelides and Ng (2000). We then aggregate all simulated market-group data to form a large panel that is comparable to the actual data. Finally, to obtain statistics that describe market structure, we average these simulated values of a_{imt} over the simulations and over the sample.

While this first approach is computationally efficient, it masks the substantial heterogeneity across markets, as different markets vary in market size, entry costs, and airline-specific operating costs. More importantly, different markets might differ in the equilibrium played. Although it would be ideal to capture market heterogeneity by estimating the dynamic game on an individual market level, in each of these markets, we only observe a sequence of state-action profiles over 15 periods. Therefore, to address this issue, we divide markets into 120 groups of similar size, pooling data across 10 markets on average. We then estimate the dynamic game separately for each of the market subgroups. We cannot reject the null that the data are aggregated at the level of these 120 market subgroups using the homogeneity test proposed by Otsu, Pesendorfer, and Takahashi (2016), which assesses whether data from distinct markets can be pooled. Details regarding the homogeneity test are in Appendix B.

We make two modifications to the estimation procedure described previously. First, because the sample size becomes much smaller, the relative frequencies of entry and exit calculated from the data are discrete in nature. To improve matching quality, we discretize the conditional choice probabilities from the model based on the frequency of observed states. The discretized conditional choice probabilities are then used in the econometric objective function, whose goal is to minimize the distance between the model and data moments.

The second modification relates to the compensation-related moments. Even when we use disaggregated profit and entry–exit data, the contract loadings are still identified by aggregate compensation moments, as our data only provides compensation information at the airline level. This feature of the estimation poses a problem because in the model, there is a mechanical multiplicative effect of market size on compensation, so identical contract loadings in different market sizes will affect the estimates of the profit-related parameters. Moreover, the main purpose of the estimation at the market-level is to capture heterogeneity in market-specific entry costs and firm–market specific fixed operating costs. Therefore, to obtain cost estimates that are less contaminated by the contract loadings, we assign weights to the compensation moments so that they decrease with the distance of market size from the sample median. In doing so, we implicitly assume that the CEO compensation contract at the aggregate level is formulated given the median market.

5. Results

5.1 Parameter Estimates

Table 3 presents the main parameter estimates from the pooled and disaggregated estimation approaches. For the latter, we report the median estimate from our 120 estimations.

In Panel A, we report the mean, serial correlation, and residual variance for the process governing market size in equation (14). Of note is the much higher estimate of the process variance for the pooled estimation. This result arises in the pooled estimation because the process variance captures both time-series and cross-sectional variation in market size. In contrast, for the disaggregated estimation, each estimation only captures time-series variation, resulting in a lower variance estimate.

In Panel B, we report the estimates of the remaining model parameters, with standard errors in parentheses. All of the parameter estimates are significantly different from zero, with one exception: the point estimate of the sensitivity of profit to competition, γ_n, in the case of the estimation using disaggregated data. Note that estimated loadings on peer firm performance for CEO compensation, λ_p, are statistically significant for both estimations. Note that the positive sign of these coefficients is consistent with RPE, as peer performance enters CEO compensation negatively. This piece of evidence provides strong support for the existence of RPE. Moreover, the economic magnitude of this implied use of RPE is large. For example, the estimate from the pooled estimation, 3.42×10^{-4}, implies a reduction in compensation of \$342 after a one million dollar increase in the peer group's net income. This effect is almost twice as large as the effect implied from our reduced-form regression in equation (17). It is also much larger than those reported in the literature. For example, using data from 1974 to 1986, Gibbons and Murphy (1990) find that in a median-sized firm, for each extra million dollars of shareholder wealth, CEO salary and bonus rise by less than \$90. For each extra million dollars of peer shareholder wealth, salary and bonus decrease by \$30. Using ExecuComp data from 1992 to 2005, Albuquerque (2009) finds that for the median firm, total CEO compensation increases \$255 for each million dollars of increased shareholder wealth and decreases \$138 for each million dollars of increased peer shareholder wealth. The estimates of the RPE parameter, λ_p, are not identical to the reduced-form regression coefficient, $\hat{\lambda}_p$. Intuitively, because we are matching the conditional choice probabilities and the reduced-form regression coefficients jointly, the contract loadings also adjust to better match the conditional choice probabilities

Next, our two estimation approaches give rise to similar profit margins. Using data pooled across markets, we find the estimated average fixed cost is $258.29 thousand, ranging from $217.62 thousand for Delta to $280.79 thousand for Southwest. The average estimate represents 91.5% of model-implied variable profits for a monopolist in a market of median size. Similarly, using data disaggregated across markets, the average fixed cost is $88.32 thousand, ranging from $60.81 thousand for Delta to $124.40 thousand for United. The average estimate represents 64.8% of model-implied variable profits for a monopolist in a market of median size. These ratios are close to the statistics provided by the Air Transport Association of America, which reports that average fixed operating costs amount to 71.2% of total operating expenses and 67.2% of revenue in 1993–1998. These results are also comparable to those reported in Aguirregabiria and Ho (2012), who find an estimate of 75% using the variable profits attributable only to nonstop flights as the denominator. This high value for the ratio between fixed costs and variable profits implies substantial economies of scale in the airline industry. In addition, the rank of the estimated fixed costs among airlines is in line with Ciliberto and Tamer (2009), who show that fixed operating costs are low for Delta and high for United.

However, the estimation using disaggregated markets produces more reasonable fixed operating cost parameter estimates that are in line with those from Aguirregabiria and Ho (2012). Adjustments are necessary to compare our results and theirs for three reasons. First, our market demand is derived directly from the 10% sample of the DB1B data. In contrast, Aguirregabiria and Ho (2012) scale these numbers back to their original levels. Second, we define a market as a trip between a pair of MSAs, while Aguirregabiria and Ho (2012) consider city pairs. In the sample we consider, the median ratio of MSA population to city population is about 2.5, and the average is about three. Third, our data, and therefore estimates, are at an annual frequency, while theirs are at a quarterly frequency.

With these differences in mind, using data disaggregated by markets, we estimate the average fixed operating costs to be \$88.32 thousand for MSA-pair market demand in the 10% sample, which corresponds to \$353.30 ($= 88.32/2.5 \times 10$) thousand for city-pair market demand scaled to the size of the full sample. Aguirregabiria and Ho (2012) estimate that the average fixed operating cost is \$119 thousand per quarter and therefore \$476 ($= 119 \times 4$) thousand per year for a city-pair. Our cost parameter estimates are therefore remarkably in line with the cost estimates in Aguirregabiria and Ho (2012). This result is encouraging given that their estimation is based upon assumptions of a hub-and-spoke network and price competition.

Moreover, using disaggregated data produces more sensible estimates of the entry cost, which we find to be \$1,289.15 thousand for a market of median size. The estimate from the pooled estimation is approximately 10 times higher at \$11,931.35 thousand, which is 46 times the average estimated fixed cost and 42 times variable profit for a monopolist in a market of median size. The pooled estimation produces such a high entry cost because market demand estimated with pooled data is quite volatile. To fit our data, which features persistent incumbency status, a high entry cost is necessary to offset this extra variation in market size.

The extremely high entry cost is the main reason for the compromised model fit for the pooled estimation approach. As in Asplund and Nocke (2006), an increase in the entry cost leads to a lower turnover. It also results in more markets with one and two incumbents because it protects incumbents from intense competition under bad market conditions. Similarly, it produces fewer markets with six or seven incumbents because it deters potential entrants under good market conditions.

5.2 External Model Validation

Table 4 compares simulated and data values of the statistics that describe market structure for two versions of the model estimation. "Pooled" corresponds to the estimation in which we use data pooled across markets, and "Separate" corresponds to the estimation in which we use data disaggregated into separate markets. In the latter case, we report estimates from the median market in terms of size. We examine three sets of statistics: the fraction of markets with a given number of incumbents, the fraction of markets with a given number of new entrants,po and the fraction of markets with a given number of new exits. Note that because we are directly matching conditional choice probabilities and not these specific statistics, this exercise constitutes an external model validity check.

The pooled estimation produces several close matches, but also some noticeable discrepancies between data and model predictions. Specifically, the model over-predicts the proportion of markets with one incumbent by 10.3 percentage points and under-predicts the proportion of markets with six incumbents by 20.7 percentage points. Moreover, it under-predicts the amount of market turnover for all markets with more than zero exits. In contrast, the disaggregated estimation does a better job of matching the simulated with the real moments, especially the tail market distribution by number of incumbents.

