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ABSTRACT

Essays on Industrial Organization

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This dissertation comprises three essays on industrial organization. In Chapter 1 I study the productivity effects of corporate diversification, where productivity is understood as a measure of sales per input at the productive unit level, and diversified firms are defined as firms that operate in different industries. I develop and estimate a dynamic structural model that allows current diversification level and research and development expenditures to affect future productivity. I then apply this model to a panel of U.S. manufacturing firms to measure the impact of diversification on productivity. My estimates suggest that diversification plays a key role in explaining the differences in productivity across firms and time. The average return to diversification is estimated at around 4% at the productive unit level, though there is considerable variation across industries and firms. Moreover, the effect of current diversification on future productivity depends crucially on already attained productivity. This non-linearity typically takes the form of complementarities between current productivity and diversification, where current productivity tends to reinforce the effect of diversification on future productivity. Finally, I use the estimates

from the model to test two different hypotheses related to firm diversification. First, I test the hypothesis that diversification is most likely to produce economies of scope in research and development. Second, I study the relationship between firm diversification and the misallocation of inputs. I find that the average gross rate of return to research and development is 3.5 times higher in diversified firms than in non-diversified firms. Finally, my results support the hypothesis that diversified firms are more efficient in the allocation of inputs.

In Chapter 2 I study how incumbents respond to a threat of entry by a competitor using nonprice modes of competition. My analysis focuses on the U.S. airline industry, by studying how incumbent airlines change their flight schedules (departure times around the clock) and the degree of product differentiation in terms of departure times when Southwest Airlines threatens entry into a market (i.e., when it establishes presence at both endpoint airports of a market) but before it starts flying non-stop flights in that market. I find that incumbents increase significantly their degree of differentiation in departure times when threatened by Southwest's entry. This implies that flights' departure times are scheduled more evenly spaced around the clock after Southwest threatens entry into the market. Around 60% of Southwest's impact on incumbent schedules takes place before Southwest enters the market. In addition, the results show that this effect depends strongly upon the level of market share that the incumbent airline has in the market. Finally, the evidence on whether incumbents are trying to deter or accommodate entry seems to point towards the deterrence motive.

Chapter 3 investigates the effects of an airline's scale of operation at an airport (or airport presence) and airport constraints on market structure and pricing for the U.S.

airline industry. I estimate a static complete information game where firms decide first whether or not to enter a market and its product offerings (conditional on entry), and then the prices to be charged for its products. The model is estimated using data from the U.S. airline industry for the period 2014- 2016, and for markets comprised by the 55 largest U.S. cities. I find that, on average, fixed entry costs represent a substantial proportion of airlines' variable profits, reflecting presumably the relevance of economies of scale in the airline industry. In addition, the fixed costs of serving a market decline significantly with airport presence at the origin and destination airports of the market, and increase if the market contains at least one capacity constrained or slot controlled airport in any of its endpoints. I study the effects of airport constraints and airport presence on market structure by running counterfactual exercises. The results indicate that airport constraints and airport presence affect pricing and market structure significantly. Elimination of airport constraints or changes in airport regulation affecting airport presence considerably encourages airlines to enter into new markets offering non-stop service, and in a greater extent, offering stop service. As a consequence, the change in market structure tend to drive prices down. The results speak to the importance of policies aimed to make market entry less costly or improve airport access for potential entrants.

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Dedication

Para Lucas y Cecilia, por llenar de felicidad mi vida.

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CHAPTER 1

The Productivity Effects of Corporate Diversification

1.1. Introduction

A diversified, or conglomerate, firm is usually defined in the economic and corporate finance literature as a firm that operates in different industries, as classified by the Standard Industrial Code (SIC).[1] Production by diversified firms represents more than 50% of production in the United States.[2] It is therefore important to understand the costs and benefits of this form of organization. Questions include whether firm diversification creates or destroys value, under what circumstances corporate diversification affects firm performance, and what are the mechanisms behind value creation or destruction. These questions go back to Coase's (1937) seminal paper on the nature and boundaries of the firm, where he asserts that boundaries are such that the costs of carrying out transactions within a firm are equal to those of carrying them out in the open market or in another firm. One can ask whether diversification affects the costs of carrying out transactions within the firm.

In this chapter, I focus on the effects of firm diversification on firm performance. Specifically, I study how diversification shapes a business unit's productivity, measured as sales per input at the business or productive unit level. The goal is then to assess

[1] The typical example is General Electric, which manufactures aircraft engines, but it is also active in other industries, such as, water processing, oil and gas, power generation, transportation, healthcare, and household appliances.
[2] See Maksimovic and Phillips (2007).

the role of firm diversification in determining the differences in productivity across business units and the evolution of firm-level productivity over time. Theoretical arguments suggest different motives and effects of diversification. Researchers have often claimed that a firm reaps efficiency gains when it diversifies production because its managerial and research and development (R&D) inputs can be shared among its various activities.[3] Similarly, by operating in different industries, a firm may increase its sales and may realize economies of scope in promoting, advertising, and distributing its products. Other performance-enhancing motives for firm diversification include lower overall firm risk through imperfectly correlated cash flows, greater market power and debt capacity, higher product compatibility, and greater operating efficiency. In principle, by operating different lines of business, a diversified firm can reallocate control of productive assets to entities that can apply them more efficiently, creating value to the firm. Similarly, under the theory of internal capital markets, a line of business's assets can be used as collateral to obtain funding for other business units. Cash flows generated by one business unit may be used to subsidize investment projects in other divisions of the firm. This cross-subsidization can be efficient if it helps the firm to reduce the costs of financial constraints. However, it might also be inefficient if the firm under-invests in lines of business with better growth opportunities and over-invests in those with worse prospects.[4]

Other theoretical models explain diversification as an *ex ante* rational and value maximizing strategy (e.g., Jovanovic, 1993; Matsusaka, 2001; Maksimovic and Phillips, 2002

[3] See, for example, Gort (1967), Teece (1980), Scherer (1983), Jovanovic (1993), Jovanovic and Rousseau (2002) or Tate and Yang (2015).

[4] For instance, Meyer, Milgrom and Roberts (1992) point out that a failing business cannot have a value below zero if operated on its own, but can have a negative value if it is part of a conglomerate that provides cross-subsidies. Then, unprofitable lines of business might create greater value losses in conglomerates than they would as stand-alone firms.

and Gomes and Livdan, 2004). In these models, firms diversify in an attempt to match organizational capabilities, or as a value maximizing response to increasing firm age and growth. Some of these models (i.e., Gomes and Livdan, 2004) explain the diversification decision as an endogenous selection mechanism, whereby firms diversify when they become relatively unproductive in their current businesses.[5] Agency theory suggests another motive for diversification. It predicts that diversification depends on the incentives of individual managers to diversify their firms, such as an increase in their power and compensation, a reduction of individual employment and firm risk, or to entrench themselves. Under this theory, managers have a tendency to over-invest and grow their firms beyond the optimal size, engaging in investment projects that are not necessarily performance-maximizing. However, it could also be that managers affect firm performance and productivity through other channels. For example, the misalignment of incentives and the information asymmetry costs that arise between central and divisional managers in diversified firms might lead to more dispersed information within the firm and, consequently, to lower profits than each of the business units would obtain separately (Myerson, 1982 and Harris, Kriebel and Raviv, 1982). On the other hand, changes in the corporate structure of the firm might spur productivity growth if it puts the firm's assets under the control of more able managers or better management practices (Bloom and Van Reenen, 2007; Bloom and Van Reenen, 2010; Bloom, Genakos, Sadun and Van Reenen, 2010; and Bloom, Eifert, Mahajan, McKenzie and Roberts, 2013a).[6]

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[5] This model rationalizes the negative correlation between diversification and firm value reported by some early studies (i.e., Lang and Stulz, 1994 and Berger and Ofek, 1995).

[6] Different papers have documented that management practices might influence firm's productivity. Bloom and Van Reenen (2007) study the effects of management practices (though not managers per se) on productivity. They surveyed plant managers from over 700 medium sized firms in the United States, the United Kingdom, France, and Germany; measuring day-to-day and close-up operations rather

Theory does not offer a clear prediction about the overall effect of diversification on firm performance. The overall effect of a diversification strategy will depend on whether the potential costs outweigh the potential benefits. A considerable amount of empirical literature has studied the relationship between diversification and firm value, though previous empirical studies of the effect of diversification on firm value have not been conclusive. Early studies on firm diversification show that diversified firms trade at a discount compared to a portfolio of comparable stand-alone firms (e.g., Lang and Stulz, 1994; Berger and Ofek, 1995). These findings led to the belief, for some time, that diversification destroys value and that conglomerates are inefficient. However, these early studies did not account for sample selection biases and the endogeneity of the diversification decision. Firms operating in different industries are systematically different than non-diversified firms and face different investment opportunities and abilities.[7] Despite efforts to control for these biases in estimation, there is still no clear agreement on whether diversification leads to higher firm value (e.g., Campa and Kedia, 2002; Villalonga, 2004;

than the broader strategic choices made at the executive level. They find that higher-quality management practices are correlated with several measures of productivity and firm performance, including labor productivity, total factor productivity, return on capital, sales growth, and the probability of survival. Bloom and Van Reenen (2010), Bloom et al. (2010), and Bloom et al. (2013a) review results from an extension of this survey program to nearly 6,000 firms in seventeen countries; the results are similar to those mentioned above.

[7] For instance, Hyland and Diltz (2002) find significant differences in firm characteristics between diversified firms and focused firms. Diversified firms have lower q's (i.e., total market value of the firm over total asset value), more cash, lower sales growth, and invest significantly less in R&D. Maksimovic and Phillips (2008) show that diversified and non-diversified firms differ both in the type of investment and in the level of total investment. Similarly, Campa and Kedia (2002) find that diversified firms differ from non-diversified firms in terms of their size, industry growth rate, capital expenditures/sales, earnings before interests and taxes/sales, and R&D/sales.

or Kuppuswamy and Villalonga, 2010), or if it is indeed a mechanism to reduce it (e.g., Lamont and Polk, 2002; or Ammann, Hoechle and Schmid, 2012).[8] [9]

Although the empirical research conducted on the topic of diversification and productivity is not as prolific as on the effects of diversification on firm value, there is still no agreement in the literature on whether diversification increases productivity or if it is indeed a mechanism to reduce it. Using data from the Longitudinal Research Database (LRD), Lichtenberg (1992) finds ambiguous results on the productivity differences between diversified and non-diversified firms. Maksimovic and Phillips (2002) find that diversified firms are less productive than non-diversified firms of a similar size. Additionally, they show that the productivity pattern within the firm is consistent with one in which the main business units are more productive than the peripheral units, and that the sales growth of a business unit varies with its productivity and industry business cycle. In a related paper, Maksimovic and Phillips (2001) find that plants, divisions, or firms acquired by other firms had low productivity before the ownership change and experience an increase in productivity afterwards. The productivity gains depend on the productivity of the acquiring and acquired firm, as well as on the productivity of the type of division (core or peripheral) that is buying or selling the assets.[10] Finally, Schoar (2002)

[8] The literature on firm diversification and firm value is very extensive. See Maksimovic and Phillips (2007), Erdorf, Hartmann-Wendels, Heinrichs and Matz (2013), or Maksimovic and Phillips (2013) for complete surveys of this literature.

[9] Different econometric techniques have been used to control for the endogeneity of the diversification decision, such as the fixed-effects estimator, instrumental variables estimation, Heckman's two-stage method, and propensity score methods.

[10] The literature on the productivity effects of acquisitions and mergers is extensive, although it is typically not directly related to the productivity effects of diversification since many mergers and acquisitions take place within the same industry. See Braguinsky, Ohyama, Okazaki and Syverson (2015) for references in this topic as well as an analysis of the productivity effects of acquisitions in the Japanese cotton spinning industry.

finds that, unlike Maksimovic and Phillips (2002), plants in diversified firms are more productive than plants in comparable non-diversified firms. However, she also finds that increases in diversification are associated with a decline in the firm's overall productivity.[11]

Although there could be different motives and effects of diversification, part of the literature's lack of agreement is due to the limitations of the approaches used to handle heterogeneities across industries and firms, as well as the difficulty in controlling for the selection bias and endogeneity of the diversification decision.[12] The empirical work described in the previous paragraph has studied the relationship between productivity and diversification under a two-stage procedure. In the first stage, a productivity estimate at the plant level is obtained as the residual from an ordinary least square regression of gross revenue on inputs (i.e., labor, materials, and capital). In the second stage, the productivity estimate is regressed on a diversification index and a set of control variables in order to study the effects of diversification on productivity. Implicit in this approach is the assumption that productivity evolves exogenously and that it is not observed by the firm when making its input and diversification decisions. Conceptually, an exogenous productivity process implies that a firm's diversification level has no impact on productivity through any of the mechanisms discussed before, namely, efficiency gains due to economies of scope in managerial practices or in promoting, advertising, and distribution

[11] She describes this as a "new toy effect." While the newly acquired plants increase their productivity, the incumbent plants show productivity declines and the total effect on firm productivity is negative.

[12] For instance, Santalo and Becerra (2008) find that the empirical correlation between diversification and firm value depends on characteristics of the industry. They also argue against the use of industry instruments since they find them to be correlated with both the diversification decision and the firm value (and thus likely to yield upward biased estimates of the average value of diversification across all industries).

of products; technological improvements; or sales through greater market power, product quality upgrading, marketing, or product innovation.

The use of this two-stage approach to study the productivity effects of firm diversification is also problematic in that it potentially suffers from three biases. The first bias, known as transmission bias in the industrial organization literature on production function estimation (i.e., Griliches and Mairesse, 1997), takes place in the first stage of the two-stage procedure described above. While an ordinary least square estimation of a production function implicitly assumes that productivity is orthogonal to input usage, it might be the case that the productivity level is observed by the firm when making its inputs decisions. This would create a positive correlation between productivity and inputs, and consequently, an upward bias in the coefficients of inputs. The second source of bias, known as selection bias or reverse causality, occurs in the second stage of the approach. When regressing the productivity estimates on the diversification level, the coefficient associated with the diversification variable might not only be capturing the effects of diversification on productivity, but also any selection mechanisms with which firms with certain productivity levels self-select into different degrees of diversification. Finally, the approach of the existing literature potentially suffers from a third bias which affects both stages of the estimation. I observe in the data that input usage at the business unit level systematically accompanies changes in the diversification level. If diversification affects sales or gross output through channels other than input usage (e.g., by increasing productivity), then the fact that input usage adjusts with diversification changes implies that the standard approach to measuring the productivity effects of diversification could bias the estimates by attributing output gains to input usage, rather than to changes in productivity.[13]

This chapter studies the role of changes in firm diversification in shaping business units' future productivity using a dynamic structural model and a production function approach. The model builds on recent advances on the identification and estimation of production functions (i.e., Gandhi, Navarro and Rivers, 2016), which allows me to control for the transmission bias in the estimation of the production function and productivity measures. In order to control for other biases in the estimation, I depart from the standard assumption made in this literature that productivity follows an exogenous process and a firm's diversification decisions do not impact the business units' future performance. I develop and estimate a model of endogenous productivity change by explicitly allowing the evolution of productivity to depend on the firm's previous diversification status and efforts, as well as R&D investments. The starting point for studying the role of firm diversification on productivity is thus a dynamic model of a firm that makes decisions regarding which industries to operate in the next period and investment decisions across industries, in addition to carrying out a series of investments in R&D to improve its productivity over time. The evolution of productivity at the business unit level follows a Markov process that can be shifted, in expectation, by the degree of a firm's diversification and R&D expenditures. At the same time, it is subject to random shocks or innovations to productivity that capture the uncertainties inherent to production. For diversified firms and firms that engage in R&D expenditures, it also captures the uncertainties related to

[13] A similar point has been discussed in other contexts. See, for instance, De Loecker (2013) for the case of productivity and exporting, or Braguinsky et al. (2015) for the case of the productivity effects of acquisitions in the Japanese cotton spinning industry.

the diversification decisions and the R&D process. The identification of the effects relies on timing assumptions, which intuitively can be interpreted as firms that are unable to immediately adjust their diversification status upon receiving productivity or demand shocks. The estimation of the effects builds on a strategy similar to the one already applied in other studies and settings, such as the productivity effects of R&D activities (e.g., Doraszelski and Jaumandreu, 2013), exporting and R&D (e.g., Aw, Roberts and Xu, 2011), or learning by exporting (e.g., De Loecker, 2013).[14]

The estimation strategy allows us to recover the law of motion for productivity, which I then use to study the link between diversification and productivity in a panel of manufacturing business units from 1980 -1998. In addition, I use the model and estimates it provides to test two different hypotheses related to firm diversification. First, I test the hypothesis that diversification is most likely to produce economies of scope in research and development since a firm with a wider range of products has more opportunities for exploiting the results of a research program. If know-how can be transferred from one activity to another, then productivity growth among diversified firms might be driven by knowledge spillovers among distinct production processes. To this end, I use the model to obtain an estimate of the firm-wide gross rate of return to R&D expenditures, and compare it between diversified and non-diversified firms. Second, I use the estimates of the model to study the relationship between firm diversification and the misallocation of inputs. Under the predictions of the theory of internal capital markets, diversification may help the firm to reduce the costs associated with financial constraints, or the costs of

[14] Other papers that build on a similar strategy are Bilir and Morales (2016) in their study of the productivity effects of R&D activities, and Braguinsky et al. (2015) in their study of the productivity effects of acquisitions in the Japanese cotton spinning industry.

adjusting capital or any other input. Then, under the predictions of this theory, the marginal revenue product of inputs of business units belonging to diversified firms should be less responsive to shocks to productivity, since these business units have more flexibility to adjust input usage when hit by shocks compared to non-diversified firms.