Several differences between the two estimation approaches underlie these results. First, as seen in Table 3, estimating the market demand process with pooled data produces volatility estimates that are higher compared to those obtained from disaggregated data. This result stems from the pooled-data estimation capturing substantial cross-section variation, as the procedure in Han and Phillips (2010) captures intercept heterogeneity but does not entirely rid the error-term of cross-sectional heterogeneity. This overstated demand volatility in turn distorts the rest of the model parameter estimates and compromises model fit. Second, the pooled estimation approach omits heterogeneity in costs across markets, which arises because airlines with hub-and-spoke networks naturally have lower operating costs in their hubs.

5.3 Counterfactuals

In this subsection, we use our estimated model to conduct counterfactual experiments to quantify the effect of RPE on competition. All these comparisons can be contaminated by multiplicity of equilibria, which are prevalent in dynamic games. Although we can identify the equilibrium observed in the data, we cannot guarantee that the same equilibrium is selected and played in the counterfactual specification of the model. To deal with this problem, we use an approach proposed in Aguirregabiria (2012) by requiring that the (unknown) equilibrium selection function does not jump discontinuously between equilibria as we change the value of the structural parameters continuously. That is, the counterfactual equilibrium is of the same type as the equilibrium in the data.

5.3.1. Comparative Statics

First, we present comparative statics in Figure 2, which show how market competition varies with four model parameters: the sensitivities of variable profits to demand and competition, γ_n and γ_s, the entry cost, k, and the contract loading on the firm's own performance, λ_o. We characterize market competition by the number of active firms, which is a common empirical measure of competition and is nearly identical to the Herfindahl-Hirschman index in our model because all incumbents have the same market share. Our intent is to observe how different features of the model affect optimal behavior under RPE.

Our comparative statics analysis is based on the same set of parameter estimates used to construct Figure 3. We obtain each panel of Figure 2 by solving and simulating the model 21 times, each time corresponding to a specific value of the parameter under scrutiny. For each of the simulations, we calculate the average of the total number of incumbents across individual markets.

We first examine the two parameters that govern the sensitivities of variable profits to demand and competition. The number of active players increases in γ_s but decreases in γ_n. Intuitively, as γ_s increases, players gain higher variable profits for the same market demand and therefore are more likely to be present in a market. Similarly, as γ_n increases, players lose more variable profits for the same level of competition and therefore are less likely to be operative in a market.

In the second row of Figure 2, we present comparatives statics with respect to the entry cost, k, and the contract loading on the firm's own performance, λ_o. As the entry cost rises, the number of active firms falls, except when the cost is small. Intuitively, as k rises, fewer firms are efficient enough to overcome the entry cost. However, if a rise in k also deters that of inefficient firms more than the entry of efficient firms, then at sufficiently low levels of k, a rise in k encourages efficient firms to be active and raises the number of active players.

The relation between the number of firms and the contract loading on own performance, λ_o, slopes upward. As λ_o rises, the relative importance of RPE falls, so all but the most efficient firms are more likely to be active, as comparisons to their low-fixed-cost peers become less important. Of course, this last comparative static needs to be interpreted with care, as, outside this particular model, contract loadings are themselves an endogenous outcome. That said, this comparative static is useful as a first step in designing optimal contracts as long as one of the contracting goals depends on competition.

5.3.2. Policy Functions

Next, we compare the policy functions of the model as estimated with a counterfactual policy function constructed by setting the contract loading on peer performance to zero. First, we consider the parameters from the disaggregated estimation, and plot in Figure 3 equilibrium conditional probabilities of being active in a market as a function of the market size, s. We calculate these probabilities at the steady-state distribution of market demand, s_{imt}, so our calculations average over different incumbency statuses. We plot these numerical policy functions for each major airline in our data. Panel A contains policy functions from the baseline model with RPE, and Panel B contains policy functions from the counterfactual model without RPE.

These policy functions highlight several aspects of the intuition that underlies the model solution. First, two patterns are common to both Panels A and B of Figure 3. In both, the equilibrium probability of being active rises sharply with market size when markets are small. It then flattens and eventually falls as market size rises. This pattern stems from two countervailing effects of size on firms' profits. On the one hand, profits increase mechanically in size. On the other hand, profits fall with size due to the presence of fixed costs combined with endogenously intensified competition. The first demand effect dominates for small markets, while the second competition effect dominates for large markets.

The response to market size, however, differs across heterogeneous players depending on their comparative cost advantage. First, firms with lower fixed operating costs, such as Delta (DL) in dashed red, are always more likely to be active than their high-fixed-costs counterparts such as US Airlines in dashed gold. Second, these hump-shaped policy functions peak earlier for firms with high fixed costs. As a result, in the stationary equilibrium, efficient players are relatively more likely to be present in large markets, while inefficient players are relatively more concentrated in small markets, as in Asplund and Nocke (2006), who call this result a selection effect. Although a rise in market size mechanically increases the variable profits of all firms, it also leads to intensified competition because it promotes endogenous entry. Thus, the marginal surviving firm has to be more efficient in larger markets.

The model dynamics amplify this selection effect because the participation decisions for incumbents and potential entrants differ. When deciding to remain in operation, incumbents compare the expected discounted future profits with their outside options after exit. In contrast, potential entrants compare the discounted future payoff from entering with the sunk entry cost. The irrelevance of the entry costs for incumbents also gives rise to hysteresis in the structure of the market. The sunk entry cost restrains potential entrants from entering and incentivizes incumbents to remain in operation rather than exit. The number of firms thus responds asymmetrically to changes in demand or, equivalently, the history of market structure. As such, in addition to current and future profit determinants, this history matters for explaining the current number of firms in a market, as in Asplund and Nocke (2006).

While this discussion thus far highlights the similarity in the optimal policies with and without RPE, Panels A and B in Figure 3 differ in several important dimensions. First, firms with low fixed costs have nearly identical policy functions with and without RPE. Second, the one difference in the policy functions of these efficient firms with and without RPE occurs in large markets, where RPE is associated with a lower probability of being active.

This pattern is a direct effect of RPE dampening the positive effect of large market size on compensation, as market size is a common shock to all players in the market. Third, and in contrast, firms with higher fixed costs are substantially less likely to be present in any market, as it is optimal for them to avoid being compared to their low-cost peers. Fourth, this drop in the probability of being active is sharper for medium and large markets than for small markets. In equilibrium, the small markets contain fewer low-cost firms, as RPE has less of an effect on the entry–exit decision of the high-cost firms. The effects are large. The probability of being active falls from .67 without RPE to .27 with RPE for US Airways. The result is that the selection effect (Asplund and Nocke 2006) becomes more pronounced, with airlines of similar profitability clustering together.

Next, in Figure 4, we again plot the estimated policy functions and the counterfactual policy functions without RPE, but we use the parameters from the pooled estimation. While, as discussed above, these parameter estimates are likely contaminated by heterogeneity, examining the policy functions under this parameterization is nonetheless instructive. These plots differ markedly from their counterparts in Figure 3, with this difference due to two specific parameters. The pooled estimation delivers a much smaller estimate of γ_n, which is the parameter in equation (1) that governs the intensity of competition, with high γ_n implying that new entrants siphon off a great deal of revenue from incumbents. This estimation also delivers a much larger estimate of the fixed entry cost, k, which intuitively leads to less intense competition.

Several features of Figure 4 stand out. First, the probability of being active rises sharply with market size and then flattens out abruptly for medium and large markets. There is no hump shape because a high entry cost implies that competition has a weak effect on the probability of being active. Second, the policy functions are much more compressed across firms with different levels of fixed costs. Intuitively, fixed operating costs matter less for entry–exit decisions when variable profits are high and depend little on the number of competitors in the market. Third, we see the same effect of RPE on policies as in Figure 3, with high-cost airlines less likely to be active to avoid comparisons with peers. However, the effect is muted relative to that in Figure 3 because higher variable profits lower the dispersion of profitability across players, so RPE has much less impact on the highest-cost firms.

5.3.3. Endogenous selection

For our final counterfactual exercise, in Figure 5, we plot the average endogenous fixed costs of the firms operating in a market as a function of the market entry cost, both for the estimated model with RPE and for a counterfactual model without RPE. Two patterns in Figure 5 are of note. First, as in (Asplund and Nocke 2006), we see a selection effect even in the absence of RPE, in which low-cost firms are more likely to operate in high-entry-cost markets, and vice versa. Two opposing forces are at work. On the one hand, high fixed costs directly make entry less attractive. On the other hand, high entry costs also lead to less intense competition, which dampens the first direct effect. For inefficient firms with high costs, the direct effect is more important, but for more efficient firms, the second effect outweighs the first. Second, RPE naturally amplifies the competitive advantage of the low-fixed-cost firms, so we see a steepening of the slope of the relation between average fixed costs and the parameter governing entry costs.

6. Conclusion

In this paper, we investigate how and to what extent the use of RPE affects firms' entry–exit decisions and thus industry competition. We develop a dynamic game of competition with heterogenous firms in an oligopoly market with the presence of RPE contracts, and we estimate the model parameters using detailed airline route data from the U.S. airline industry, combined with CEO compensation data. Using this framework, we obtain three main findings. First, RPE encourages the sorting of inefficient firms into low-entry-cost markets and efficient firms into high-entry-cost markets. Second, RPE discourages firms with high fixed operating costs from participating in any market, but especially medium and large markets, with the probability of being active in a market falling up to 40 percentage points. Because RPE has little effect on the entry–exit decisions of efficient firms with low fixed operating costs, RPE also encourages the sorting of inefficient firms into small markets, and vice versa. Finally, we find that when markets are characterized by high entry costs or weak competition, RPE has little effect on entry–exit decisions.

The model also provides insight into the economic rationale behind these findings. Because RPE makes CEO compensation less sensitive to market conditions beyond their control, managers, under RPE contracts, make entry–exit decisions while facing a tradeoff between the lower sensitivity to market conditions and the gain or loss from being compared to competing agents. We find that the second consideration, an unintended consequence of RPE, is the dominant empirical force, with airline decisions dependent more on their relative cost advantages than the sensitivity of profits to factors beyond their control.

One direction for future research is based on our assumption of modeling observed instead of optimal contracts. We do not characterize an optimal contract, so the contract loadings on firms' own and peer performance are exogenous and fixed. While the rationale for this choice is based on the natural assumption of an incomplete contracting environment, we cannot ascertain whether the unintended effects on industry competition induced by the use of RPE is optimal or whether carefully designed contracts could mitigate these effects. However, this empirical strategy has the advantage of demonstrating the effects of RPE on firm decisions that have not already been explored in the theoretical contracting literature. For example, the simple and insightful models that explore the interaction between competition and RPE (Aggarwal and Samwick 1999; Vrettos 2013, e.g.[]) do not consider any effects of relative cost advantages across competitors or heterogeneity in markets. Thus, our work provides interesting results on the responses to contracting features that are of interest to both economic theorists and compensation committees who set executive pay.

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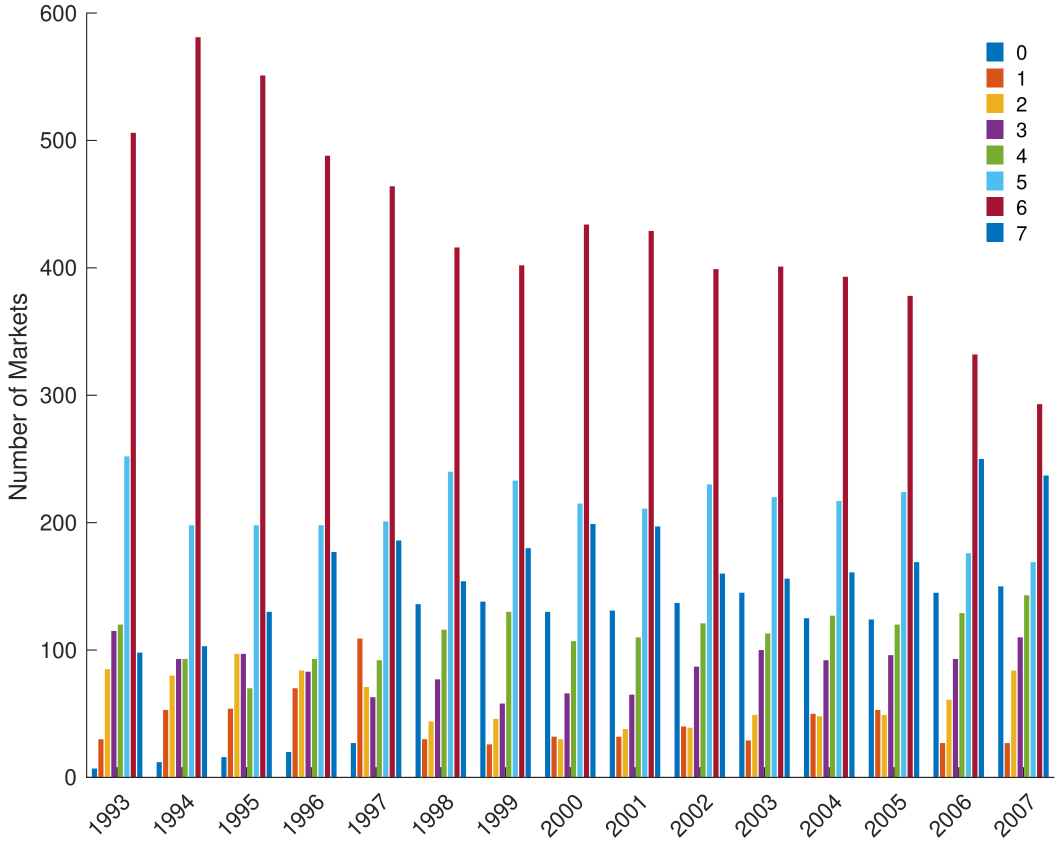
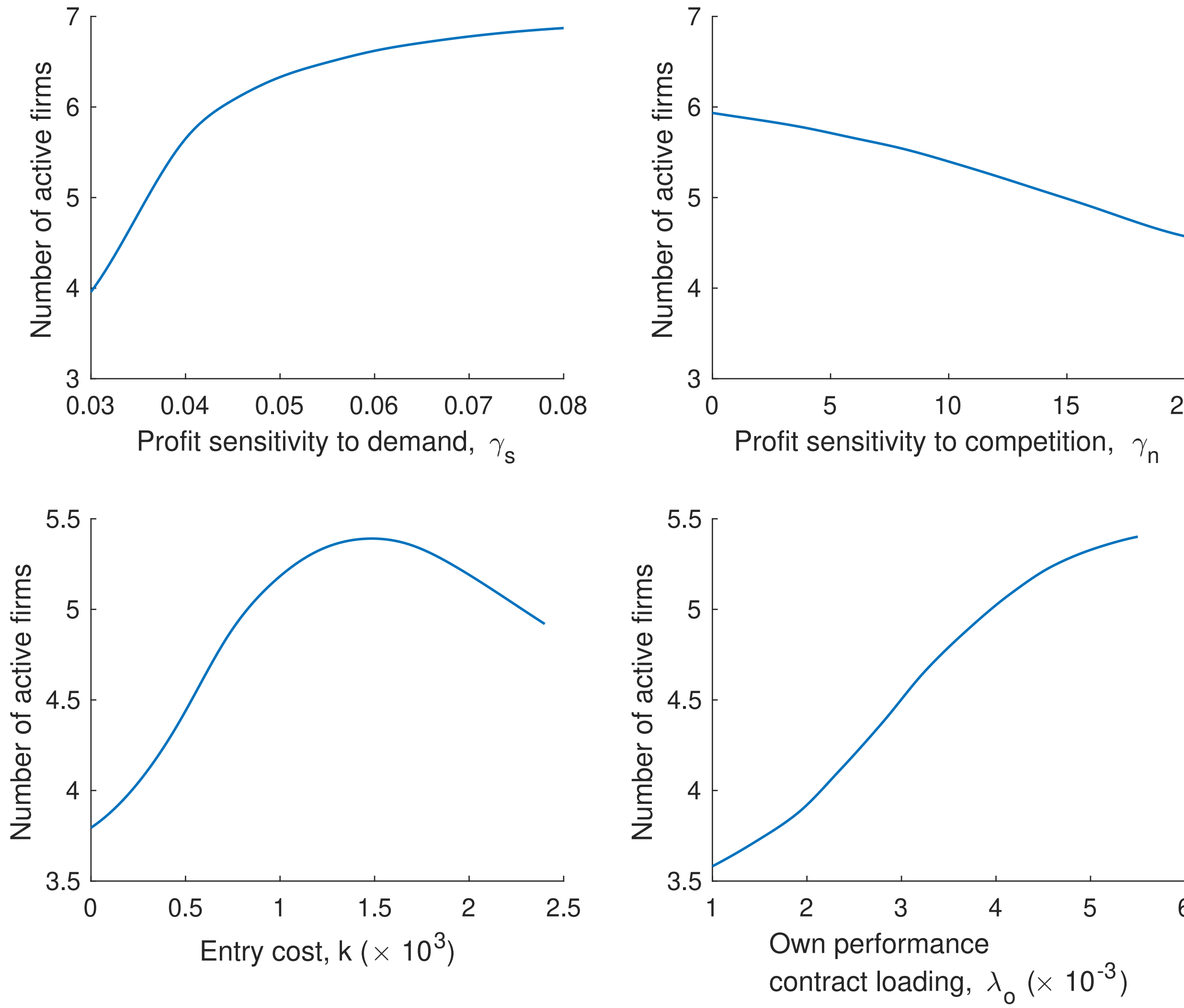
Figure 1. Market Structure and Dynamics