One of the advantages of my estimation strategy is that I can assess the productivity effects of diversification across the current distribution of firm productivity, allowing heterogeneities across firms and industries. I estimate the model using Compustat data, for a panel of U.S. manufacturing business units for the period 1980 -1998. My findings draw a more comprehensive picture of the effects of firm diversification on firm performance than the more simplistic reports of the previous literature on diversification enhancing performance or diversification reducing performance. I find that the productivity effects of diversification vary considerably, with significant heterogeneity across industries and firms. My estimates of the law of motion for productivity suggest important nonlinearities and uncertainties in the diversification process. The effect of the diversification level on future productivity largely depends on current productivity. Nonlinearities typically take the form of complementarities between diversification and current productivity. In addition, the diversification process is inherently uncertain. I estimate that, depending on the industry, between 20% and 62% of the variance in productivity is explained by innovations that cannot be predicted based on current productivity and diversification decisions. Moreover, my estimates suggest that significant variations in the level of diversification substantially increase the degree of uncertainty in the productivity process.

The estimate for the law of motion for future expected productivity allows me to assess the role of diversification in determining the differences in productivity across business units, as well as the evolution of firm-level productivity over time. I find that the distribution of expected productivity for business units belonging to diversified firms first order stochastically dominates the distribution of non-diversified firms. Additionally, I find that business units belonging to diversified firms grow faster than non-diversified firms, suggesting that the mechanisms that affect productivity when firms diversify might be a source of productivity growth. The estimate for the law of motion for future expected productivity also allows me to study the return at the margin of diversification, measured by the revenue elasticity with respect to the degree of diversification. Although there is considerable variation across industries, the average return at the margin is positive in most industries, as well as for the full sample. Additionally, I estimate the average return to diversification for the average diversified firm in the sample at around 4%.

The estimation of the model provides us with an estimate for the elasticity of revenue with respect to R&D expenditures. I use these estimates to compute the firm-wide gross rate of return to R&D expenditures, and then compare the results between diversified and non-diversified firms. I find that the average firm-wide gross return to R&D is 0.20 dollars for non-diversified firms and 0.73 dollars for diversified firms. This implies an average firm-wide gross return to R&D 3.5 times higher for diversified firms than non-diversified firms. The results are consistent with the hypothesis that knowledge can be transferred from one activity to another, and thus knowledge spillovers among distinct production processes might constitute the drivers of productivity growth among diversified firms. Finally, I use the estimates of the model to study the relationship between input misallocation and diversification. Input misallocation measures are constructed using static measures of marginal revenue product of inputs. The results provide evidence consistent with the internal market capital hypothesis that firm diversification helps to reduce adjustment and transaction costs related to input usage and, consequently, helps in the allocation of inputs within the firm.

The remainder of the chapter is organized as follows. In Section 1.2, I describe the model in which I base the estimation. Section 1.3 presents the data and descriptive statistics about diversification and the firms' characteristics. Section 1.4 describes the estimation approach. In Section 1.5, I report the main results on firm diversification and productivity. In Section 1.6 I study the relationship between diversification, R&D investment, and firm performance. Finally, Section 1.7 concludes.

1.2. Model

This section presents a dynamic model which is used to evaluate the relationship between firm diversification and productivity. The details regarding the estimation of the model are left for Section 1.4, after describing the data at hand in Section 1.3. The model builds on the framework presented by Olley and Pakes (1996) and extended by Levinsohn and Petrin (2003), Ackerberg, Caves and Frazer (2015), and Doraszelski and Jaumandreu (2013). In the model, each business unit within a firm is associated with an idiosyncratic revenue productivity measure that reflects both the physical productivity and the demand shifter of the unit. Diversification decisions and investment in R&D may influence the stochastic process governing the evolution of the productivity of a firm's business units. The model delivers a set of moment conditions and explicit estimating equations that allow us to recover the parameters governing revenue at the business unit level and those associate with the law of motion for productivity, which in turn determine the return to diversification.

The industry is characterized by firms that make production, investment, and diversification decisions in a discrete time, infinite horizon model.[15] At any given point in time, each firm is composed of a core business unit and potentially one or more business units located in other industries. Firms with operations outside their core industry are diversified, while non-diversified firms are those that only produce within their core industry. Firms with core operations within the manufacturing sector are indexed by $i = 1, 2, ..., \mathcal{I}_t$. The set of firm-$i$ business units active in period t is represented by $\mathcal{J}_{it}$. Business units in $\mathcal{J}_{it}$ are indexed by j. I assume that each business unit produces and sells its output in a single market, represented by the industry it belongs to. Markets, or industries, are indexed by s, being s_{ijt} the industry in which business unit j, belonging to firm i, produces and sells its output at time t.

Each firm i makes diversification and R&D investment decisions, and also decides about production and physical investment for each of its business units. Each business unit determines the amount of materials (static input) to be used in production. I assume that investment, production and diversification decisions are made with the goal of maximizing the firm-wide expected net present value of future cash flows.

The production, demand, and productivity processes of each firm's business units are described below. Then I briefly discuss the firm's dynamic optimization problem.

[15] For simplicity I will not consider entry or exit decisions at the firm level, but they could be easily incorporated into the model. I will also leave out strategic considerations.

1.2.1. Production, Demand, and Revenue

Business unit j belonging to firm i produces output Q_{ijt} combining labor, materials and capital according to the following translog production function:

$$\begin{aligned} q_{ijt} = \psi_{ijt} &+ \alpha_{l_s} l_{ijt} + \alpha_{m_s} m_{ijt} + \alpha_{k_s} k_{ijt} + \alpha_{ll_s} l_{ijt}^2 + \alpha_{mm_s} m_{ijt}^2 + \alpha_{kk_s} k_{ijt}^2 + \\ &+ \alpha_{ml_s} m_{ijt} l_{ijt} + \alpha_{mk_s} m_{ijt} k_{ijt} + \alpha_{lk_s} l_{ijt} k_{ijt} + \alpha_{mlk_s} m_{ijt} l_{ijt} k_{ijt} \end{aligned}$$

where $q_{ijt} = \ln(Q_{ijt})$, l_{ijt} denotes (log) number of employees, k_{ijt} the (log) stock of capital, and m_{ijt} (log) materials usage. Hicks-neutral physical productivity at time t is represented by ψ_{ijt}. I assume that ψ_{ijt} is observed by the firm when making its output decisions, but not to the econometrician. The vector of parameters $\alpha = (\alpha_{l_s}, \alpha_{m_s}, \alpha_{k_s}, \alpha_{mm_s}, \alpha_{ll_s}, \alpha_{kk_s}, \alpha_{ml_s}, \alpha_{mk_s}, \alpha_{lk_s}, \alpha_{mlk_s})$ translates inputs into output. I make the assumption that production technology is the same for business units belonging to diversified and non-diversified firms within the same industry. To the extent that this is not true, I will be introducing a bias in the estimation. However, the above equation allows output elasticities with respect to inputs to be heterogeneous across industries, reflecting differences in technologies of productions across industries. Moreover, unlike a Cobb-Douglas production function, a translog production function allows output elasticities with respect to inputs to be heterogeneous across production units within an industry.[16] Although technology that translates inputs into output is the same for production units belonging to diversified and non-diversified firms operating in the same industry, I allow diversification to affect

[16] In a translog production function the output elasticities with respect to inputs are a function of input usage. Given this, variations in input usage across business units within an industry will be reflected in differences in output elasticities across units.

output through physical productivity. I provide details about this mechanism in the next section when describing the productivity process. Finally, I assume that business units take prices of labor P^l_{ijt}, capital P^k_{ijt}, and materials $P^m_{s_{ij}t}$ as given. Unlike the prices of labor and capital, the prices for materials are assumed to be common across all production units within an industry-year.

Each business unit j belonging to firm i sells a single variety as a monopolistically competitive firm in market s_{ij}. I assume that business unit j faces the following isoelastic demand curve for its output Q_{ijt}:[17]

$$Q_{ijt} = Q_{s_{ij}t}(P_{ijt}/P_{s_{ij}t})^{-\sigma_s} \exp(\nu_{ijt}(\sigma_s - 1))$$

where P_{ijt} is the output price set by business unit j, $\sigma_s > 1$ is the elasticity of substitution across output varieties, and where $P_{s_{ij}t}$ and $Q_{s_{ij}t}$ are the period t aggregate price index and aggregate demand level, respectively. The variable ν_{ijt} represents a demand shock that is observed by the firm when making its output decisions, but not to the econometrician.

Revenue of business unit j belonging to firm i is represented by:

$$\tilde{Y}_{ijt} = P_{ijt}Q_{ijt}$$

Given the production and demand structures described above, log revenue $\tilde{y}_{ijt}$ can be expressed as:

$$\tilde{y}_{ijt} = h_s(m_{ijt}, l_{ijt}, k_{ijt}; \beta) + \omega_{ijt} + \mu_{st}$$

[17] A demand system like the one described here has been widely used in the estimation of production functions for manufacturing firms. See, for instance, Klette and Griliches (1996) or De Loecker (2011).

where

$$h_s(m_{ijt}, l_{ijt}, k_{ijt}; \beta) = \beta_0 \quad + \quad \beta_{l_s} l_{ijt} + \beta_{m_s} m_{ijt} + \beta_{k_s} k_{ijt} + \beta_{ll_s} l_{ijt}^2 + \beta_{mm_s} m_{ijt}^2 + \beta_{kk_s} k_{ijt}^2$$
$$+ \quad \beta_{ml_s} m_{ijt} l_{ijt} + \beta_{mk_s} m_{ijt} k_{ijt} + \beta_{lk_s} l_{ijt} k_{ijt} + \beta_{mlk_s} m_{ijt} l_{ijt} k_{ijt}$$

and $\beta = (\beta_{l_s}, \beta_{m_s}, \beta_{k_s}, \beta_{mm_s}, \beta_{ll_s}, \beta_{kk_s}, \beta_{ml_s}, \beta_{mk_s}, \beta_{lk_s}, \beta_{mlk_s})$ is a vector of parameters that translate inputs into revenue. Each parameter in β combines the corresponding element in α and the elasticity of substitution across output varieties. Revenue productivity is denoted by ω_{ijt} and comprises physical productivity (ψ_{ijt}) as well as shocks to demand (ν_{ijt}). The variable μ_{st} is an industry-year effect that accounts for variation in market level variables across time. In Appendix A.1 I provide details on the derivation of the revenue equation.

I allow revenue to be measured with error, and represent observed revenue $y_{ijt} = \tilde{y}_{ijt} + \epsilon_{ijt}$ as:

$$y_{ijt} = h_s(m_{ijt}, l_{ijt}, k_{ijt}; \beta) + \omega_{ijt} + \mu_{st} + \epsilon_{ijt} \tag{1.1}$$

where measurement error ϵ_{ijt} is assumed to be mean independent of all variables contained in the firm's information set at time t, $E_t(\epsilon_{ijt}) = 0$. Thus, firms do not observe ϵ_{ijt} when making optimal input and investment decisions.

1.2.2. Productivity Process

Firms' profits and production depend also on their productivity level. The productivity of business unit j belonging to firm i at time t is given by ω_{ijt}. Productivity is assumed to be known by the firm when it makes its decisions, and thus it is a state variable in the firm's problem. I adhere to most of the industrial organization literature on production function estimation (i.e., Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2015; and Gandhi et al., 2016) by assuming that the productivity level is not observed by the econometrician. However, I depart from the assumption usually made by this literature in that productivity is governed by an exogenous first order Markov process. Note that relying on an exogenous Markov process does not allow us to distinguish between the two mechanisms potentially explaining the correlation between productivity and firm diversification highlighted in the literature. In particular, it is important to know if this correlation is due to an underlying process whereby firms with exogenously high productivity in their current businesses incur the costs of expanding their lines of business, or if it is a consequence of diversification activities directly affecting productivity. Given that these two mechanisms are not mutually exclusive, and since the goal of this chapter is to assess the role of the introduction (or destruction) of lines of business segments (or the change on the intensity of production decisions across different business lines) on differences in productivity across firms and the evolution of firm-level productivity over time, I endogenize the productivity process.

I consider a general model in which firm diversification and expenditure on R&D are allowed to impact future productivity as given by

$$\omega_{ijt+1} = E_t(\omega_{ijt+1}) + \xi_{ijt+1} \tag{1.2}$$

where the expectation of revenue productivity ω_{ijt+1} conditional on the information available to firm i at time t is represented by a function $g_s(.)$ which depends on past productivity (ω_{ijt}), diversification efforts and R&D investment:

$$E_t(\omega_{ijt+1}) = g_s(\omega_{ijt}, div_{it}, r_{it})$$

where div_{it} is a vector measuring the diversification efforts and experience of firm i at time t, and r_{it} is firm i's expenditure on R&D at time t.[18] ξ_{ijt+1} captures unexpected effects on future productivity. The only restriction imposed over the marginal distribution of ξ_{ijt+1} is the mean independence implied by equation (1.2).

The important assumption in equation (1.2) is that the impact of the current diversification level and R&D on productivity is represented by the dependence of the expected future productivity function $g_s(.)$ on these two variables. In contrast, ξ_{ijt+1} does not depend on the diversification level or the R&D expenditures. Thus, when firms make optimal decisions at time t, they are only able to anticipate the expected effect of diversification and R&D on productivity in period t as given by $g_s(.)$. The actual effect will also depend on the realization of the productivity innovation ξ_{ijt+1} that occurs after these decisions has been made.

[18] The literature following Olley and Pakes (1996), Levinsohn and Petrin (2003) and Ackerberg et al. (2015) typically assumes an exogenous first order Markov process where $\omega_{it+1} = g(\omega_{it}) + \xi_{it+1}$. Some recent papers have relaxed this assumption. The list includes Aw et al. (2011) and their study of the R&D investment and exporting effects on productivity dynamics; De Loecker (2011) and De Loecker (2013) in his studies of productivity, trade liberalization, and exporting; Doraszelski and Jaumandreu (2013) and Bilir and Morales (2016) who study the productivity effects of R&D activities; and Braguinsky et al. (2015) on the productivity effects of acquisitions in the Japanese cotton spinning industry.