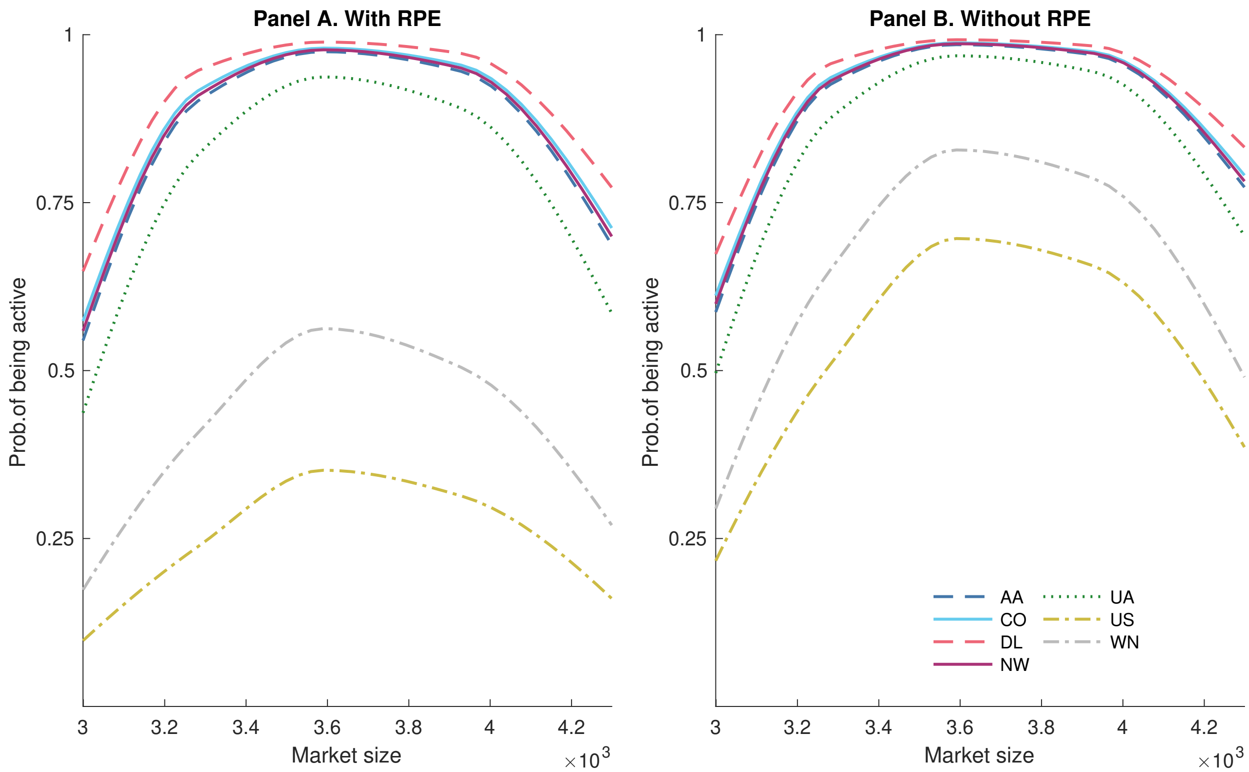
This figure presents the distribution of the 1,225 markets examined across the number of incumbent airlines between 1993 and 2007.

Figure 2. Comparative Statics



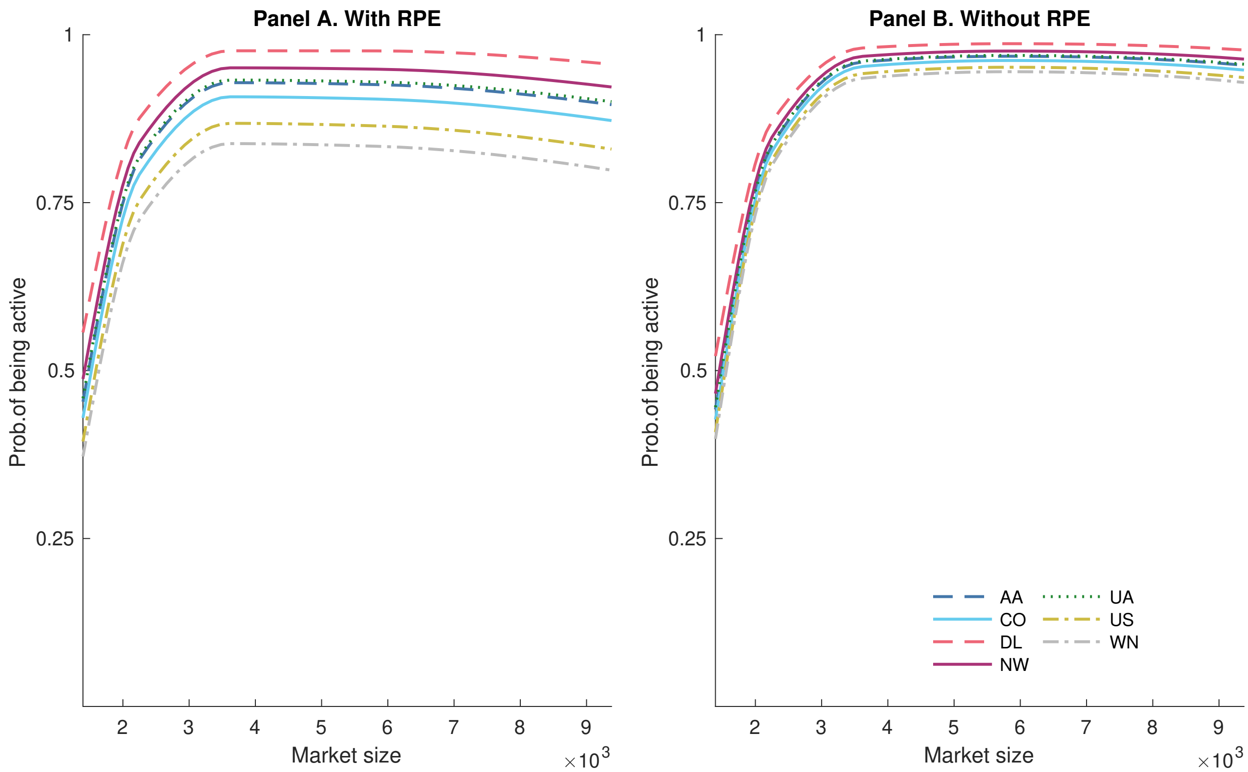
This figure depicts how market competition varies with the four parameters we estimate: the sensitivities of variable profits to demand, γ_s, and competition γ_n, the entry cost, k, and the contract loading on firms' own performance, λ_o.