1.2.3. Firm Optimization

In every period t, firm i decides the optimal levels of materials (M_{it}) and labor (L_{it}) for each of its business units active at time t. It also determines the level of R&D expenditure (R_{it}), the set of business units to be active at time $t+1$, $\mathcal{J}_{it+1}$, and the optimal level of capital investment (I_{it}) for each of its business units active at either time t or time $t+1$. The firm makes these decisions after realizing the innovations to revenue productivity ξ_{ijt} for each of its business units. The Bellman equation associated with firm i's dynamic optimization problem is given by:

$$\begin{aligned} V(S_{it}) \quad &= \max_{\mathcal{J}_{it+1}, I_{it}, R_{it}, L_{it}, M_{it}} \Bigg\{ \sum_{j \in \mathcal{J}_{it}} \pi(S_{ijt}, I_{ijt}, R_{it}, L_{ijt}, M_{ijt}) - C_k(P^k_{it}, K_{it}, I_{it}, X^k_{it}) - C_{\mathcal{J}}(\mathcal{J}_{it}, \mathcal{J}_{it+1}, X^J_{it}) \\ &- \quad C_r(R_{it}, X^r_{it}) - C_l(P^l_{it}, L_{it-1}, L_{it}, X^l_{it}) + \delta E\left[V(S_{it+1}) \mid S_{it}, I_{it}, R_{it}, L_{it}, \mathcal{J}_{it+1}\right] \Bigg\} \end{aligned}$$

where $V(.)$ is the value function, δ is a discount factor, $E_t[.]$ denotes the expectation over future states conditional on the information at time t, S_{it} is a vector representing the state variables of the problem, described by the collection of S_{ijt} =(ω_{ijt}, K_{ijt}, L_{ijt-1}, P^l_{ijt}, P^m_{ijt}, P^k_{ijt}, F_{ijt}, $\mathcal{J}_{it}$, Z_{ijt}) for any business unit j active at time t, and where Z_{ijt} is a vector including other variables potentially affecting input and diversification decisions (i.e., $X^k_{it}, X^r_{it}, X^r_{it}, X^J_{it}$).

Operating profit of business unit j is represented by:

$$\pi(S_{ijt}, I_{ijt}, R_{it}, L_{ijt}, M_{ijt}) = \tilde{Y}_{ijt} - P^l_{ijt}L_{ijt} - P^m_{s_{ij}t}M_{ijt} - F_{ijt}$$

where F_{ijt} is a fixed operating cost.

The functions $C_k(.)$, $C_r(.)$, $C_l(.)$, and $C_{\mathcal{J}}(.)$ are adjustment cost functions for capital, R&D, labor, and corporate diversification, respectively. They are functions of the state variables of the problem, the decisions taken at time t, and exogenous shocks to the cost of investment in physical capital, R&D, hiring or firing employees, and diversification, represented by X_{it}^k, X_{it}^r, X_{it}^l and X_{it}^J. The functional forms for these functions are irrelevant for the estimation approach and for the goal of this chapter.[19] The only restriction we need to impose over them is to exist, and rationalize the patterns observed in the data. The solution to the dynamic programming problem is given by a set of policy functions $I_{it} = h_i(S_{it})$, $R_{it} = h_r(S_{it})$, $L_{it} = h_l(S_{it})$ and $\mathcal{J}_{it+1} = h_{\mathcal{J}}(S_{it})$ for investment in physical capital, R&D, labor, and diversification efforts respectively.

I assume that capital accumulates according to $K_{ijt+1} = (1-\delta_k)K_{ijt} + I_{ijt}$, where δ_k is the physical capital depreciation rate. This law of motion for capital implies that there is one period to build capital, and thus capital becomes productive with a one period lag. Even though labor is also a dynamic input in the firm's problem, I assume that it becomes productive immediately, unlike capital. Materials are static inputs in the problem and also become productive immediately. I assume that materials are chosen after the optimal level of labor has been decided. The diversification decision consists of two stages. First, firms decide on which lines of business to be active next period. Similar to capital, I assume that there is a time to build new lines of business. Thus, at time t, firm i chooses its next period diversification position $\mathcal{J}_{it+1}$ (how many, and what lines of business to operate). In a second stage, conditional on the number and type of active segments, firms decide how to allocate capital across different lines. I assume

[19] The functions $C_k(.)$, $C_r(.)$, $C_l(.)$, and $C_{\mathcal{J}}(.)$ could be simple linear functions or more complex functions including non-convex components, fixed costs or adjustment costs.

that the inputs of production (labor, capital, and materials) are substitutable across the firm's distinct lines of business. However, I assume that not all factors of productions are continuously divisible across segments, and that there are potential adjustment costs in the allocation of inputs across business lines.[20]

1.3. Data

My main source of data is Standard & Poor's Compustat. I collect firm-level data from Compustat Annual Fundamentals, which report a rich set of economic and financial information on the publicly traded firms in the U.S. The data collected cover the period 1980-1998.[21] I restrict the data to those firms with core activities in the manufacturing sector and headquartered in the U.S.

The data contain firm level information on sales, capital, employment, and total expenses, which are the variables needed to estimate the coefficients of the production function. They also report information on R&D expenditures that will be used to characterize the innovation behavior of diversified and non-diversified firms. The book value of capital is measured by the gross stock of property, plant, and equipment. It includes gross plant, property and equipment, inventories, investments in unconsolidated subsidiaries, and intangibles other than R&D. Employment is measured by the number of employees, while

[20] The model shares some similarities with recent models on multi-product firms, mostly written in the field of international trade given the importance of these firms on international trade flows (see, for instance, Feenstra and Ma, 2007; Eckel and Neary, 2010; Arkolakis and Muendler, 2010; Bernard, Redding and Schott, 2011; Mayer, Melitz and Ottaviano, 2014; and Nocke and Yeaple, 2014). These models assume that firms can add new goods to their products offerings without varying considerably their production technology (i.e., flexible manufacturing assumption). Many of these models assume that the firm has a core competency in a variety or product (the one with lowest marginal cost), and that marginal costs might increase as the firm moves away from its core competence variety.

[21] Compustat data provide information on the publicly traded firms in the U.S. over the years 1964 to present.

materials are constructed as the difference between total expenses and labor expenses.[22] I use sales as my measure of output. Expenditure in R&D is used to create R&D capital stocks calculated using a perpetual inventory method with a 15% depreciation rate.[23] All monetary variables are deflated using industry price deflators taken from the NBER-CES Manufacturing Industry database, which contains shipment, materials, and investment deflators at the 4-digit level of the Standard Industrial Classification (SIC) system for the period 1958-2009. Table 1.1 reports some summary statistics of the data at the firm level. It summarizes information on sales, capital stock, materials, R&D stock, and R&D expenditure (all of them expressed in constant U.S. dollars). The table also provides information on the number of employees, business segments, and diversification level.

Table 1.1. Summary Statistics - Firm Level: 1980-1998

Variable	Obs.	Mean	Std. Dev.	Min	Max
Sales	44281	541.618	1411.637	0.600	13051.280
Labor	44281	4.152	9.995	0.010	85.099
Materials	44281	286.067	780.381	0.170	7407.270
Capital Stock	44281	183.143	544.804	0.086	5639.330
R&D Stock	44281	60.141	218.879	0.000	2536.711
R&D Expenditure	44281	11.346	40.687	0.000	464.203
Business Segments	44281	1.683	1.164	1.000	10.000
Diversification Index	44281	1.399	0.748	1.000	8.899

Note: The table summarizes the data at the firm level for the period 1980-1998. All variables are in levels. Monetary variables are measured in prices of 1987 in $million. Labor is measured in thousands of employees.

22 Total expenses are approximated as the difference between sales and operating income before depreciation and amortization. Labor expenses are calculated as the product between the number of employees reported by Compustat and the average wage for the core industry where the firm is active.

23 To construct the R&D stock, I follow the methodology used by Hall, Jaffe and Trajtenberg (2005). Thus, the R&D stock, G, for firm i in year t is $G_{it} = (1-\delta)G_{it-1} + R_{it}$, where R_{it} is the R&D flow expenditure in year t and $\delta = 0.15$. For the first year I observe a firm, I input its R&D stock as if it were in steady state, so $G_0 = R_0/(\delta + g)$, where $g = 8\%$ is the steady state growth rate of the R&D stock G.

Information at the business segment level comes from Compustat segmented data.[24] These data contain information at the business unit level on sales, assets, capital expenditures, and operating profits among other variables. Since 1976, publicly traded firms have been required by the Statement of Financial Accounting Standards (SFAS) 14 to report disaggregated information for different major segments. Under SFAS 14, a segment is defined as a component of an enterprise engaged in providing a product or service or a group of related products and services primarily to unaffiliated customers for a profit. Distinct segments that represent at least 10% of a firm's sales, profits, or assets should be separately reported. Segments are identified by name by the reporting firm and assigned a 4-digit SIC code by Compustat. In June 1997, due to segment under-reporting concerns, and in order to reduce the discretion that managers had to disclose segment level information, SFAS 131 superseded SFAS 14 in the regulation of segment reporting. This new standard defines segments following a management approach, where the disaggregated information is presented based on how a firm's management internally evaluates the operating performance of its business units.[25] Firms started to adjust to the new regulation after the fiscal year of 1998. Although SFAS 131 provides greater insight into the management strategy of each firm and has effectively increased the number of reported segments, it also reduces the comparability of segment information between similar lines of business within the same industry.[26] For this reason, I focus on the period where firms

[24] Various papers have used these data to study not only firms' diversification behavior, but also other economic questions. One example is Bloom, Schankerman and Van Reenen (2013b) who use these data to determine the product market positioning of a firm in their study of R&D spillovers.

[25] Berger and Hann (2003a) mention that some of the goals of SFAS 131 were to provide more disaggregated information and to allow users to assess the performance of individual operating segments in the same way that management does.

[26] Unlike the old reporting regime, the new rule does not specify the definition of segment profit to be disclosed, allowing any measure used internally for decision making to be reported as the segment

were required to report according to the previous standard (SFAS 14).[27] In Appendix A.2 I show that under the under-reporting concerns discussed in the literature and by practitioners in the industry, the baseline estimates reported in this chapter would suffer from an asymptotic downward bias.

Although segmented data report sales and assets at the business unit level, they do not report measures of labor or intermediate inputs at this level of analysis. Typical production data do not record input usage by either product or business segment, as in this case. The standard practice in the empirical literature for multi-product firms is either to allocate inputs equally across products (see, for example, De Loecker, 2011) or according to revenue share (as in Foster, Haltiwanger and Syverson, 2008). I allocate inputs across different business units according to the asset share of the unit. This implies, for instance, that material demand (M_{ijt}) for business unit j belonging to firm i at time t will be given by $M_{ijt} = \frac{assets_{ijt}}{assets_{it}} M_{it}$, where M_{it} is material demand at the firm level, and $assets_{ijt}$ and $assets_{it}$ represent total assets at the business unit and firm level, respectively.

Table 1.2 shows the average transition matrix in the number of segments over the period 1980-1998. On average, around 3.5% of non-diversified firms transition into multi-segment firms, while 9% of firms active in two or more segments transition into a lower number of segments. In practice, to identify the effects of firm diversification on productivity I will not only be exploiting variation on the number of business units, but also on the degree of concentration of activities across the different lines of business.

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profit. In addition, it does not require the measure of segment profit used to be consistent with the assets attributed to the segment (see Berger and Hann, 2003a for more details).

[27] Bloom et al. (2013b) argue that these under-reporting concerns are a far greater problem in the service sector than in the manufacturing sector due to the difficulties in classifying service sector activity.

Table 1.2. Average Transition Matrix: 1980-1998

	Non-Diversified	Two Business Units	At least 3 Business Units	Total
Non-Diversified	96.47	2.22	1.31	100.00
Two Business Units	9.29	86.67	6.04	100.00
At least 3 Business Units	1.82	7.00	91.17	100.00
Total	64.42	16.60	18.98	100.00

Note: The table reports the average transition matrix in the number of business units over the period 1980-1998.

One important characteristic of the data is that they not only report the number of segments in which a firm is active, but also sales and assets in each of them. This feature of the data allows me to create a diversification index for each firm by incorporating both kinds of information. I follow most of the existing literature on corporate diversification and define the diversification level (DIV_{it}) for firm i at time t as:[28]

$$DIV_{it} = 1 / \left(\sum_{j \in \mathcal{J}_{it}} \left(\frac{assets_{ijt}}{assets_{it}} \right)^2 \right) \tag{1.3}$$

where $\mathcal{J}_{it}$ represents the number of business segments in which firm i is active at time t. By construction this variable is 1 for non-diversified firms and it is increasing in the number of business segments $\mathcal{J}_{it}$, holding the variance of segment size constant. In the empirical application, I measure the degree diversification of firm i at time t div_{it} by the log of DIV_{it}.

[28] Several papers have used this measure as a proxy for the degree of diversification at the firm level. See, for instance, Teece (1980), Jovanovic (1993), Schoar (2002), Maksimovic and Phillips (2002), or Villalonga (2004), among others.

By focusing on segmented data, I am implicitly assuming that diversification can only be achieved by either varying the intensity of activities within each of a firm's active business segments, or by adding new lines of segments. Although this is the standard assumption made by most of the literature on diversification, it is important to note that this definition is broader than those traditionally used in the literature to define a product.[29] In this sense, it is important to be cautious when interpreting the results, since greater diversification does not necessarily imply a higher number of products, but could simply reflect a greater diversity of activities measured by operating multiple lines of business in different industries.[30] On the other hand, this broad description of activities used to measure diversification is advantageous to answer the empirical question asked by this chapter, since presumably the identifying assumption in this scenario is more credible than in the case of considering the introduction of new products.[31]

1.3.1. Descriptive Statistics

Table 1.3 presents simple mean differences in various characteristics (size, factor intensity, productivity, and innovation) between firms operating in only one segment and diversified firms. Size is measured using four different variables: (log of) sales, (log of) capital stock,

[29] Usually, a product is defined at a 7-digit SIC, and the industry at a 2-digit SIC. New segments are assigned a new 4-digit SIC code by Compustat.

[30] Some recent papers have studied the relationship between the number of products and productivity. For example, Bernard, Redding and Schott (2010), using Census data for the U.S., find evidence that a firm's productivity is correlated positively across its products. They conclude that single-product firms with relatively high productivity in their existing product are more likely to add a new product to their mix of goods than a relatively low-productivity firm producing the same initial product. Similarly, Balasubramanian and Sivadasan (2011), also using microdata from the U.S. Census, find that increases in patent stock are associated with increases in firm size, scope, skill and capital intensity, and total factor productivity.

[31] This would hold true if, for example, fixed costs of entering into a new segment are considerably higher than those associated with the introduction of a new product within a business segment.

(log of) employment (in thousands of employees), and (log of) materials. Comparing the means of these variables, it is clear that, on average, diversified firms are bigger: sales are 151% larger, capital stock by 206%, employment by 177%, and materials by 148%.[32] Diversified firms also exhibit greater capital intensity, measured by capital per worker. This ratio is about 10.5% higher for diversified firms than non-diversified.

Diversified firms are less productive based on labor productivity (i.e., the ratio between sales and employment) and total factor productivity. On average, the output per employee is 9.2% higher for non-diversified firms than diversified firms. Finally, diversified firms engage in more innovative activities, as measured by the stock and expenditure in R&D. On average, the stock of R&D is 12.8% higher in diversified firms, and they spend 9.1% more than non-diversified entities.

[32] Since the variables are in logarithm, the percentage increase for the case of sales, for example, is given by $(e^{0.9226} - 1) \times 100 =$151%.

Table 1.3. Mean Firm Characteristics: Diversified vs. Non-Diversified Firms

		(1) **Non-Diversified**	(2) **Diversified**	(3) Difference (2)-(1)	(4) **Highly Diversified**	(5) Difference (4)-(1)	Obs.
Size							
	Sales	3.8329***	4.7555***	0.9226***	6.1649***	2.3320***	44,281
		(0.0117)	(0.0232)	(0.0260)	(0.0217)	(0.0247)	
	Capital	2.2184***	3.3381***	1.1197***	4.8826***	2.6642***	44,281
		(0.0130)	(0.0258)	(0.0289)	(0.0241)	(0.0274)	
	Labor	-0.8798***	0.1398***	1.0196***	1.4868***	2.3666***	44,281
		(0.0107)	(0.0212)	(0.0237)	(0.0198)	(0.0225)	
	Materials	3.0586***	3.9678***	0.9092***	5.4000***	2.3415***	44,281
		(0.0125)	(0.0248)	(0.0277)	(0.0231)	(0.0263)	
Factor Intensity							
	Capital Intensity (K/L)	3.0982***	3.1984***	0.1001***	3.3958***	0.2976***	44,281
		(0.0054)	(0.0108)	(0.0121)	(0.0101)	(0.0115)	
Productivity							
	Sales/Employment	4.7128***	4.6157***	-0.0970***	4.6781***	-0.0347***	44,281
		(0.0042)	(0.0084)	(0.0094)	(0.0079)	(0.0089)	
	TFP - OLS	0.0105***	-0.0151***	-0.0256***	-0.0230***	-0.0335***	44,281
		(0.0018)	(0.0036)	(0.0041)	(0.0034)	(0.0039)	
Innovation							
	R&D Stock	2.0516***	2.1723***	0.1207***	3.2553***	1.2037***	44,281
		(0.0132)	(0.0262)	(0.0293)	(0.0245)	(0.0278)	
	R&D Expenditure	1.1415***	1.2290***	0.0875***	2.0840***	0.9425***	44,281
		(0.0099)	(0.0197)	(0.0221)	(0.0184)	(0.0209)	

Note: The columns Non-Diversified, Diversified and Highly Diversified report the mean of the variables for non-diversified firms, firms active in two business units, and firms active in three or more business units respectively. All variables are in logs and measured at the firm level. Variable TFP-OLS is obtained as the residual from an ordinary least squares regression of sales on inputs (i.e., labor, materials, and capital) and core-industry-year effects. Standard errors are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

In summary, the statistics presented in Table 1.3 suggest that diversified firms are larger, tend to choose higher levels of capital, and engage in more innovative activities (measured by R&D stock and expenditure) than non-diversified firms. However, they are less productive in terms of labor productivity. One may ask whether these differences also hold at the productive or business unit level. Table 1.4 reports mean differences in size, factor intensity and productivity (labor and total factor productivity) between non-diversified firms and business units belonging to diversified firms. We observe that business units of diversified firms are approximately 85% larger in terms of sales and input usage, and are 17% more capital intensive than non-diversified firms. Additionally, although these business units are less productive in term of labor productivity the differences between them is small (1%). In the next section, I explore whether some of these differences in firms' characteristics are associated with changes in the diversification level within firms. The productivity effects of firm diversification are studied in Section 1.5.

Table 1.4. Difference in Mean Business Unit Characteristics

		(1) Non-Diversified Mean	(2) Diversified Mean	(3) Difference (2)-(1)	Obs.
Size					
	Sales	3.8800***	4.4853	0.6053***	66,118
		(0.0119)		(0.0161)	
	Capital	2.3292***	3.1055	0.7763***	66,118
		(0.0129)		(0.0175)	
	Labor	-0.8015***	-0.1857	0.6158***	66,118
		(0.0112)		(0.0151)	
	Materials	3.1224***	3.6794	0.5570***	66,118
		(0.0124)		(0.0167)	
Factor Intensity					
	Capital Intensity (K/L)	3.1307***	3.2912	0.1605***	66,118
		(0.0046)		(0.0062)	
Productivity					
	Sales/Employment	4.6816***	4.6711	-0.0105*	66,118
		(0.0041)		(0.0056)	
	TFP - OLS	-0.0046	0.0035	0.0081**	66,118
		(0.0029)		(0.0039)	

Note: The columns Non-Diversified and Diversified report the mean of the variables for non-diversified firms, and business units belonging to diversified firms, respectively. All variables are in logs and measured at the business unit level. Variable TFP-OLS is obtained as the residual from an ordinary least squares regression of sales on inputs (i.e., labor, materials, and capital) and year effects at the industry level. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

1.3.1.1. Diversification and Firm Characteristics. In this section I examine whether changes in the diversification level are related to changes in firm characteristics. To explore this, I use the following regression model:

$$y_{it} = \upsilon_0 + \upsilon_1 div_{it} + \delta_{jt} + \mu_i + \varepsilon_{it} \tag{1.4}$$

where y_{it} is the variable of interest (i.e., sales, input usage, capital intensity, labor productivity, and innovation activities) for firm i in period t; div_{it} is the (log of) diversification index described by equation (1.3), δ_{jt} are core-industry-year effects, μ_i is a firm fixed effect, and ε_{it} is an error term.[33]

The results are summarized in panel A of Table 1.5, indicating an economically and statistically significant effect on the variables under analysis with respect to changes in diversification. A 1% increase in the diversification index is associated with a 0.54% increase in sales, approximately a 0.55% increase in input usage (capital, labor, and materials), and a 0.04% increase in capital intensity. In addition, a 1% increase in the index of diversification is associated with a 0.17% increase in the stock of R&D, and with a 0.19% increase in the R&D expenditure. These findings suggest, at least, that firm diversification accompanies expansion in firm size (measured by either sales or input usage) and innovation activities.[34]

[33] For multi-segment firms, the core-industry refers to the 2-digit SIC code reported by the firm as its main activity.

[34] Other papers have already reported associations between innovation activities and firm scope, measured by the number of products instead of diversification. For instance, Balasubramanian and Sivadasan (2011) using microdata from the U.S. Census, find that increases in innovation activities (measured by patent stock) are associated with increases in firm size, scope (number of products), skill and capital intensity, and total factor productivity.

As mentioned previously, a firm can achieve a higher level of diversification by varying the intensity of activities given a fixed line of segments, and/or by adding new lines of business. Since the above analysis does not distinguish between the two mechanisms, Panel B of Table 1.5 shows the results of running a similar specification to equation (1.4), but using the total number of business units as an explanatory variable instead of the (log of) diversification index div_{it}. The results indicate that operating a higher number of lines of business is associated with higher revenues, input usage, and innovation activities. An additional business unit is associated with a 5% increase in R&D stock, a 6.5% increase in R&D expenditure, and a 1.4% increase in capital intensity. Moreover, an additional unit is associated, on average, with an approximately 18% increase in revenue and input usage.

Finally, in panel C of Table 1.5 I study whether changes in business units' characteristics accompany changes in the diversification level. To analyze this, I use a regression model similar to (1.4), but I include business unit fixed effects instead of firm fixed effects, and industry-year effects at the business unit level. The results suggest that both output and input usage at the business unit level accompany changes in diversification at the firm level. On average, a 1% increase in the index of diversification is associated with a 10% increase in business unit output, and with a 8-11% increase in input usage.

Table 1.5. Diversification and Firm Characteristics

	Panel A			Panel B			Panel C		
Dependent Variable	**Diversification Index**	Obs.	R^2	**Number of Segments**	Obs.	R^2	**Diversification Index**	Obs.	R^2
Sales	0.5361***	44,281	0.946	0.1818***	44,281	0.946	0.1005***	66,118	0.957
	(0.0150)			(0.0047)			(0.0141)		
Capital	0.5958***	44,281	0.945	0.1945***	44,281	0.945	0.1125***	66,118	0.956
	(0.0168)			(0.0053)			(0.0157)		
Labor	0.5534***	44,281	0.950	0.1801***	44,281	0.950	0.0886***	66,118	0.956
	(0.0134)			(0.0042)			(0.0132)		
Materials	0.5438***	44,281	0.930	0.1792***	44,281	0.931	0.0799***	66,118	0.943
	(0.0178)			(0.0056)			(0.0171)		
Capital Intensity	0.0425***	44,281	0.838	0.0144***	44,281	0.838	0.0239**	66,118	0.884
	(0.0110)			(0.0035)			(0.0100)		
R&D Stock	0.1700***	44,281	0.954	0.0536***	44,281	0.954			
	(0.0144)			(0.0046)					
R&D Expenditure	0.1941***	44,281	0.930	0.0657***	44,281	0.930			
	(0.0134)			(0.0042)					

Note: The table reports the results of a regression of each of the dependent variables on (log) the diversification index (Panels A and C) or number of business units (Panel B). All dependent variables are logged. Regressions in panels A and B include core-industry-year effects, and firm fixed effects. Regressions in panel C include business unit fixed effects and industry-year effects. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

1.4. Estimation

In order to recover productivity measures, as well as its law of motion, we first have to obtain consistent estimates of the production function, controlling for unobserved productivity shocks, which are potentially correlated with input choices. The estimator builds on the insights of the control function approach literature (Olley and Pakes, 1996; Levinsohn and Petrin, 2003 and Ackerberg et al., 2015) in that certain decisions made by the firm (i.e., investment or static input demand decisions) contain information about current productivity and therefore can be used to recover unobserved productivity. Unlike this literature, I follow Gandhi et al. (2016) in exploiting the fact that demand for static inputs (materials in this case) is the solution to the firm's short-run maximization problem. Given a parametric specification of the production function, the functional form of the firm's first order condition is known and contains information about the intermediate input demand, which is an implicit function of the elasticity of these inputs.[35] Using the parametric restrictions between the firm's first order condition for a flexible input and the production function allows us to parametrically recover unobserved productivity without making assumptions on the firm's dynamic programing problem.[36]

[35] Gandhi et al. (2016) show that traditional control function approach methods face a fundamental identification problem when a gross output production function contains flexible inputs. They propose an identification strategy that solves the problem associated with flexible inputs in the production function, exploiting the information about the production function that is contained in the firm's first order condition for a flexible input.

[36] Doraszelski and Jaumandreu (2013) follow a similar approach and exploit the parametric form of the production function and first order conditions of static inputs. They use lagged prices as instruments for flexible inputs assuming that prices are serially correlated and vary by firm, and that lagged price variation is exogenous.

Profit maximization requires that the firm sets the marginal revenue product of the static input (i.e., materials) equal to its marginal cost,

$$\frac{\partial \tilde{Y}_{ijt}}{\partial M_{ijt}} = P^m_{s_{ij}t}$$

or equivalently,

$$\frac{\partial \tilde{Y}_{ijt}}{\partial M_{ijt}} \frac{M_{ijt}}{\tilde{Y}_{ijt}} = \frac{P^m_{s_{ij}t} M_{ijt}}{\tilde{Y}_{ijt}} \tag{1.5}$$

where the left hand side of the equation represents the revenue elasticity with respect to materials, and the right hand side is the share of materials on revenue. Note also that the first order condition implies that the demand for materials is an implicit function of $(k_{ijt}, l_{ijt}, \omega_{ijt})$, i.e.,[37]

$$m_{ijt} = m_t(k_{ijt}, l_{ijt}, \omega_{ijt})$$

Equation (1.5) can be used to identify the parameters of the model. The goal is to estimate the parameters determining the revenue of business units in (1.1), β, as well as the law of motion for productivity $g_s(.)$. Given the parametric assumptions made, the model is characterized by the following three equations:

$$\begin{aligned} y_{ijt} &= h_s(m_{ijt}, l_{ijt}, k_{ijt}; \beta) + \omega_{ijt} + \mu_{st} + \epsilon_{ijt} \\ \omega_{ijt} &= g_s(\omega_{ijt-1}, div_{it-1}, r_{it-1}) + \xi_{ijt} \\ \frac{P^m_{s_{ij}t} M_{ijt}}{Y_{ijt}} \exp(\epsilon_{ijt}) &= \beta_{m_s} + 2\beta_{mm_s} m_{ijt} + \beta_{ml_s} l_{ijt} + \beta_{mk_s} k_{ijt} + \beta_{mlk_s} l_{ijt} k_{ijt} \end{aligned}$$

[37] Note that for a translog production function the inverse material demand function cannot be characterized in closed form. However, estimation and identification only require material demand to be an implicit function of $(k_{ijt}, l_{ijt}, \omega_{ijt})$, where m_t is strictly monotone in ω_{ijt} for any (k_{ijt}, l_{ijt}).

Estimating the parameters of the model and the law of motion for productivity requires dealing with two identification challenges. First, labor and material demand by business unit j at time t are determined after innovation to productivity ξ_{ijt} is observed by firm i. This creates a correlation between labor (l_{ijt}) or material demand (m_{ijt}) and ξ_{ijt}. This issue is known in the production function literature as transmission bias (see Griliches and Mairesse, 1997). Additionally, the error term in the revenue equation (1.1) is not only a function of unobserved (to the econometrician) productivity, but also of measurement error ϵ_{ijt}, which needs to be accounted for in order to obtain consistent estimates of the production function. I simultaneously address both challenges by estimating the parameters of interest and the law of motion for productivity in two stages.

In the first stage I use the material optimality condition (1.5) associated with each business unit j to estimate the parameters determining the elasticity of revenue with respect to materials (β_{m_s},β_{mm_s},β_{ml_s},β_{mk_s},β_{mlk_s}), as well as the measurement error component of revenue (ϵ_{ijt}) for each business unit j and period t. In the second stage, I condition on these first stage estimates to recover the remaining model parameters (β_{l_s},β_{ll_s},β_{lk_s},β_{k_s},β_{kk_s}) and the law of motion of productivity $g_s(.)$. I describe these two stages below.

The first stage relies on the assumption that materials are a static input in the firm's problem and its optimality condition described by:

$$\frac{P^M_{ijt} M_{ijt}}{Y_{ijt}} \exp(\epsilon_{ijt}) = \beta_{m_s} + 2\beta_{mm_s} m_{ijt} + \beta_{ml_s} l_{ijt} + \beta_{mk_s} k_{ijt} + \beta_{mlk_s} l_{ijt} k_{ijt}$$

Moment condition $E_t[\epsilon_{ijt}] = 0$ implies that parameters (β_{m_s},β_{mm_s},β_{ml_s},β_{mk_s},β_{mlk_s}) can be estimated according to the following moment:

$$E[mshare_{ijt} - \ln(\beta_{m_s} + 2\beta_{mm_s}m_{ijt} + \beta_{ml_s}l_{ijt} + \beta_{mk_s}k_{ijt} + \beta_{mlk_s}l_{ijt}k_{ijt}) \mid m_{ijt}, l_{ijt}, k_{ijt}] = 0$$

where $mshare_{ijt} = \ln\left(\frac{P^M_{ijt}M_{ijt}}{Y_{ijt}}\right)$, which is directly observed in the data. I estimate the parameters of the above equation (β_{m_s},β_{mm_s},β_{ml_s},β_{mk_s},β_{mlk_s}) relying on Non-Linear Least Squares (NLLS). The parameters estimates ($\hat{\beta}_{m_s}$,$\hat{\beta}_{mm_s}$,$\hat{\beta}_{ml_s}$,$\hat{\beta}_{mk_s}$,$\hat{\beta}_{mlk_s}$) allows us to recover an estimate of measurement error ($\hat{\epsilon}_{ijt}$) as:

$$\hat{\epsilon}_{ijt} = \ln(\hat{\beta}_{m_s} + 2\hat{\beta}_{mm_s}m_{ijt} + \hat{\beta}_{ml_s}l_{ijt} + \hat{\beta}_{mk_s}k_{ijt} + \hat{\beta}_{mlk_s}l_{ijt}k_{ijt}) - mshare_{ijt}$$

The second stage provides an estimate for the remaining production function coefficients and for the law of motion for productivity. I use θ to denote the vector of parameters $\theta = (\beta_0, \beta_l, \beta_{ll}, \beta_{lk}, \beta_k, \beta_{kk}, \mu_{st})$. Using the estimates ($\hat{\beta}_{m_s}$,$\hat{\beta}_{mm_s}$,$\hat{\beta}_{ml_s}$,$\hat{\beta}_{mk_s}$,$\hat{\beta}_{mlk_s}$) and ($\hat{\epsilon}_{ijt}$), and defining $\hat{\phi}_{ijt}$ as,

$$\hat{\phi}_{ijt} = \hat{\beta}_{m_s}m_{ijt} + \hat{\beta}_{mm_s}m^2_{ijt} + \hat{\beta}_{ml_s}m_{ijt}l_{ijt} + \hat{\beta}_{mk_s}m_{ijt}k_{ijt} + \hat{\beta}_{mlk_s}m_{ijt}l_{ijt}k_{ijt} + \hat{\epsilon}_{ijt}$$

it is possible to compute, for any given value of θ, productivity as

$$\omega_{ijt}(\theta) = y_{ijt} - \hat{\phi}_{ijt} - \beta_0 - \beta_{l_s}l_{ijt} - \beta_{ll_s}l^2_{ijt} - \beta_{lk_s}l_{ijt}k_{ijt} - \beta_{k_s}k_{ijt} - \beta_{kk_s}k^2_{ijt} - \mu_{st}$$

Then, by nonparametrically regressing $\omega_{ijt}(\theta)$ on its lag $\omega_{ijt-1}(\theta)$ and potentially a set of variables div_{it-1} and r_{it-1} affecting productivity, I recover the innovation to productivity given θ, $\xi_{ijt}(\theta)$.