Figure 3. Policy Functions with and without RPE: Disaggregated Estimation



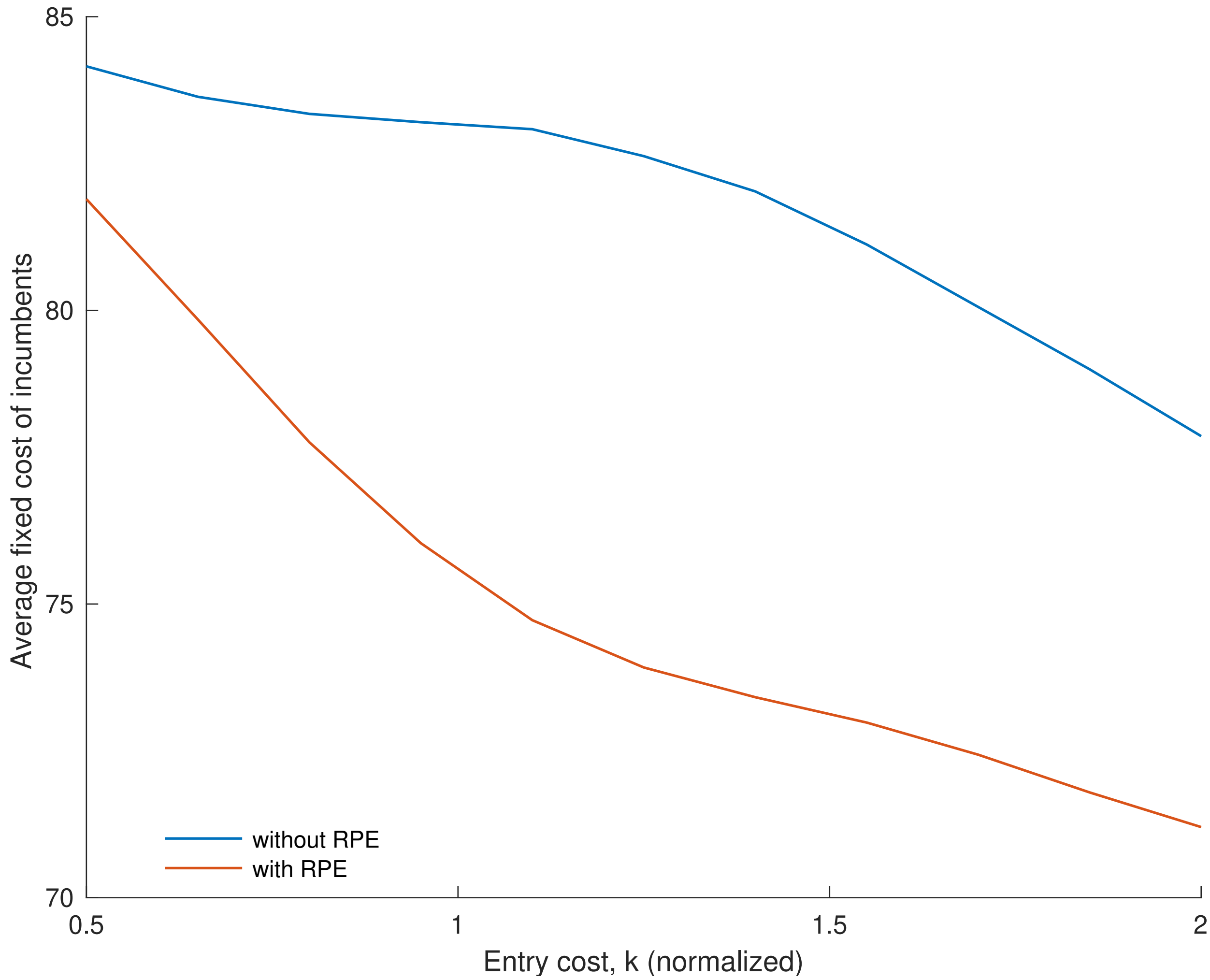
This figure depicts the equilibrium conditional probabilities for each airline as a function of market size, s, evaluated at the steady-state distribution. Panel A contains policy functions from the model and Panel B contains policy functions from a model with the same parameterization, except with the contract loading on peer performance set to zero. Model parameter values are taken from the set of estimation results for disaggregated markets in Table 3. The airlines considered are American (AA), Continental (CO), Delta (DL), Northwest (NW), United (UA), US Airways (US) and Southwest (WN).

Figure 4. Policy Functions with and without RPE: Pooled Estimation



This figure depicts the equilibrium conditional probabilities for each airline as a function of market size, s, evaluated at the steady-state distribution. Panel A contains policy functions from the model and Panel B contains policy functions from a model with the same parameterization, except with the contract loading on peer performance set to zero. Model parameter values are taken from the set of estimation results for pooled markets in Table 3. The airlines considered are American (AA), Continental (CO), Delta (DL), Northwest (NW), United (UA), US Airways (US) and Southwest (WN).

Figure 5. Fixed Costs versus Entry Costs



This figure depicts average fixed costs as a function of market entry costs, k, in the cases of RPE and no RPE. Fixed costs are normalized to one for the median market.

Table 1. Airlines by the Number of Passengers and Markets

This table presents the seven airlines in our sample, together with the annual number of passengers and the number of operating markets served. The sample is based on the DB1B database and covers the period from 1993 to 2008.

Code	Airline	Number of passengers	Number of markets
WN	Southwest	2,445,857	637
AA	American	2,107,029	1,064
UA	United	1,971,053	1,059
DL	Delta	1,843,527	1,119
US	US Airways	1,472,839	1,116
CO	Continental	1,282,698	1,139
NW	Northwest	1,236,952	998

Table 2. Market Structure and Dynamics

This table presents summary statistics regarding market structure and dynamics. The sample is based on the DB1B database and covers the period from 1993 to 2008. Panel A presents the distribution of market-year observations by the number of entries and exits, respectively. Panel B presents statistics describing the differences of airline operations.

Panel A: Fraction of market-year observations with entries or exits				
	0	1	2	>=3
Entries	87.69%	11.27%	1.00%	0.04%
Exits	84.46%	13.66%	1.75%	0.14%

Panel B: Fraction of markets with entries or exits				
	0	1	2	>=3
Entries		82.19%	53.59%	30.42%
Exits		84.42%	65.13%	44.85%

Panel C: Heterogeneity across airlines							
	AA	CO	DL	NW	UA	US	WN
Monopoly markets							
No. of market-year obs	40	34	195	46	41	259	77
Market %	6%	5%	28%	7%	6%	37%	11%
Probability of staying in a market							
	75%	68%	87%	80%	70%	75%	79%

Table 3. Parameter Estimates

The table reports the parameter estimates with their corresponding standard errors in parentheses. Panel A reports the estimates of the AR(1) process governing market demand dynamics, with μ, ρ, and σ representing the drift, serial correlation, and volatility. Panel B reports the structural parameter estimates from the dynamic game. γ_s and γ_n capture the impacts of demand and competition, respectively, on equilibrium industry revenues. f stands for airline-specific fixed operating costs, and k is the market entry cost. λ_o and λ_p are parameters representing the contract loadings on the airline's own and peer performance, respectively. We consider two versions of the model estimation: *Pooled* corresponds to the results using data pooled across markets, and *Disaggregated* corresponds to the results using data disaggregated across markets.

Panel A: Market demand dynamics

	Pooled	Disaggregated
μ	8.194	8.186
ρ	0.770	0.892
ω	0.475	0.190

Panel B: Structural parameter estimates

	Pooled		Disaggregated	
	Estimates	Std. errors	Estimates	Std. errors
Variable profits				
γ_s	0.078	(0.004)	0.038	(0.006)
γ_n	0.550	(1.064)	10.460	(7.756)
Fixed operating costs (in thousands)				
f(AA)	259.988	(2.174)	76.864	(20.789)
f(CO)	267.392	(2.191)	72.535	(21.568)
f(DL)	217.618	(2.140)	60.811	(22.355)
f(NW)	247.721	(2.143)	74.729	(22.327)
f(UA)	258.273	(2.185)	91.640	(20.408)
f(US)	276.255	(2.220)	124.403	(24.073)
f(WN)	280.794	(2.228)	117.289	(21.981)
Entry cost (in thousands)				
k	11,931.351	(0.634)	1,289.145	(43.804)
Compensation ($\times 10^{-3}$)				
λ_o	1.388	(0.001)	5.200	(0.056)
λ_p	0.342	(0.002)	0.325	(0.050)

Table 4. Market Structure: Data- and Model-Predicted Statistics

This table compares simulated and actual statistics that describe market structure. We consider two versions of the model estimation. The label "Pooled" corresponds to the estimation in which we use pooled data across markets, and the label "Disaggregated" corresponds to the estimation in which we use data disaggregated across markets.

	Data	Model	
		Pooled	Disaggregated
Distribution of markets by number of incumbents			
0	7.9%	6.7%	2.7%
1	3.6%	13.9%	6.1%
2	5.0%	13.7%	8.7%
3	7.1%	15.0%	11.4%
4	9.3%	14.7%	13.1%
5	17.5%	13.9%	16.8%
6	35.5%	14.8%	24.4%
7	14.1%	7.3%	16.8%
Distribution of markets by number of new entrants			
0	87.7%	92.3%	83.3%
1	11.3%	5.6%	13.3%
2	1.0%	1.7%	2.7%
>= 3	0.0%	0.4%	0.8%
Distribution of markets by number of new exits			
0	84.5%	93.4%	84.5%
1	13.7%	6.0%	11.2%
2	1.8%	0.6%	2.7%
>= 3	0.1%	0.0%	1.5%

Appendix A. U.S. Airline Industry Description and Evolution

Appendix A.0.1. Entry and exit

The DB1B survey classifies information at the coupon, market, and tickets level separately. The ticket data set contains summary characteristics for each itinerary, including reporting carrier, origin/destination, and prorated airfare. The market data set contains ticket characteristics disaggregated at the level of a single direction within the ticket. The coupon data set contains the characteristics of each leg of the air tickets, such as the operating carrier, origin and destination airports, number of passengers, and fare class.

We construct the airline entry and exit data following Ciliberto and Tamer (2009). We start with a sample of data from the first quarter of 1993 to the last quarter of 2015. We then take three steps to link all information in the DB1B survey. First, we merge the DB1B coupon data set with operating carrier information from a separate data source: the T-100 Domestic Segment data set from the BTS, which reports all flights that occur in the United States in a given month of the year. We then drop the unmatched coupons and merge this reduced DB1B coupon data set with the DB1B ticket data set, using ticket identification numbers. Finally, we merge the cleaned ticket-coupon data set with the DB1B market data set to get the information on origin and destination airports.

Following Ciliberto and Tamer (2009), we drop observations with the following characteristics: (i) tickets with more than six coupons; (ii) tickets whose fare credibility is questioned by the Department of Transportation (the variable dollarcred with a value of zero); (iii) tickets that are neither one-way nor round-trip travel; (iv) tickets including travel on more than one airline on a unidirectional trip (know as interline tickets); (v) tickets with a fare less than 20 dollars; (vi) tickets involving U.S. nonreporting carriers flying within North America (small airlines serving big airlines) and foreign carriers flying between two U.S. points; (vii) tickets that are part of international travel; (viii) tickets involving noncontiguous domestic travel (Hawaii, Alaska, and territories); and (ix) tickets in the top and bottom fifth percentile of the year-quarter fare distribution.

Appendix A.0.2. Markets

We define a market as a trip between a pair of MSAs, irrespective of intermediate stops and of the direction of the flight. This definition is in line with the previous literature. For example, Ciliberto and Tamer (2009) consider airport pairs and Aguirregabiria and Ho (2012) consider city pairs. The sample includes markets between the top 50 MSAs ranked by average population from the U.S. Census Bureau during the sample period. Table A.1 in Appendix A presents the list of the 50 MSAs and their populations. Briefly, from 1993 to 2015, the top 50 MSAs cover on average 63.8% of the U.S. population. The markets between these 50 MSAs serve more than 66.61% of all passengers and generate more than 66.77% of all revenues over all reported market segments in the DB1B data.

For each MSA, we cluster all the primary airports classified by the Federal Aviation Administration, excluding any general aviation airports, which are civilian airports that typically serve only small charter and private aircraft. This clustering implies perfect substitution in demand and supply between two routes with the same MSAs but different airports and cities. In the end, we have $M = (50 \times 49)/2 = 1,225$ possible markets. Table A.2 presents the top 20 markets ranked by the average annual number of passengers served.

Appendix A.0.3. Airline identification

A ticket can involve more than one airline because of code shares, with approximately one third of the tickets in our sample involving more than one airline. We therefore use the reporting carrier at the ticket level in the DB1B data to identify the airline, where the reporting carrier is the airline that submits the ticket information to the Office of Airline Information. This convention implies that we assume that the reporting carrier pays the cost of operating the flight and receives the revenue for providing this service.

Next, we restrict our attention to the top airlines ranked by the annual number of passengers served for two reasons. First, we need comparable peers. Second, the state space grows exponentially with the number of airlines, as N airlines implies 2^N possible combinations of choice sets. To avoid the clear computational burden, we combine any regional affiliates with their holding parent airlines, and we drop the regional carriers whose core business is not in cooperation with a major carrier. This process leaves us with seven airlines in the final sample. Table 1 in Appendix A presents these carriers, together with the annual number of passengers and the number of operating markets. Southwest is the airline that flies the most passengers (about 2.5 million passengers in the 10% sample), while American, United, and Delta follow in the ranking. These 7 carriers in total serve 80.49% of passengers and generate 82.14% of revenues in the markets between top 50 MSAs during the 1993–2008 time period.

Appendix A.0.4. Mergers, acquisitions, and code-share agreements

The U.S. airline industry has experienced substantial consolidation over the past few decades. Table A.3 in Appendix A describes the recent airline mergers and code-share agreements in the U.S. airline industry.

Mergers and acquisitions (M&As) can be considered as extreme cases of entry–exit decisions. However, we do not explicitly model the M&A decisions in our dynamic model for two reasons. Theoretically, M&A decisions are sufficiently rare that the expectation of future mergers does not influence equilibrium play. Empirically, M&As in the U.S. airline industry are heavily regulated. In the wake of the Airline Deregulation Act of 1978 and the closure of the Civil Aeronautics Board in 1985, policy makers adopted a strong stance against excessive concentration. Therefore, mergers between airlines on the verge of collapse were approved to maintain competition, while mergers between fiscally healthy airlines were generally prevented.

Nevertheless, the mergers and acquisitions have important implications for the estimation of our dynamic game because they change the number of global players. Therefore, instead of modeling the mergers and acquisitions explicitly, we take into account industry evolution by estimating our dynamic game for the sample period 1993–2008. In this period, the global players are Southwest, American, Delta, United, US Airways, Northwest, and Continental.

One final important feature of the airline data is code-share agreements, which allow an airline to sell seats on a partner's plane as if they were its own. This practice could potentially affect our estimation, depending on whether the code-shared routes are complementary or overlapping. On the one hand, routes are complementary when together they allow travel between two cities that is not possible on either airline. A code-share agreement effectively enables the two airlines to enter a market jointly. The use of the reporting carrier takes care of these cases. On the other hand, routes are overlapping when both airlines offered competing service in the same market prior to the code-share alliance. In these instances, an alliance could facilitate price collusion, which violates the model assumption of a negative relation between the number of incumbents and profits. Nevertheless, we view the concern over price collusion as minimal for several reasons. First, from a practical perspective, code-share agreements are subject to careful review by the U.S. Department of Transportation, which ensures that the agreements are not anticompetitive or contrary to the public interest. Second, from an academic perspective, Gayle (2007) uses a structural framework to examine the competitive effects of the code-share alliances among Continental, Delta, and Northwest in 2002, finding few significant departures between collusive and prealliance prices. Finally, strategic alliances formed by code-sharing can have an impact on deterring potential competitors from entering a relevant market. In our model, this entry deterrent effect is captured by the market-specific entry costs.

Table A.1. MSA and Population

This table presents the list of the top 50 metropolitan statistical areas (MSAs), ranked by average annual population between 1993 and 2008 from the U.S. Census Bureau.

CBSA	MSA, State	Population
35620	New York-Newark-Jersey City, NY-NJ	18,306,651
31080	Los Angeles-Long Beach-Anaheim, CA	11,751,734
16980	Chicago-Naperville-Elgin, IL-IN-WI	9,004,264
14460	Boston-Cambridge-Newton, MA-NH	6,175,536
37980	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	5,680,094
19100	Dallas-Fort Worth-Arlington, TX	5,195,236
33100	Miami-Fort Lauderdale-West Palm Beach, FL	4,975,916
47900	Washington-Arlington-Alexandria, DC-VA-MD-WV	4,842,885
26420	Houston-The Woodlands-Sugar Land, TX	4,789,770
19820	Detroit-Warren-Dearborn, MI	4,456,654
12060	Atlanta-Sandy Springs-Roswell, GA	4,263,447
41860	San Francisco-Oakland-Hayward, CA	4,057,384
40140	Riverside-San Bernardino-Ontario, CA	3,409,758
38060	Phoenix-Mesa-Scottsdale, AZ	3,317,283
42660	Seattle-Tacoma-Bellevue, WA	3,029,570
33460	Minneapolis-St. Paul-Bloomington, MN-WI	2,957,210
41740	San Diego-Carlsbad, CA	2,825,013
41180	St. Louis, MO-IL	2,668,021
12580	Baltimore-Columbia-Towson, MD	2,557,779
45300	Tampa-St. Petersburg-Clearwater, FL	2,413,157
38300	Pittsburgh, PA	2,380,470
39300	Providence-Warwick, RI-MA	2,164,859
19740	Denver-Aurora-Lakewood, CO	2,130,799
17460	Cleveland-Elyria, OH	2,125,131
17140	Cincinnati, OH-KY-IN	2,014,202
38900	Portland-Vancouver-Hillsboro, OR-WA	1,926,834
40900	Sacramento–Roseville–Arden-Arcade, CA	1,840,168
28140	Kansas City, MO-KS	1,832,935
41700	San Antonio-New Braunfels, TX	1,694,097
41940	San Jose-Sunnyvale-Santa Clara, CA	1,681,379