Then we can form moments and use standard Generalized Method of Moments (GMM) techniques to obtain the estimates of the production function. I rely on the following moment condition:

$$E\left(\xi_{ijt}(\theta)\begin{pmatrix} l_{ijt-1} \\ l^2_{ijt-1} \\ m_{ijt-1} \\ k_{ijt} \\ k^2_{ijt} \\ l_{ijt-1}k_{ijt} \\ k_{ijt-1} \\ \mathcal{J}_{it} \\ \mu_{st} \end{pmatrix}\right) = 0 \tag{1.6}$$

where $\mathcal{J}_{it}$ denotes the number of business segments in which firm i is active at time t. The moments above exploit the fact that both capital and the number of business segments are assumed to be decided a period ahead and therefore should not be correlated with the innovation on productivity. I rely on lagged labor and material to identify the coefficient on labor since the current value of these variables are expected to react to shocks to productivity and hence both $E(l_{ijt}\xi_{ijt})$ and $E(m_{ijt}\xi_{ijt})$ are expected to be nonzero.

The above procedure generates a separate estimate of the diversification effect on productivity, through $g_s(.)$. The model assumes that the variation in productivity that is not explained by $g_s(.)$, is represented by ξ_{ijt}. The timing assumption on the arrival of the productivity shock ξ_{ijt+1} identifies the diversification effect and the impact of R&D

expenditures on productivity. This assumption implies that unexpected shocks to the firm's production process are orthogonal to its diversification decision or, formally, that $E(\xi_{ijt+1} div_{it}) = 0$ and $E(\xi_{iit+1}\mathcal{J}_{it+1}) = 0$. In other words, ξ_{ijt} is assumed to be uncorrelated with past diversification levels div_{it-1} and R&D investment at $t-1$, r_{it-1}. This follows from the mean independent assumption of ξ_{ijt} with respect to the information known to the firm at period $t-1$. Intuitively, these assumptions mean that the decision on the number (and type) of business segments in which to operate (or the diversification level given a number of business segments) was made prior to the firm receiving the productivity shock. An example where this condition would hold is one in which moving resources from a business unit to another, or entering into new markets (i.e., new lines of business), is a costly undertaking for the firm. In this case, any fixed or sunk entry costs associated with starting new businesses would prevent firms from adjusting their diversification level instantaneously upon receiving shocks to their underlying productivity.

Under the stated assumptions, identification of the effect of firm diversification and R&D investment on productivity exploits variation in div_{it-1} and r_{it-1} conditional on past productivity ω_{ijt-1}. This, in turn, implies that the estimation of the impact of firm diversification and R&D expenditure on productivity of business units can be achieved by comparing the productivity growth of two different business units in the same industry with equal productivity levels at $t-1$ but that differ in past diversification experience and firm R&D investment. Predicted productivity given a firm's past diversification level is thus identified by the difference in current productivity between firms with different diversification levels at period t, while holding their input use constant. Furthermore, industry-year fixed effects μ_{st} control for market or industry characteristics that may affect both the productivity of business units and a firm's incentives to diversify or invest in R&D. For instance, certain industries may have higher productivity levels and may also be more appealing to diversified firms or for R&D investment.

Conditioning on productivity at time t controls for unobserved time-varying differences among firms and guarantees that the estimates are not affected by reverse causality.[38] The typical concern in studies that have looked at the relationship between productivity and diversification is the possibility that less productive firms self-select into a higher number of business segments. More specifically, the concern is that when we compare a firm acting in several markets to a firm acting in a few markets, we would attribute the future productivity differences to the higher diversification level, although it is simply explained by the fact that the less-productive firms become more diversified. However, by including ω_{ijt-1} in the function $g_s(.)$ this potential self-selection process is controlled for.[39]

Finally, it is important to note that the estimation strategy relies on observed choices in the data for identification of the effects. Note that, conditional on past productivity levels and number and identity of business units, the observed firms' optimal diversification levels and R&D investment may differ due to differences in realized cost shocks to capital investment (X_{it}^K), R&D investment (X_{it}^R), or business units operations $(X_{it}^{\mathcal{J}})$. Relying on observed choices implies that identification does not require specifying the impact of cost shocks to capital investment (X_{it}^K), R&D investment (X_{it}^R), or business units operations

[38] Additionally, the standard Olley-Pakes control for selection can be used to further control for diversified firms with a higher propensity to survive in a marketplace.

[39] A similar argument would hold for the case in which more productive firms self-select into more lines of business. The argument made here about reverse causality also extends to R&D. In particular, controlling for past productivity ω_{ijt-1} the estimates do not reflect the correlation between R&D and current productivity that may arise if for example r_{it-1} is determined by past productivity ω_{ijt-1} and productivity is persistent.

($X_{it}^{\mathcal{J}}$) on optimal firm's decisions (i.e., the firm's optimal diversification level and R&D investment). The only restriction on the model is the existence of costs shocks and adjustment cost functions associated with these optimal firm's decisions that rationalize the data, as well as the assumption that these decisions (i.e., diversification and R&D expenditure) are mean independent of innovation to productivity ξ_{ijt}.

To assess whether a firm's past diversification decisions impact its future productivity, I rely on $\frac{\partial g_s(.)}{\partial div_{it}}$, which also depends on the firm's past productivity level. This allows for an estimate of the effect of diversification on future productivity to vary with the firm's own productivity level. This heterogeneous response of diversification is incorporated into the nonparametric function $g_s(.)$.

1.5. Results

In this section I first analyze the empirical relationship between firm diversification and productivity. The goal is to verify whether firms engaging in diversification activities exhibit a change in productivity as a consequence of it. Then I analyze the relationship between firm diversification and uncertainty, and test some restrictions on the function $g_s(.)$. I conclude the section studying the link between firm diversification and input misallocation. To ease the exposition of results, I describe the results of the production function estimation in Appendix A.3. In Section 1.6 I explore firms' R&D investment decisions in order to analyze how diversification and R&D investment interact in shaping a firm's future productivity.

1.5.1. Productivity Effects of Diversification

In this section I study the effects of diversification on productivity. I start by describing the results of a restrictive and simpler model in which the expected future productivity function is simply a function of current productivity, diversification, and an interaction term between these two terms. I then turn to a more complex model similar to the one described in Section 1.2. I estimate these models by primary industry or sector of activity, defined by the 2-digit SIC code. The industries considered in the analysis (with their respective 2-digit SIC codes) are the following: Food and Beverages (20); Textile, Apparel, and Leather (22, 23, and 31); Timber and Furniture (24 and 25); Paper and Printing (26 and 27); Chemicals (28); Pete Refining (29); Rubber and Misc. Manufacturing Industries (30 and 39); Stone, Clay, Glass, and Concrete Products (32); Primary Metal and Fabricated Metal Products (33 and 34); Machinery and Equipment (35); Electrical Machinery and Apparatus (36); Transportation Equipment (37); and Medical Instruments (38).[40]

Table 1.6 reports the results of the restrictive model; the results confirm that productivity is persistent and increasing in past productivity. Additionally, expected future productivity is increasing in firm diversification. On average, a 1% increase in the diversification level is associated with a 0.042% increase in the productivity of business units. The average effects vary by industry, ranging from -0.003% to 0.089% depending on the industry in which the business unit operates. The results of the restrictive model also show that current productivity and firm diversification are complementary in most of the industries.[41] This complementarity implies that business units do not benefit equally from

[40] Misc. Manufacturing Industries include, for example, jewelry, games and toys, musical instruments, pens, etc.
[41] The exceptions in this case are Primary Metals and Metals Products, and Transportation Equipment.

firm diversification and that current productivity reinforces the impact of diversification on future productivity.

Table 1.6. Productivity Effects of Diversification. Restrictive Model

	Variables			
Industry	ω_{ijt-1}	div_{it-1}	$\omega_{ijt-1} \times div_{it-1}$	**Obs.**
Food and Beverages	0.7857***	0.0148*	0.0346	2,183
	(0.0200)	(0.0081)	(0.0244)	
Textile, Apparel and Leather	0.6034***	0.0572***	0.2004***	2,271
	(0.0247)	(0.0122)	(0.0269)	
Timber and Furniture	0.5164***	0.0279***	0.3343***	1,624
	(0.0266)	(0.0097)	(0.0313)	
Paper and Printing	0.6866***	0.0672***	0.1771***	2,680
	(0.0216)	(0.0102)	(0.0266)	
Chemicals	0.6966***	0.0443***	0.0708**	4,055
	(0.0192)	(0.0142)	(0.0310)	
Pete Refining	0.5786***	0.0627**	0.0357	492
	(0.0465)	(0.0313)	(0.0508)	
Rubber and Misc Manuf. Industries	0.6423***	0.0145**	0.1059***	2,774
	(0.0204)	(0.0068)	(0.0337)	
Stone, Clay, Glass and Concrete Products	0.5616***	0.0186	0.1490***	1,036
	(0.0346)	(0.0113)	(0.0467)	
Primary Metal Industries and Metal Products	0.5688***	0.0186*	-0.0283	4,484
	(0.0177)	(0.0109)	(0.0291)	
Machinery and Equipment	0.6459***	0.0530***	0.0838***	6,625
	(0.0128)	(0.0045)	(0.0187)	
Electrical Machinery and Apparatus	0.6187***	0.0451***	0.0927***	6,066
	(0.0124)	(0.0083)	(0.0218)	
Transportation Equipment	0.9802***	0.0450***	-0.0842***	2,376
	(0.0162)	(0.0100)	(0.0168)	
Medical Instruments	0.5224***	0.0265***	0.2291***	4,211
	(0.0154)	(0.0057)	(0.0283)	

Note: The table reports the results of a restrictive and simpler model in which the expected future productivity function $g_s(.)$ is simply a function of current productivity (i.e., ω_{ijt-1}), diversification (i.e., div_{it-1}), and an interaction term between these two terms (i.e., $\omega_{ijt-1} \times div_{it-1}$). Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

To better understand the productivity effects of firm diversification, I take to the data the baseline specification described in Section 1.2, where $g_s(.)$ is characterized by a high order polynomial in current productivity, diversification and R&D investment. Given the estimates of the function $g_s(.)$, we can assess different features of the link between productivity and diversification in more detail. Specifically, I assess productivity levels, productivity growth, and the effects of firm diversification on productivity by looking at $\frac{\partial g_s(.)}{\partial div_{it}}$, where div_{it} measures the degree of firm diversification. We can interpret this derivative as the return to diversification at the margin.

1.5.1.1. Return to Diversification. I start by discussing the results concerning the returns to diversification, which can be studied by looking at the estimated value of $\frac{\partial g_s(.)}{\partial div_{it}}$. Table 1.7 presents the results of the estimation. Since the estimated value of $\frac{\partial g_s(.)}{\partial div_{it}}$ depends on the current productivity level ω_{ijt} and firm diversification div_{it}, the table shows different moments for the estimated distribution of the effects. In particular, it shows different percentiles of the distribution of estimated effects, along with a weighted average computed as $\frac{1}{T}\sum_t \sum_i w_{it} \times \frac{\partial g_s(.)}{\partial div_{it}}$, where T is the number of years used in the computation, and the weights w_{it} are defined as the share of a firm's sales on total sales (i.e., $Y_{it}/\sum_k Y_{kt}$). Figures 1.1 and 1.2 plot a Kernel density and a cumulative function of the estimated effects. A 1% increase in the diversification index div_{it} leads, on average, to a 0.051% increase in productivity. This implies an expected positive return to diversification for all firms in the manufacturing sector. To better understand the economic impact of this effect, note that firms active in two (three) segments exhibit, on average, a diversification index 65% (115%) higher than firms operating in only one segment. These numbers would imply an average return to diversification experience of 3.315% and 5.865% for a firm active in two and three segments respectively, and with a value for its diversification index equal to the conditional mean.[42]

[42] The mean value for the diversification index is conditional on the number of business segments. For this computation I am also holding everything else constant.

Table 1.7. Productivity Effects of Diversification

	Moments					
Industry	**Mean**	**p5**	**p25**	**p50**	**p75**	**p95**
All	0.0510	-0.0660	-0.0150	0.0190	0.0630	0.1360
Food and Beverages	-0.0260	-0.0980	-0.0240	0.0120	0.0610	0.1320
Textile, Apparel and Leather	0.2170	-0.1590	-0.0640	-0.0290	0.0390	0.2100
Timber and Furniture	-0.0230	-0.0910	-0.0310	0.0150	0.0640	0.1470
Paper and Printing	0.0020	-0.0660	-0.0250	-0.0100	0.0280	0.0970
Chemicals	0.0110	-0.0520	-0.0210	0.0150	0.0660	0.0810
Pete Refining	0.1720	-0.2070	-0.0930	0.0730	0.2090	0.5260
Rubber and Misc Manuf. Industries	-0.0160	-0.0450	-0.0160	-0.0080	0.0040	0.0440
Stone, Clay, Glass and Concrete Products	0.0060	-0.0470	-0.0330	0.0040	0.0760	0.1140
Primary Metal Industries and Metal Products	0.0160	-0.0420	-0.0160	0.0040	0.0390	0.1020
Machinery and Equipment	0.0660	-0.0500	-0.0090	0.0240	0.0720	0.1450
Electrical Machinery and Apparatus	0.0350	-0.0590	0.0130	0.0630	0.0920	0.1560
Transportation Equipment	0.0490	-0.1120	-0.0050	0.0580	0.1120	0.2660
Medical Instruments	0.0220	-0.0100	0.0090	0.0450	0.0460	0.0550

Note: The table reports the estimates of the productivity effects of firm diversification, measured by $\frac{\partial g_s(.)}{\partial div_{it}}$. The table shows different moments for the estimated distribution of the effects (i.e., percentiles of the distribution of estimated effects) along with a weighted average computed as $\frac{1}{T}\sum_t \sum_i w_{it} \times \frac{\partial g_s(.)}{\partial div_{it}}$, where T is the number of years used in the computation, and the weights w_{it} are defined as the share of a firm's sales on total sales (i.e., $Y_{it}/\sum_k Y_{kt}$).

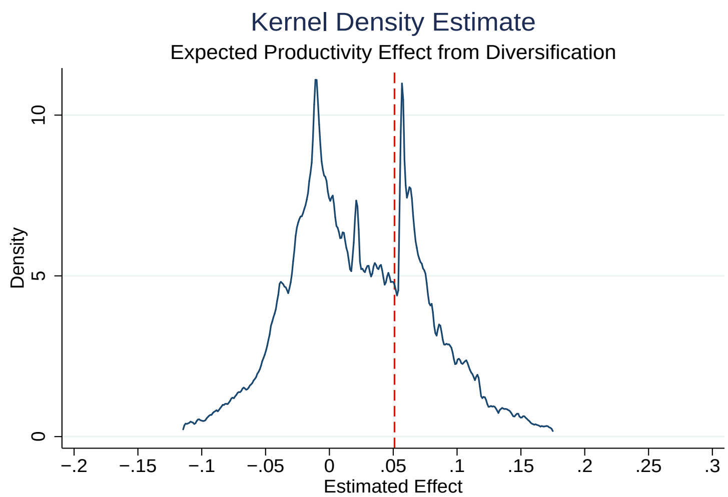

Figure 1.1. Estimated Effect of Firm Diversification.
Notes: The figure shows a Kernel density estimate of the expected productivity effect from diversification. The red (dash) vertical line represents the mean effect.

Table 1.7 also shows that there is considerable variation across and within industries in the return to diversification experience. The average returns to diversification vary from -0.026% to 0.217% across industries. The returns at the 25th, 50th, and 75th percentiles range from -0.064% to 0.013%, -0.029% to 0.073%, and from 0.004% to 0.209%, respectively. Negative returns at the margin are consistent with an overall positive effect of diversification on revenue, and therefore are justifiable in the model. A firm may diversify to the point of driving returns below zero for different reasons, with the most prominent in the current setting being indivisibilities in investment, allocation of capital, or entry into new lines of business. Moreover, negative returns at the business unit level are consistent with an overall positive firm-wide return to diversification.

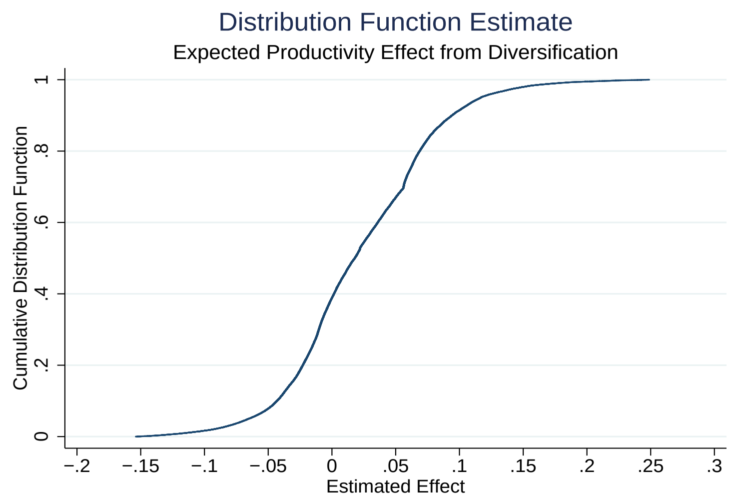

Figure 1.2. Estimated Effect of Firm Diversification.
Notes: The figure shows a distribution function estimate of the expected productivity effect from diversification.

Even though the revenue elasticity with respect to diversification provide us with an estimate for the rate of return at the margin, it does not provide detailed information on the size of the effect. To understand this, it is possible to compute an estimate for the average return to diversification as given by $g_s(\omega_{ijt}, div_{it}, r_{it}) - g_s(\omega_{ijt}, 0, r_{it})$, where $g_s(\omega_{ijt}, 0, r_{it})$ represents the counterfactual value for expected future productivity in the scenario where the business unit is a stand-alone unit. With some algebra, it is easy to show that $g_s(\omega_{ijt}, div_{it}, r_{it}) - g_s(\omega_{ijt}, 0, r_{it}) \approx [Y_{ijt}(\omega_{ijt}, div_{it}, r_{it}) - Y_{ijt}(\omega_{ijt}, 0, r_{it})]/Y_{ijt}(\omega_{ijt}, 0, r_{it})$. On average, the average rate of return to diversification is estimated at 0.039, implying a 4% increase in revenue at the business unit level. In addition, the mean (median) effect ranges from 0.001 (-0.002) to 0.070 (0.034) across industries.[43]

[43] Percentile 25th (75th) ranges from -0.011 (0.005) to 0.021 (0.066) across different industries.

To better understand the variation in the returns to diversification across and within industries, I use the estimate of $g_s(.)$ to analyze how the marginal effect $\frac{\partial g_s(.)}{\partial div_{it}}$ varies across the distribution of initial productivity (ω_{ijt}). To this end, Figure 1.3 plots a nonparametric estimate of the predicted return to diversification conditional on the current productivity level.[44] We observe that the mean value of the estimated effect $\frac{\partial g_s(.)}{\partial div_{it}}$, conditional on current productivity ω_{ijt}, is positive along the distribution of current productivity. In addition, the estimated return at the margin is increasing in the current productivity level (a result that holds along the entire distribution of current productivity). This result suggests that current productivity and diversification experience are complements for expected future productivity, implying that current productivity tends to reinforce the impact of diversification on future productivity.

[44] I use a local linear estimator with a Epanechnikov Kernel.

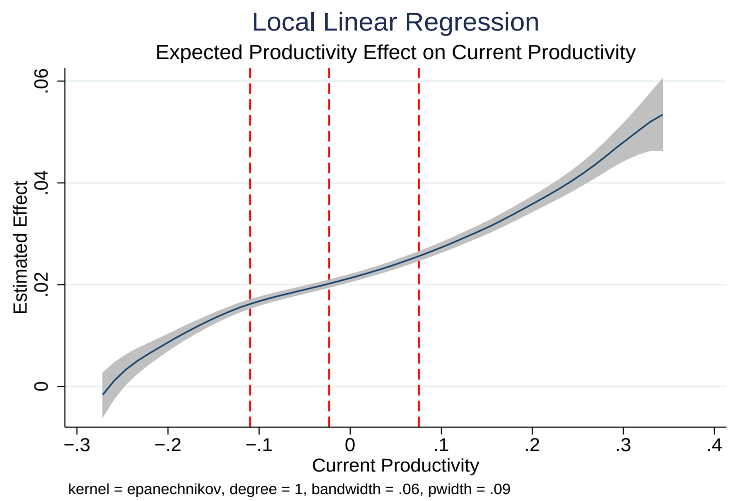

Figure 1.3. Non-Parametric Regression of Expected Productivity Effect on Current Productivity.
Notes: The blue solid line shows the results of a local linear regression of the estimated effect on current productivity (demeaned values). The red (dash) vertical lines represent the quartiles of the distribution of current productivity. The gray shaded area around the blue line represents the bands of a 95% confidence interval.

1.5.1.2. Productivity Levels. In this section I describe differences in future expected productivity between business units that belong to diversified firms and business units that do not. Figure 1.4 plots the cumulative distribution function of productivity for business units belonging to diversified firms and non-diversified firms. The figure pools all business units within the manufacturing sector. We observe that the cumulative distribution function for business units operating within diversified firms is to the right of the distribution function for non-diversified firms. This result strongly suggests first order stochastic dominance.

Before testing for the equality of the distributions, I test for difference in means in the expected future productivity function between non-diversified firms and business units

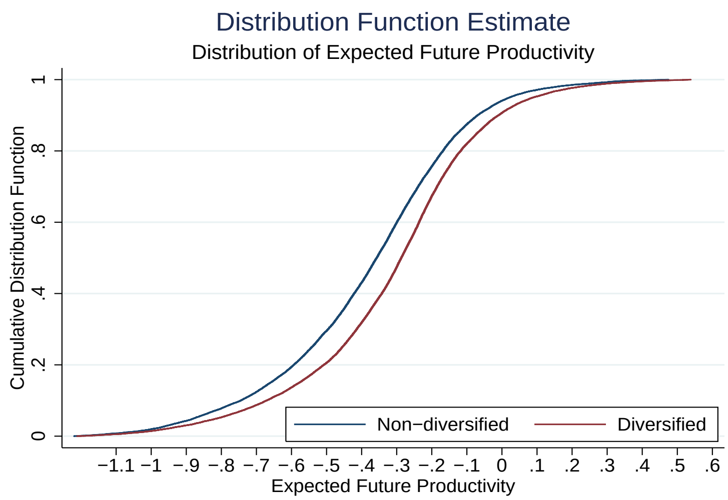

Figure 1.4. Distribution of Expected Productivity.
Notes: The figure shows the cumulative distribution of expected future productivity for non-diversified firms and business units belonging to diversified firms.

belonging to diversified firms. I compute the difference in means as:

$$\bar{g}_{MS} - \bar{g}_{SS} = \frac{1}{N_{MS}} \sum_j \sum_t 1_{[j \in MS]} g(\omega_{ijt}, div_{it}, r_{it}) - \frac{1}{N_{SS}} \sum_j \sum_t 1_{[j \in SS]} g(\omega_{ijt}, 0, r_{it})$$

where $\bar{g}_{MS}$ and $\bar{g}_{SS}$ denote the means of business units of diversified firms and non-diversified firms, respectively. N_{MS} and N_{SS} are the size of the subsamples of observations with and without diversified business units. The test statistic for testing equality of means is given by:

$$t = \frac{\bar{g}_{MS} - \bar{g}_{SS}}{\sqrt{Var(g(\omega_{ijt}, div_{it}, r_{it}))/(N_{MS} - 1) + Var(g(\omega_{ijt}, 0, r_{it}))/(N_{SS} - 1)}}$$

Columns (1) to (3) of Table 1.8 show the results of the test. We observe that the difference in means is positive in all industries, with the exception of "Rubber and Misc. Manufacturing Industries."[45] Moreover, from columns (2) and (3) we can note that the test rejects (at conventional levels of significance) the null hypothesis of equality of means. Instead, the results favor the alternative hypothesis that the mean of expected productivity is higher for diversified units than for non-diversified firms, with the only exception again being "Rubber and Misc. Manufacturing Industries." These results are consistent with previous findings in the literature (e.g., Schoar, 2002), which have documented higher average productivity levels for plants belonging to diversified firms than non-diversified plants.

To compare the distribution in future expected productivity, I apply a Kolmogorov-Smirnov test. This test requires independence of the observations in each sample. To accommodate this, I consider the variable of interest to be the average of expected productivity for each business unit.[46] Columns (4) and (5) of Table 1.8 report the results of the test, where the null hypothesis is the equality of the two distributions. I reject equality of the distributions for non-diversified firms and business units belonging to diversified firms in almost all cases, at a 5% level, being the exceptions "Pete Refining" and "Rubber and Misc. Manufacturing Industries."

[45] A possible explanation for this result is the considerable heterogeneity in activities across business units within this industry, which arises as a consequence of the level of aggregation I am using, pooling Rubber with Misc. Manufacturing Industries.

[46] For business units that transition between non-diversification to diversification, I average only over the years in which the firm operates in multiple industries (and discard the years in which it operates as a non-diversified firm).

1.5.1.3. Productivity Growth. I study (expected) productivity growth, which is defined as the difference between future expected productivity and current productivity:

$$E[\omega_{ijt} - \omega_{ijt-1} \mid \omega_{ijt-1}, div_{it-1}] = g_s(\omega_{ijt-1}, div_{it-1}, r_{it-1}) - \omega_{ijt-1}$$

where the above equation relies on the fact that ω_{ijt-1} is known to the firm at the time it makes decisions on diversification.

In order to assess if the productivity of business units belonging to diversified firms grow faster than non-diversified firms, I regress the measure of expected productivity growth described above on year fixed effects and a dummy indicating whether the business unit belongs to a diversified firm or not. To estimate the average of the expectation of productivity growth, I weight (w_{ijt}) the regressions by the share of output of a business unit two periods ago (i.e., $w_{ijt} = Y_{ijt-2}/\sum_j Y_{ijt-2}$). I assume that the weights are orthogonal to the previous period productivity innovation (i.e., $E[w_{ijt}\xi_{ijt-1} \mid \omega_{ijt-2}, div_{it-2}] = 0$), which is reasonable since the value of ξ_{ijt-1} is not known to the firm when it makes the decisions that determine Y_{ijt-2} and thus w_{ijt}.

Column (6) of Table 1.8 shows the results of the estimation. Productivity growth is higher for business units of diversified firms than non-diversified firms in 9 of the 13 industries. In these industries, the average productivity growth rate of business units belonging to diversified firms is between 0.3% and 2.1% higher than the productivity growth of non-diversified firms. These results, together with those presented in the previous section, suggest that diversified firms are not only more productive on average than those that are not diversified, but also tend to grow even larger over time. Therefore, diversification seems to be a primary source of productivity growth.

Table 1.8. Productivity Levels and Growth

		Mean of diversified is greater		*Kolmogorov-Smirnov test Distributions are equal*		
	Diff. of means	*t*	*p-val*	*K-S stat*	*p-val*	*Diff. in Productivity Growth*
Industry	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Food and Beverages	0.072	9.027	0.000	0.295	0.000	-0.022
Textile, Apparel and Leather	0.016	1.522	0.064	0.179	0.002	-0.014
Timber and Furniture	0.099	8.921	0.000	0.447	0.000	-0.043
Paper and Printing	0.012	1.629	0.052	0.162	0.010	0.003
Chemicals	0.070	13.702	0.000	0.300	0.000	0.015
Pete Refining	0.360	7.421	0.000	0.276	0.180	-0.032
Rubber and Misc. Manuf. Industries	-0.013	-2.485	0.994	0.071	0.515	0.009
Stone, Clay, Glass and Concrete Products	0.052	4.704	0.000	0.235	0.034	0.004
Primary Metal Industries and Metal Products	0.056	12.049	0.000	0.286	0.000	0.017
Machinery and Equipment	0.111	26.712	0.000	0.374	0.000	0.021
Electrical Machinery and Apparatus	0.059	9.637	0.000	0.186	0.000	0.015
Transportation Equipment	0.159	16.735	0.000	0.474	0.000	0.015
Medical Instruments	0.026	6.623	0.000	0.148	0.001	0.015

Note: Column (1) of the table reports the difference in means in the expected future productivity function $g_s(.)$ between diversified and non-diversified business units. Columns (2) and (3) report the t-statistic and p-value of a difference in means test, where the null hypothesis is the equality in means in the expected future productivity function between non-diversified and diversified business units, and the alternative is that the mean is higher for diversified business units. Columns (4) and (5) show the Kolmogorov-Smirnov statistic and p-value associated with a Kolmogorov-Smirnov test on equality of distributions of expected future productivity for diversified and non-diversified business units. Column (6) reports the difference in expected productivity growth between diversified and non-diversified business units. Expected productivity growth is defined as $g_s(\omega_{ijt-1}, div_{it-1}, r_{it-1}) - \omega_{ijt-1}$.

1.5.2. Unexpected Shocks to Production and Productivity

The estimates of the production function also provide us with estimates for the conditional expectation function $g_s(.)$, unexpected shocks to productivity ξ_{ijt+1}, and unexpected shocks to production ϵ_{ijt}. This section reports the results obtained regarding the degree of persistence in productivity and the unexpected shocks to productivity and production.

In Table 1.9 I report different moments to describe the degree of persistence and uncertainty in productivity. The degree of persistence is given by $\frac{\partial g_s(.)}{\partial \omega_{ijt}}$, and measures the elasticity of expected future productivity to current productivity. The higher the degree of persistence, the higher the fraction of current productivity that is carried into future productivity. Since this measure of inertia depends on both current productivity and diversification decisions, I report different moments of the distribution (the mean, the median, and percentiles 25 and 75). The degree of persistence in productivity is considerable for most of the industries (columns (2) to (5) of Table 1.9). With the exception of Pete Refining, Primary and Fabricated Metal Products, and Transportation Equipment where the average values for the degree of persistence are 0.633, 0.714, and 0.701 respectively, the mean values for $\frac{\partial g_s(.)}{\partial \omega_{ijt}}$ range from 0.798 to 0.860. Similar results are found in most of the industries when looking at the 25th percentile of the distribution.