Table A.1. *(Continued)* MSA and Population

CBSA	MSA, State	Population
36740	Orlando-Kissimmee-Sanford, FL	1,677,544
25540	Hartford-West Hartford-East Hartford, CT	1,612,177
47260	Virginia Beach-Norfolk-Newport News, VA-NC	1,595,074
18140	Columbus, OH	1,587,790
26900	Indianapolis-Carmel-Anderson, IN	1,565,532
33340	Milwaukee-Waukesha-West Allis, WI	1,499,327
16740	Charlotte-Concord-Gastonia, NC-SC	1,420,926
29820	Las Vegas-Henderson-Paradise, NV	1,382,835
34980	Nashville-Davidson-Murfreesboro-Franklin, TN	1,289,531
35380	New Orleans-Metairie, LA	1,268,270
12420	Austin-Round Rock, TX	1,264,960
14860	Bridgeport-Stamford-Norwalk, CT	1,228,752
32820	Memphis, TN-MS-AR	1,173,752
35300	New Haven-Milford, CT	1,165,669
15380	Buffalo-Cheektowaga-Niagara Falls, NY	1,156,330
27260	Jacksonville, FL	1,128,611
31140	Louisville/Jefferson County, KY-IN	1,109,337
49340	Worcester, MA-CT	1,096,765
36420	Oklahoma City, OK	1,065,238
40060	Richmond, VA	1,060,857

Table A.2. Market and Number of Passengers in DB1B

This table presents the top 20 markets ranked by the average annual number of passengers served. The sample is based on DB1B and covers the period from 1993 to 2008.

	MSA Pair		Passengers
1	Los Angeles-Long Beach-Anaheim, CA	San Francisco-Oakland-Hayward, CA	209,215
2	Chicago-Naperville-Elgin, IL-IN-WI	New York-Newark-Jersey City, NY-NJ-PA	196,532
3	Boston-Cambridge-Newton, MA-NH	New York-Newark-Jersey City, NY-NJ-PA	153,296
4	New York-Newark-Jersey City, NY-NJ-PA	Orlando-Kissimmee-Sanford, FL	152,015
5	Atlanta-Sandy Springs-Roswell, GA	New York-Newark-Jersey City, NY-NJ-PA	143,795
6	Los Angeles-Long Beach-Anaheim, CA	New York-Newark-Jersey City, NY-NJ-PA	142,341
7	New York-Newark-Jersey City, NY-NJ-PA	Washington-Arlington-Alexandria, DC-VA-MD-WV	125,781
8	Miami-Fort Lauderdale-West Palm Beach, FL	New York-Newark-Jersey City, NY-NJ-PA	113,117
9	New York-Newark-Jersey City, NY-NJ-PA	San Francisco-Oakland-Hayward, CA	95,598
10	Dallas-Fort Worth-Arlington, TX	Houston-The Woodlands-Sugar Land, TX	92,642
11	San Diego-Carlsbad, CA	San Francisco-Oakland-Hayward, CA	85,216
12	Chicago-Naperville-Elgin, IL-IN-WI	Los Angeles-Long Beach-Anaheim, CA	84,643
13	Boston-Cambridge-Newton, MA-NH	Washington-Arlington-Alexandria, DC-VA-MD-WV	80,666
14	New York-Newark-Jersey City, NY-NJ-PA	Tampa-St. Petersburg-Clearwater, FL	77,839
15	Las Vegas-Henderson-Paradise, NV	Los Angeles-Long Beach-Anaheim, CA	76,098

Table A.2. *(Continued)* Market and Number of Passengers in DB1B

	MSA Pair		Passengers
16	Chicago-Naperville-Elgin, IL-IN-WI	Minneapolis-St. Paul-Bloomington, MN-WI	74,020
17	Chicago-Naperville-Elgin, IL-IN-WI	Washington-Arlington-Alexandria, DC-VA-MD-WV	72,702
18	Atlanta-Sandy Springs-Roswell, GA	Chicago-Naperville-Elgin, IL-IN-WI	71,288
19	Dallas-Fort Worth-Arlington, TX	New York-Newark-Jersey City, NY-NJ-PA	70,436
20	Las Vegas-Henderson-Paradise, NV	San Francisco-Oakland-Hayward, CA	68,181

Table A.3. U.S. Airline Mergers, Acquisitions, and Code-Share Agreements

Panel A: Mergers and Acquisitions	
1993	Southwest (WN) acquires Morris Air
1997	ValuJet merges with AirWays Corp. and becomes AirTran (FL)
1999	American (AA) acquires Reno Airways (QX)
2001	American (AA) acquires Trans World Airlines
2005	US Airways (US) merges with America West (HP)
2008	Delta (DL) merges with Northwest (NW)
2010	United (UA) merges with Continental (CO)
2011	Southwest (WN) merges with AirTran (FL)
2013	American (AA) merges with US Airways (US)
Panel B: Code-Share Agreements	
1998	American (AA) and Alaska (AS)
1998	Northwest (NW) and Continental (CO)
1999	Continental (CO) and Alaska (AS)
1999	Northwest (NW) and Alaska (AS)
2003	United (UA) and US Airways (US)
2003	Northwest (NW), Continental (CO), and Delta (DL)
2005	Delta (DL) and Alaska (AS)

Source: Mountford (2003), Ito and Lee (2007), Mills (2010)

Appendix B. Test of Pooling Data across Markets

In this section, we give a brief outline of the homogeneity test for assessing whether data from distinct markets can be pooled. The test draws from Otsu et al. (2016) and is adapted to our setting.

The test directly compares the set of conditional choice probabilities estimated from the pooled sample with those estimated from individual markets. It builds on the idea that under the null hypothesis, two conditions hold: the observed state-action profiles are generated from an identical data-generating process and the same equilibrium was played in all markets. This null hypothesis is a maintained assumption for estimation based on pooled data.

The test statistic is defined as

$$\mathcal{T} = \sum_{j=1}^{M} \sum_{d \in D} W_j(d) \left[\hat{p}_j(d) - \hat{p}(d)\right]^2,$$

where for each state-action profile, $d = (a \mid x, s)$, $\hat{p}_j(d)$ and $\hat{p}(d)$ denote the conditional choice probabilities for a market j and pooled markets respectively. $W_j(d)$ is a weight that is given by:

$$W_j(d) = f_j(x, s)/\hat{p}(d),$$

where $f_j(x, s)$ denotes the frequency of state (x, s) in market j. The test statistic has an asymptotic chi-squared distribution.

We obtain the critical values of the test statistic by bootstrapping, where we consider 1,000 bootstrap iterations. For each iteration, b, we first simulate the game of the same size as the original and then compute the bootstrap counterpart of the test statistic $\mathcal{T}_b$. The data-generating process used in the simulation is characterized by the state transition probabilities from the pooled sample.

Appendix C. Weight Matrix

We use a block diagonal weight matrix, with the first block corresponding to the regression coefficients from equation (17). For these moments, we use a simple identity matrix. The second block is the weight matrix for the state-specific entry probabilities, which is a diagonal matrix with elements equal to the data frequency for each state. This choice implies that we assign the most weight to the state-specific entry probabilities that are observed most frequently. Note that the compensation moments are small in magnitude compared to the state-specific entry probabilities. As such, a simple combination of the two weight matrices implicitly undermines the importance of the compensation moments. To compensate, we therefore multiply the identity weight matrix of the compensation regression coefficients by the total number of observations.

The construction of the second block requires justification. In contrast to most of the simulated method of moments estimators applied in finance (e.g. Bazdresch, Kahn, and Whited 2018), in which the data moments are derived using the total number of observations in the sample, each of the state-specific entry probabilities is calculated using a subset of observations that depends on how often a state occurs. Because the number of observations per state can be as small as two or three, small-sample bias can contaminate estimation of the data moments, so we opt to use the state frequencies to construct the weight matrix as in Pakes, Ostrovsky, and Berry (2007). They show that, for small sample sizes, estimation requiring no calculation of the optimal weight matrix has a lower mean squared error than estimation based on the optimal weight matrix. When we calculate the standard errors, we use the moment covariance matrix, as the variation of the conditional entry probabilities is dwarfed by the variation in the state frequencies.

Appendix D. Narrative Evidence for the Use of Relative Performance Evaluation

Below are excerpts from the proxy disclosures and newspaper articles for the use of relative performance evaluation (under construction).