The last two columns of Table 1.9 report measures of uncertainty in production and productivity, respectively. Production uncertainty is measured as $\frac{Var(\epsilon_{ijt})}{Var(\omega_{ijt})}$; while uncertainty on productivity is defined as $\frac{Var(\xi_{ijt})}{Var(\omega_{ijt})}$. The ratio of the variance of the unobserved shock ϵ_{ijt} to the variance of productivity ω_{ijt} is similar across industries and is lower than 1 for most of the industries. This suggests that productivity is at least as important in explaining the variability in production as other unobserved factors embedded in ϵ_{ijt}.

However, there are industries such as Medical Instruments, Machinery and Equipment, Chemicals, and Electrical Machinery and Apparatus, where unobserved shocks to production ϵ_{ijt} account for a significantly larger fraction of the variability in firms' revenue. Finally, the ratio of the variance of the productivity innovation ξ_{ijt} to the variance of productivity ω_{ijt} is very similar across industries, ranging from 0.21 to 0.62, and indicating that the innovation to productivity ξ_{ijt} accounts for a large part of productivity.

To further explore the relationship between diversification decisions and productivity uncertainty, I study whether engaging in diversification activities affect the uncertainties linked to the productivity process, which would be absent if the firms did not diversify. In the model, the innovation to productivity ξ_{ijt} can be thought as a measure of the uncertainties inherent to productivity ω_{ijt} and diversification decisions. I construct a measure of uncertainty as the ratio between the variance of productivity innovation ξ_{ijt} and the variance of productivity ω_{ijt}.[47] In order to assess whether diversification activities affect business units' productivity uncertainty, I take the following two equations to the data:

$$\begin{aligned}
\ln\left(\frac{\xi_{ijt}^2}{Var(\omega_{ijt})}\right) &= x'_{ijt}\gamma + \varphi_1 1_{[\mathcal{J}_{it}-\mathcal{J}_{it-1}>0]} + \varphi_2 1_{[\mathcal{J}_{it}-\mathcal{J}_{it-1}<0]} + \mu_j + \lambda_t + \varepsilon_{ijt} \\
\ln\left(\frac{\xi_{ijt}^2}{Var(\omega_{ijt})}\right) &= x'_{ijt}\gamma + \varphi_1 1_{[div_{it}-div_{it-1}\geq 0.05]} + \varphi_2 1_{[div_{it}-div_{it-1}\leq -0.05]} + \mu_j + \lambda_t + \varepsilon_{ijt}
\end{aligned}$$

where x_{ijt} is a vector of control variables which includes a constant term, (log of) capital stock (as a proxy for business unit size), investment rate, and (log of) investment in R&D. μ_j and λ_t are business unit and year fixed effects, respectively. The first equation relates uncertainty levels to variations in the total number of business segments in which the firm

[47] I estimate the variance of productivity $Var(\omega_{ijt})$ separately for non-diversified and diversified firms.

is active. These are captured by two dummies representing increments and decrements in the total number of business units, respectively. The second equation relates uncertainty in productivity to changes in the diversification index. These are also captured by two dummies representing increments or decrements in the diversification index greater than 5% in absolute value. Finally ε_{ijt} is an error term.

Table 1.10 shows the results from estimating both models. We observe a positive impact of changes in the diversification level on the degree of uncertainty in all industries. The coefficients are statistically significant at conventional levels in most of the cases. The results suggest that the uncertainties inherent in the diversification process are economically significant, and that diversification indeed introduces further uncertainties into the productivity process. This might be linked to the success of the implementation, successful adoption, and integration of common resources or technologies across different units, etc.

Table 1.9. Uncertainty and Persistence

Industry	**Degree of Persistence**[a] **p25**	**Median**	**p75**	**Mean**	**Production Uncertainty**	**Productivity Uncertainty**
Food and Beverages	0.749	0.889	0.918	0.807	0.534	0.328
Textile, Apparel and Leather	0.812	0.906	0.959	0.860	0.167	0.300
Timber and Furniture	0.743	0.768	0.908	0.801	0.427	0.383
Paper and Printing	0.726	0.855	0.936	0.800	0.345	0.231
Chemicals	0.798	0.833	0.918	0.841	0.808	0.483
Pete Refining	0.512	0.628	0.793	0.633	0.445	0.425
Rubber and Misc Manuf. Industries	0.757	0.831	0.892	0.803	0.691	0.468
Stone, Clay, Glass and Concrete Products	0.780	0.881	0.948	0.845	0.068	0.248
Primary Metal Industries and Metal Products	0.685	0.723	0.777	0.714	0.521	0.621
Machinery and Equipment	0.790	0.855	0.913	0.827	1.039	0.318
Electrical Machinery and Apparatus	0.752	0.830	0.913	0.815	1.542	0.210
Transportation Equipment	0.624	0.746	0.816	0.701	0.670	0.605
Medical Instruments	0.760	0.816	0.854	0.798	0.922	0.480

Note: The table reports different moments to describe the degree of persistence and uncertainty in productivity and production. The degree of persistence is measured by $\frac{\partial g_s(.)}{\partial \omega_{ijt}}$. Production uncertainty is measured as $\frac{Var(\epsilon_{ijt})}{Var(\omega_{ijt})}$, while productivity uncertainty is defined as $\frac{Var(\xi_{ijt})}{Var(\omega_{ijt})}$.

[a] I trim observations below zero and above one.

Table 1.10. Productivity Uncertainty and Diversification

Industry	(1) $1_{[J_{it}>J_{it-1}]}$	(2) $1_{[J_{it}<J_{it-1}]}$	(3) $1_{[div_{it}-div_{it-1}\geq 0.05]}$	(4) $1_{[div_{it}-div_{it-1}\leq 0.05]}$	Obs.
Food and Beverages	2.0966***	1.3825***	0.9677***	1.0021***	2,183
	(0.2902)	(0.2341)	(0.2141)	(0.2024)	
Textile, Apparel and Leather	0.7730**	1.0897***	0.7505***	0.5662***	2,271
	(0.3635)	(0.2915)	(0.2368)	(0.2150)	
Timber and Furniture	0.2119	0.4539	0.4248*	0.9406***	1,624
	(0.4308)	(0.3261)	(0.2494)	(0.2371)	
Paper and Printing	1.9987***	2.0896***	0.7404***	0.9044***	2,680
	(0.2802)	(0.2653)	(0.1938)	(0.1751)	
Chemicals	1.2669***	1.0798***	0.5785***	0.6374***	4,055
	(0.2301)	(0.1797)	(0.1647)	(0.1399)	
Pete Refining	0.7533*	0.0421	0.1939	0.2126	492
	(0.4486)	(0.4222)	(0.3398)	(0.3495)	
Rubber and Misc Manuf. Industries	0.7087**	1.0818***	0.4039**	0.9386***	2,774
	(0.2819)	(0.2208)	(0.1833)	(0.1616)	
Stone, Clay, Glass and Concrete Products	2.1184***	0.6393**	1.1307***	0.6668***	1,036
	(0.3805)	(0.3025)	(0.2538)	(0.2231)	
Primary Metal Industries and Metal Products	1.1469***	0.4281***	0.6418***	0.4290***	4,484
	(0.2256)	(0.1584)	(0.1202)	(0.1091)	
Machinery and Equipment	1.7192***	1.6831***	0.4164***	1.0523***	6,625
	(0.1957)	(0.1693)	(0.1143)	(0.1084)	
Electrical Machinery and Apparatus	0.9281***	0.9277***	0.6508***	0.5823***	6,066
	(0.2361)	(0.1864)	(0.1450)	(0.1324)	
Transportation Equipment	0.5373**	0.5228***	0.2519*	0.4927***	2,376
	(0.2402)	(0.1900)	(0.1451)	(0.1355)	
Medical Instruments	1.1177***	1.6799***	0.6481***	0.9055***	4,211
	(0.3141)	(0.2501)	(0.1811)	(0.1605)	

Note: Columns (1) and (2) of the table report the results of a regression of productivity uncertainty at the business unit level, defined as $\ln(\frac{\xi^2_{ijt}}{Var(\omega_{ijt})})$, on dummies for expansion (i.e., $1_{[J_{it}>J_{it-1}]}$) and contraction (i.e., $1_{[J_{it}<J_{it-1}]}$) at the firm level (i.e., dummies for entry into new business units and exit from existing lines of business). Columns (3) and (4) report the results of a regression of productivity uncertainty at the business unit level on dummies for expansion (i.e., $1_{[div_{it}-div_{it-1}\geq 0.05]}$) and contraction (i.e., $1_{[div_{it}-div_{it-1}\leq 0.05]}$) at the firm level defined according to the diversification index div_{it}. Both regressions contain a vector of control variables which includes a constant term, (log of) capital stock (as a proxy for business unit size), investment rate, and (log of) investment in R&D, and business unit and year fixed effects. Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

1.5.3. Tests on the Expected Productivity Function $g_s(.)$

This section tests some of the assumptions made on the expected productivity function $g_s(.)$. One of the main assumptions made in this chapter is that firms' future productivity might react endogenously to past diversification in a flexible and complex way, whereby the effects of firm diversification on productivity might vary across the distribution of current productivity and past diversification level. In this section I test whether the data support this assumption or not. To do so, I first compare the estimated function $g_s(\omega_{ijt}, div_{it}, r_{it})$ to an alternative law of motion, in which expected future productivity is only a function of current productivity and R&D expenditures (i.e., $g_s(\omega_{ijt}, r_{it})$). Column (1) of Table 1.11 shows the results of this test. As we observe, the data reject the alternative assumption of the conditional expectation function $g_s(.)$ in almost all of the industries, thus ruling out the hypothesis in which we can exclude firms' past diversification level from $g_s(.)$.[48]

Additionally, I test for nonlinearities between current productivity ω_{ijt} and the vector div_{it}. To this end, I test whether the conditional expectation function $g_s(.)$ is separable in ω_{ijt} and div_{it}. Column (2) of Table 1.11 reports the results of the test. Separability in ω_{ijt} and div_{it} is rejected at the 10% level of significance in most of the industries.[49] These results indicate that the effects of firm diversification on future expected productivity depend on the current level of productivity, and that these interact in a complex way to affect future productivity. I will discuss in more detail the non-linear relationship between current productivity and diversification when interpreting the rate of return of

[48] I fail to reject the null hypothesis in Pete Refining and Stone, Clay, Glass, and Concrete Products. These results are likely associated with both the smaller number of observations and small number of diversified firms operating in these industries.

[49] As in the previous test, I fail to reject the null hypothesis in the following two industries: Pete Refining and Stone, Clay, Glass, and Concrete Products.

firm diversification. However, a natural question is whether current productivity and firm diversification are substitutes or complements on expected future productivity. To answer this, I compute $\frac{\partial^2 g_s(.)}{\partial \omega_{ijt} \partial div_{it}}$. Since this is a function of both ω_{ijt} and div_{it}, I look at the percentage of observations within each sector that are significantly positive (negative) at a 5% level, so that productivity and diversification are complements (substitutes) in the accumulation of productivity. While productivity and diversification are strategic substitutes for approximately half of the observations in industries 1, 8 and 11, I find strong evidence of complementarities in industries 2, 3, 4, 5, 9, 10, 12 and 13, suggesting that current productivity tends to reinforce the impact of diversification on future productivity.

Finally, I also test if expected future productivity depends only on the diversification status of the firm as opposed to the degree of firm diversification. The results are presented in column (3) of Table 1.11 (Extensive Margin). I fail to reject this restriction at the 10% level of significance in only three industries (Timber and Furniture, Chemicals, and Primary Metal Industries and Metal Products), meaning that the degree of firm diversification seems to be relevant for explaining the evolution and differences in productivity across firms.

Table 1.11. Tests on $g_s(.)$

Industry	**(1) Exogeneity Test F(16, df.)**	**(2) Separability Test F(5, df.)**	**(3) Extensive Margin χ^2(19)**	**df.**
Food and Beverages	8.567	10.809	57.954	2173
	(0.000)	(0.000)	(0.000)	
Textile, Apparel and Leather	6.468	10.086	61.827	2261
	(0.000)	(0.000)	(0.000)	
Timber and Furniture	2.448	3.481	20.901	1614
	(0.000)	(0.000)	(0.340)	
Paper and Printing	8.885	12.433	56.500	2670
	(0.000)	(0.000)	(0.000)	
Chemicals	2.272	3.396	23.755	4045
	(0.003)	(0.000)	(0.210)	
Pete Refining	0.827	1.130	56.071	482
	(0.650)	(0.350)	(0.000)	
Rubber and Misc Manuf. Industries	1.841	2.054	57.589	2764
	(0.002)	(0.070)	(0.000)	
Stone, Clay, Glass and Concrete Products	1.144	1.386	67.873	1026
	(0.310)	(0.230)	(0.000)	
Primary Metal Industries and Metal Products	9.093	13.667	26.106	4474
	(0.000)	(0.000)	(0.130)	
Machinery and Equipment	8.434	10.610	172.269	6615
	(0.000)	(0.000)	(0.000)	
Electrical Machinery and Apparatus	5.509	7.078	126.945	6056
	(0.000)	(0.000)	(0.000)	
Transportation Equipment	5.863	7.503	111.796	2366
	(0.000)	(0.000)	(0.000)	
Medical Instruments	5.781	7.159	58.756	4201
	(0.000)	(0.000)	(0.000)	

Note: The table reports the results of three different tests conducted to assess the assumptions made on the expected productivity function $g_s(.)$. The first column tests if firms' past diversification level div_{it} can be excluded from $g_s(.)$. The second column tests if the conditional expectation function $g_s(.)$ is separable in ω_{ijt} and div_{it}. Finally, column (3) tests if the conditional expectation function $g_s(.)$ is a function of the diversification status (i.e., diversified vs. non-diversified) rather than the actual diversification level as measured by div_{it}. p-values are in parentheses.

1.5.4. Capital Misallocation

In this section I turn attention to the relationship between diversification and misallocation of inputs. The literature on misallocation has focused on the marginal revenue product (MRP) of an input to study the degree of misallocation of resources within a firm or in an industry. In a static model with no frictions, profit maximization implies that the marginal revenue product of an input should be equal to its unit input cost. In the case of capital, this measure (MRPK) is given by:

$$MRPK_{ijt} = \frac{\partial Y_{ijt}}{\partial K_{ijt}} = (\beta_k + 2\beta_{kk}k_{ijt} + \beta_{mk}m_{ijt} + \beta_{lk}l_{ijt} + \beta_{mlk}m_{ijt}k_{ijt})\frac{Y_{ijt}}{K_{ijt}}$$

In a dynamic setting, when firms face different adjustment costs to capital, shocks to productivity should induce differences in the MRPK among firms.[50] In the absence of adjustment costs, producers could simply adjust their capital, leading to the equalization of MRPK across producers. The theory of internal capital markets is usually presented as one of the most important motives for diversification. Under this theory, a segment's assets can be used as collateral for obtaining funding for other segments, and cash flows generated by one segment may be used to subsidize investment projects in other divisions of the firm. This cross-subsidization can be efficient if it helps the firm to eliminate any cost associated with financial constraints or any cost of adjusting capital. Then, under the predictions of this theory, the MPRK of business units belonging to diversified firms should be less responsive to shocks to productivity. To test this mechanism, I run the following regression equation:[51]

$$\ln(MRPK_{ijt}) = \gamma_0 + \gamma_1\xi_{ijt} + \gamma_2\xi_{ijt}div_{it} + \gamma_3 k_{ijt} + \gamma_4\omega_{ijt-1} + \lambda_t + \lambda_s + \nu_{ijt}$$

[50] This point has been discussed by Asker, Collard-Wexler and De Loecker (2014).
[51] This regression equation is similar to the one fitted by Asker et al. (2014). In this paper the authors test whether differences in the innovation to productivity are associated with differences in MRPK, which would suggest the presence of adjustment costs or frictions to capital, preventing firms to adjust the stock of capital immediately upon receiving these productivity shocks.

where $\xi_{ijt} = \omega_{ijt} - g(\omega_{ijt-1}, div_{it-1})$ is the innovation to productivity, div_{it} is the (log) diversification index, k_{ijt} is logged capital stock, λ_t and λ_s are year and industry fixed effects, and ν_{ijt} is an error term.