Continental In its 1999 proxy statement, Continental states:

> The Committee believes that appropriate base salaries must be coupled with incentive compensation that not only attracts and retains qualified employees, but rewards them for increased performance. Compensation linked to the performance of the Company's common stock is one of the best incentives to align employees' interests with those of stockholders and to enhance performance. In addition, through the Incentive Plan 2000 proposed for stockholder approval in this proxy statement, **the Committee has sought to define performance criteria relative to the Company's competitors,** mitigate the dilutive effect of relying solely on common stock-based awards as incentive compensation, and develop programs designed to retain management in the face of significant employment opportunities from other companies.
>
> As discussed elsewhere in this proxy statement, the Committee recommended and the Board adopted the Company's Incentive Plan 2000, providing for the award of cash and stock-based incentives, including long-term incentive awards, to non-employee directors, officers and key employees. The plan is designed to align participants' interests with those of stockholders and to reduce the Company's historic dependence solely on stock options to achieve its goal of attracting, retaining and incentivizing qualified personnel. The Committee has adopted, subject to stockholder approval of the Incentive Plan 2000, three incentive programs under the Incentive Plan 2000. *The first program, the Executive Bonus Performance Award Program, is similar to (and will replace) the Company's recently terminated executive bonus program, but also provides an alternate target for bonus payments of achievement of number 1, 2 or 3 in EBITDAR margin ranking by the Company as compared to an industry group, together with an operating income hurdle. The second program, the Long Term Incentive Performance Award Program ("LTIP"), provides for cash incentive payments determined by the Company's achievement over multi-year performance periods of targeted EBITDAR margin rankings compared with an industry group, together with an operating income hurdle.* [emphasis added] If the Incentive Plan 2000 is approved by stockholders, the Committee

anticipates reducing the size of future annual option grants by approximately one-half to executives who participate in the LTIP. The third program, the Officer Retention and Incentive Award Program ("Retention Program"), is designed to retain executives in light of significant employment opportunities for such executives in other businesses, including the e-commerce and internet industries, and to incentivize the Company's executives to grow the value of the Company's investments in e-commerce and internet businesses, including distribution and marketing channels for the Company. This program permits executives to receive a cash payment measured by a portion of the gain and profits associated with the Company's investments in e-commerce or internet businesses. The Committee believes that the Retention Program will act as a powerful retention tool for Company management, and will benefit the Company from the direct incentive to foster investment in and growth of e-commerce and internet businesses.

In its 2006 proxy statement, Continental states

> Relative performance targets validate the absolute performance targets by indicating whether the company's goals are sufficiently aggressive in comparison to the industry. Relative performance targets also provide flexibility to deal with unforeseen events and industry-wide challenges. In such circumstances, the company could fail to achieve its absolute performance targets, but the relative performance measures will reward management that is able to outperform its peer group in the face of such adversity.

Delta In its 1999 proxy statement, Delta states:

> Early in fiscal 1999, the Committee approved a compensation formula for Executive Vice Presidents and above to determine the annual incentive awards for those officers whose compensation may be subject to the deductibility limitations of Section 162(m) of the Internal Revenue Code. Awards for these officers, and for other participants in the plan, are based on the Company's achieving specific financial goals (net income and return on investment), as well as effectiveness and efficiency goals (safety, reliability, customer satisfaction, revenue per available seat mile, and non-fuel costs per available seat mile). *All financial, effectiveness and efficiency goals were established in light of Delta's fiscal 1998 performance, its fiscal 1999 business plan and the performance of Delta's peer airlines.* [emphasis added] The awards also are based on key initiative goals related to Delta's strategic objectives (for example, the implementation of strategies related to business

structure, airport master plans, technology and human resources, including labor relations and employee morale). The Chief Executive Officer and the Chief Operating Officer are measured solely on overall corporate results. All other participants are measured based on the achievement of individual performance goals as well as the overall corporate results.

The potential value of long-term incentive opportunities comprises the largest portion (60% or more) of the targeted total compensation package for executive officers. The Committee believes this approach to total compensation opportunities provides the appropriate focus for those executives who are charged with the greatest responsibility for managing the Company and achieving success for all of Delta's stakeholders. *The performance-based restricted stock program provides rewards based on Delta's financial and operational performance relative to peer domestic airlines over three-year performance cycles. As with stock options, formula awards may be adjusted based on the factors listed above. At the end of each three-year performance cycle (the first cycle ends on June 30, 2001), participants may earn nothing, or a number of shares ranging from 40% to a maximum of 200% of the target award. Performance goals measured include Delta's ranking relative to its peer domestic airlines with respect to total shareholder return and three key U.S. Department of Transportation measures related to operations and customer satisfaction.* [emphasis added]

American Airlines In their 2008 proxy statement, American Airlines states

Annual Incentive Plan. As part of the Turnaround Plan, we established the Annual Incentive Plan (the "AIP") to link the interests of our stockholders, customers and employees. All U.S.-based employees, including the named executive officers, participate in the AIP, which provides cash incentive payments upon the achievement of monthly customer service and annual financial goals.

Awards are earned under the customer service component of the AIP if we achieve at least one of two customer service targets relative to our competitors:

- A top six performance for on-time arrival, as determined by the U.S. Department of Transportation; or
- A top six performance for customer satisfaction, as determined by Survey America, an independent organization.

American Airlines grants long-term equity compensation to the named executive officers in approximately the following proportions: 70% in performance shares; 20% in stock options and/or SSARs; and 10% in deferred shares. Performance shares are grants of stock-based compensation that vest after the completion of a three-year measurement period. Performance goals measured are centered around American's ranking relative to its peer domestic airlines with respect to total shareholder return. The designated competitors for the total shareholder return component are AirTran Airways, Alaska Airlines, Continental Airlines, JetBlue Airways, Southwest Airlines and US Airways. The company did not include Delta Air Lines, Northwest Airlines or United Airlines as competing airlines since their stock was not listed on a national stock exchange at the inception of the 2006/2008 Performance Share Plan due to their then-pending bankruptcy proceedings.

Northwest Starting from 1994, Northwest Airlines explicitly outlines that performance goals may be based for performance-based awards. Such Performance-Based Awards are based upon one or more of the following factors: stock price, market share, earnings per share, return on equity, costs, operating margins, revenue or sales, pre-tax income, cash flow, net income, return on assets as well as other financial goals. These criteria may be applied on an absolute basis and/or be relative to one or more peer group companies or indices.

United United Airlines does not mention anything about the use of relative performance evaluation in its 2007 10-K or DEF 14A reports. Yet the description of the CEO compensation contract contained in these reports is not necessarily representative. As the report states, "At various times after the Company's emergence from bankruptcy protection in February 2006, the Company determined that it would be advisable to make changes to the compensation programs for senior executives that were in place during the reorganization process."

Since 2011, United has made explicit its use of RPE in its proxy statements. In the 2011, proxy statements, it states:

> Approximately 93% of the CEO's 2013 total targeted pay was tied to Company performance, with long-term incentives representing the single largest component (82%). The long-term incentive opportunity contains three awards, each of which has a three-year performance or vesting period. This design was put in place for 2011 awards following the Merger and has continued.
>
> As part of the long-term incentives, the Long-Term Relative Performance Awards (LTRP) measure and reward performance based on the Company's cumulative pre-tax margin over a three-year performance period as compared with an industry peer group (American Airlines Group, Inc., Delta Air Lines Inc., Southwest Airlines Co., JetBlue Airways Corporation, and Alaska Air Group, Inc.).
>
> Performance is generally measured as (A) the Company's pre-tax income over

the performance period divided by its revenue over such period as compared to (B) the peer companies' aggregate pre-tax income over the performance period divided by the peer companies' aggregate revenue over such period.

The target performance level established for the 2013 LTRP awards was set by the Compensation Committee so that executives would earn market-competitive rewards ("target" level) for achieving a pre-tax margin performance level (equal to the peer group average) that was designed to be achievable with strong performance through the performance period. The entry performance level was designed to be achievable with solid performance (peer group average pre-tax margin minus 60 basis points), while the stretch performance level (peer group average pre-tax margin plus 80 basis points) was set at a high level requiring exceptional performance. In determining the performance goals, the Committee considered the historic performance of the Company and the peer group and the economic and market conditions at the time the goals were established.

US Airways US Airways grants long-term incentives under the 2005 Performance-Based Award Plan. According to this performance plan, the participating key executives receive cash and/or stock awards depending on its relative total stockholder return ranking against a pre-defined competitive peer group. The current competitive peer group used for purposes of the Performance Plan consists of AirTran, Alaska, American, ATA Holdings, Continental, Delta, Frontier, Hawaiian, JetBlue, Midwest Express, Northwest, Southwest and United. The performance cycles are the usual three-year periods beginning each January 1.