From the one period to build assumption, the innovation to productivity ξ_{ijt} has not been observed when the firm makes its diversification decision div_{it} or investment decision about capital stock k_{ijt} at time $t-1$. I include business units' past productivity ω_{ijt-1} in order to compare units with the same productivity level at time $t-1$ and that are making the same investment decisions in physical capital. Then we ask whether business units' MRPK is different if they are hit by different productivity shocks, and whether these differences vary by the level of diversification. Under the predictions of a static model, coefficients γ_1 and γ_2 should be zero, since there should be no dispersion in MRPK as a function of the innovation to productivity. Under any cost of adjusting capital we expect γ_1 to be positive. Finally, under the internal capital markets hypothesis, the coefficient for the interaction between ξ_{it} and firm diversification should be negative, since the impact of shocks to productivity should be moderated for diversified firms.

Column (1) of Table 1.12 reports the results of the estimation. We observe a positive and statistically significant coefficient for γ_1, as predicted. Similarly, γ_2 is estimated to be negative and statistically significant at conventional levels of significance, confirming the predictions of the theory. The results thus confirm that the MRPK of business units of diversified firms are less responsive to productivity shocks, supporting the hypothesis that diversification helps to eliminate costs in the efficient allocation of inputs.

A dynamic setting in which firms face different adjustment costs to inputs and shocks to productivity also has implications in terms of industry measures. In particular, this setting predicts a positive relationship between productivity volatility, measured by the standard deviation of innovations to productivity (i.e., $std_{st}(\xi_{ijt})$), and MRPK dispersion $std_{st}(mrpk_{ijt})$, dispersion in the change of MRPK $std_{st}(\Delta mrpk_{ijt})$, and dispersion in the change of capital $std_{st}(\Delta k_{ijt})$, where all these variables are measured at the industry-year level and are proxies for the degree of static misallocation for the industry.[52] If the MRPK of business units belonging to diversified firms is less responsive to productivity shocks, then we should observe a lower correlation between productivity volatility and the degree of static misallocation at the industry level the higher the fraction of business units of diversified firms operating in the industry. To test this, I regress each of these static misallocation measures on productivity volatility, the interaction between productivity volatility and the fraction of diversified business units operating in the industry, and year fixed effects. The results are reported in columns (2) to (4) of Table 1.12 and confirm the predictions discussed above. More specifically, we observe that the correlation between productivity volatility and the measures of static misallocation decreases in the percentage of business units belonging to diversified firms operating in the industry

[52] See Asker et al. (2014) for further details about this.

Table 1.12. Diversification and Misallocation

	(1)	**(2)**	**(3)**	**(4)**
	Firm Level		Industry Level	
Variables	$log(mrpk_{ijt})$	$Std_{st}(\Delta mrpk_{ijt})$	$Std_{st}(\Delta k_{ijt})$	$Std_{st}(mrpk_{ijt})$
$Std_{st}(\xi_{ijt})$		1.1437	0.6601	0.7047
		(0.2040)	(0.1247)	(0.1135)
$Std_{st}(\xi_{ijt}) * (\%Div.Firms)$		-1.3994	-0.3366	-0.6453
		(0.3508)	(0.1819)	(0.1655)
ξ_{ijt}	0.2909			
	(0.0232)			
$\xi_{ijt} * div_{it}$	-0.0936			
	(0.0336)			
Year FE	Y	Y	Y	Y
Industry FE	Y	N	N	N
R^2	0.2446	0.2775	0.3279	0.3472

Note: Column (1) reports the coefficients of a regression of (log of) marginal revenue product of capital (i.e., log($mrpk_{ijt}$)) against the innovation to productivity ξ_{ijt} and the interaction of the innovation to productivity and the diversification level (i.e., $\xi_{ijt} \times div_{it}$). The regression includes as additional controls logged capital, past productivity (i.e., ω_{ijt-1}), and industry and year fixed effects. Columns (2) to (4) report the coefficients of a regression of three different measures of static misallocation at the industry level against productivity volatility $Std_{st}(\xi_{ijt})$ (defined as the standard deviation of the innovation to productivity in a given industry-year), the interaction between productivity volatility and the fraction of diversified business units operating in the industry, and year fixed effects. In column (2) the measure of static misallocation is represented by the standard deviation in the change of the marginal revenue product of capital (i.e., $Std_{st}(\Delta mrpk_{ijt})$). In column (3) the measure of static misallocation is represented by the standard deviation in the change of capital (i.e., $Std_{st}(\Delta k_{ijt})$), while in column (4) by the standard deviation in marginal revenue product of capital (i.e., $Std_{st}(mrpk_{ijt})$).

1.6. Diversification, R&D, and Productivity

The literature has emphasized the importance of studying the productivity- diversification relationship, while acknowledging that firms often simultaneously decide to diversify and invest substantially in R&D (see, for example, Jovanovic, 1993 for theoretical work related to this topic). The theoretical foundations for explaining this relationship between diversification and R&D expenditure usually rely on spillovers of knowledge among distinct production units. By considering a law of motion for expected future productivity which incorporates information not only about diversification but also R&D efforts, we can not only learn about the complementarity or spillovers between diversification and R&D investment, but it also allows us to separately identify the productivity effects of diversification when firms jointly invest in R&D and diversify.[53]

In the estimated model, I allow R&D expenditures r_{it} to affect future expected productivity differently as a function of a firm's diversification status. Additionally, I allow the coefficients associated with R&D investment to vary by type of business unit (i.e., core units and peripheral units).[54] This distinction is, of course, irrelevant for non-diversified firms. Note that in the above equation, expected future productivity of business unit j at firm i is affected by total expenditure (at the firm level) in R&D, r_{it}. Unfortunately, I do not observe expenditures in R&D at the business unit level. Although the empirical evidence suggests that most of R&D investment is conducted at the core unit, having information on R&D at the business unit level would allow us to distinguish spillovers

[53] The concern here is that if firms diversify while also engaging in other productivity-enhancing actions, such as investing in R&D, we might be overstating the effects of diversification on productivity.
[54] The core business unit is defined as the line of business which the firm reports as its main activity. It typically matches the unit in which the firm concentrates its activities (measured by either assets or sales).

across different line of business. Thus, we should interpret the estimates reported below as the direct effect of a business unit's own R&D expenditure plus spillovers effects coming from investments in R&D performed by other units.

Table 1.13 reports the estimated revenue elasticities with respect to R&D expenditure by industries for the full sample, and also differentiates the results for business units belonging to diversified firms and non-diversified firms. These elasticities are measured by $\frac{\partial g_s(.)}{\partial r_{it}}$, and can be interpreted as the return to R&D at the margin. There is a considerable amount of variation across industries and across production units within an industry. The average elasticities range from 0.004 to 0.06 across industries. The results are similar to previous findings in the literature (e.g., Doraszelski and Jaumandreu, 2013).

Table 1.13. Revenue Elasticities with respect to R&D

Industry	**All** Mean	**All** Median	**Non-diversified Firms** Mean	**Non-diversified Firms** Median	**Diversified Units** Mean	**Diversified Units** Median
Food and Beverages	0.0203	0.0115	0.0179	0.0109	0.0226	0.0123
Textile, Apparel and Leather	0.0099	0.0035	0.0158	0.0073	0.0019	0.0006
Timber and Furniture	0.0051	0.0017	0.0020	0.0009	0.0076	0.0032
Paper and Printing	0.0082	0.0038	0.0028	0.0010	0.0112	0.0065
Chemicals	0.0116	0.0048	0.0080	0.0021	0.0138	0.0073
Pete Refining	0.0613	0.0581	0.0488	0.0475	0.0654	0.0602
Rubber and Misc Manuf. Industries	0.0062	0.0010	0.0064	0.0016	0.0061	0.0006
Stone, Clay, Glass and Concrete Products	0.0092	0.0049	0.0001	0.0003	0.0123	0.0069
Primary Metal Industries and Metal Products	0.0090	0.0025	0.0047	0.0021	0.0107	0.0028
Machinery and Equipment	0.0075	0.0011	0.0070	0.0012	0.0080	0.0009
Electrical Machinery and Apparatus	0.0087	0.0015	0.0053	0.0011	0.0136	0.0024
Transportation Equipment	0.0140	0.0046	0.0100	0.0018	0.0155	0.0065
Medical Instruments	0.0048	0.0007	0.0020	0.0005	0.0087	0.0015

Note: The table reports the average and median revenue elasticity with respect to R&D expenditure. The revenue elasticity at the business unit level is computed as $\frac{\partial g_s(.)}{\partial r_{it}}$.

The estimated output elasticities with respect to R&D investment can be used to compute the gross rate of return to R&D. The gross firm-i return to R&D is described by:

$$GR_{it} = \frac{\partial \sum_{k>t} \sum_{j \in \mathcal{J}_{ik}} \delta^{k-t} E_t[\tilde{Y}_{ijk}]}{\partial R_{it}}$$

With some algebra, and assuming for simplicity that expected revenue for firm i is represented by value added at period $t+1$ levels, the above equation becomes,

$$GR_{it} = \sum_{j \in \mathcal{J}_{it}} \frac{\partial E_t[\omega_{ijt+1}]}{\partial r_{it}} \frac{VA_{ijt+1}}{R_{it}}$$

where VA_{ijt+1} represents value added of business unit j, belonging to firm i, at time $t+1$.[55] Intuitively, multiplying the revenue elasticity with respect to R&D by a measure of expected value (value added in this case) gives us the rent that the firm can expect from this investment at the time it makes its decisions. Then, dividing this by R&D expenditures R_{it} gives an estimate of the gross rate of return (GR_{it}), or dollars obtained by spending one dollar on R&D.

Table 1.14 shows the results for the average gross return to R&D for the full sample, and across industries. The average firm-wide gross return to R&D is estimated at around 0.20 dollars for non-diversified firms, and 0.73 dollars for diversified firms. This implies an average firm-wide gross return to R&D 3.5 times higher for diversified firms than non-diversified firms.

[55] I follow Doraszelski and Jaumandreu (2013) in using value added instead of revenue, since value added is closer to profits than gross revenue.

Table 1.14. Average Gross Returns to R&D

Industry	**Gross Return** Non-diversified	Diversified
All	0.2062	0.7275
Food and Beverages	0.8378	1.5913
Textile, Apparel and Leather	0.2130	0.6662
Timber and Furniture	0.2710	0.7634
Paper and Printing	0.1727	0.4862
Chemicals	0.3605	0.5437
Pete Refining	0.0258	0.3666
Rubber and Misc Manuf. Industries	0.7512	0.9118
Stone, Clay, Glass and Concrete Products	0.0266	0.9491
Primary Metal Industries and Metal Products	0.1173	0.8045
Machinery and Equipment	0.1877	0.4598
Electrical Machinery and Apparatus	0.1520	0.4334
Transportation Equipment	0.4799	0.7030
Medical Instruments	0.0573	0.2959

Note: The table shows the average gross return to R&D expenditure for diversified and non-diversified firms. Average gross returns to R&D by industry are computed after classifying diversified firms by their main industry. Gross return to R&D at the firm level is calculated according to $\sum_{j \in \mathcal{J}_{it}} \frac{\partial g_s(.)}{\partial r_{it}} \frac{Y_{ijt+1}}{R_{it}}$.

1.7. Conclusions

This chapter estimates a dynamic structural model that describes how a firm's diversification level and R&D expenditures endogenously affect the future productivity trajectories of a firm's business units. The estimation strategy allows for a general process for productivity, whereby the level of diversification and R&D expenditures are flexibly allowed to affect a business unit's productivity. This flexible approach allows the effects of diversification to be heterogeneous across producers. I estimate the model using data for U.S. manufacturing business units from the period 1980-1998.

There are five broad conclusions I draw about the productivity and the sources of productivity evolution among the producers studied in this chapter. First, the distribution of expected productivity for business units belonging to diversified firms first order stochastically dominates the distribution of non-diversified firms. Moreover, I find that business units belonging to diversified firms grow faster than non-diversified firms, suggesting that those mechanisms in place that affect firm productivity when firms diversify might be a source of productivity growth. Second, business unit productivity evolves endogenously in response to the firm's diversification level or investment in R&D. The relationship between future expected productivity, current productivity, diversification and R&D investment is complex and characterized by non-linearities. Relative to non-diversified firms, diversification raises, on average, future expected productivity at the business unit level by 4%. However, I find that the productivity effects of diversification vary considerably, with significant heterogeneity across industries and firms. Additionally, the average revenue elasticity with respect to R&D expenditure ranges between 0.005 and 0.061 depending on the industry under consideration. Third, the marginal benefits of firm diversification typically increase with the business unit's productivity. This non-linearity typically takes the form of complementarities between current diversification level and current productivity: high-productivity business units exhibit large benefits from diversification. Fourth, I find that the average firm-wide gross return to R&D is 0.20 dollars for non-diversified firms and 0.73 dollars for diversified firms. This implies an average firm-wide gross return to R&D 3.5 times higher for diversified firms than non-diversified firms. The results are consistent with the hypothesis that knowledge spillovers among distinct activities might constitute the drivers of productivity growth among diversified firms. Finally, I use the estimates of the model to study the relationship between static input misallocation and diversification both at the business-unit and industry level. The results provide evidence consistent with the internal market capital hypothesis that firm diversification helps to reduce adjustment and transaction costs related to input usage, helping consequently in the allocation of inputs within the firm.

Overall, the empirical findings emphasize the important role of firm diversification in shaping a firm's productivity and in determining productivity growth among manufacturing producers. Although the estimation strategy used in this chapter allows us to flexibly recover the productivity effects of firm diversification at the business-unit level, it does not allow us to learn about the exact theoretical and underlying mechanisms whereby firm diversification is affecting productivity. This raises the important issue of the specific sources behind the productivity effects associated with firm diversification, a topic on which I provide some suggestive evidence (e.g., R&D investment, input allocation), but otherwise leave open for future research. If more detailed data were available on the diversification structure of the firm, and particularly on how this diversification strategy maps into the different theoretical mechanisms discussed in the introduction, then it would be possible to distinguish the return to the various motives for firm diversification.

CHAPTER 2

Location Choice and Product Differentiation under a Threat of Entry

2.1. Introduction

Understanding how firms compete along dimensions other than price is a topic that has recently been the focus of attention, given its relevance from a policy point of view.[1] One question that has received considerable attention in the theoretical literature is how the level of competition in a market, firm entry into a market as well as a threat of entry affect the location choice of stores in some characteristic space of the products. Product differentiation through location allows firms to better serve consumers' differing preferences and to acquire a degree of local market power. Questions include how market power and profits of firms depend on the location of its outlets relative to the location of competitors, and how important the location differentiation is in explaining market power. Despite the considerable theoretical debate and the importance of understanding the strategic effects of product location choices within a market, this topic has received little attention in empirical work. Most of the existing literature has relied on entry models limited to study the tradeoff between market size and intensity of competition

[1] There has been a recent explosion of research on product repositioning and differentiated product competition, where product characteristics are allowed to react to market structure and competition. Some papers in this literature include Mazzeo (2002), Seim (2006), Fan (2013), Draganska, Mazzeo and Seim (2009), Eizenberg (2014), Nosko (2014), Wollmann (2015), or Sweeting (2013) among others.

while allowing for product differentiation, leaving the question of the effects of a threat of entry on the repositioning of a product virtually unanswered.

This chapter studies how incumbents respond in terms of location choices to a threat of entry by a competitor. The empirical literature has focused on other kinds of preemptive actions, such as price cuts and capacity investment (e.g., Goolsbee and Syverson, 2008; Gedge, Roberts and Sweeting, 2014), strategic alliances (e.g., Goetz and Shapiro, 2012), advertising to influence the size of the market (e.g., Ellison and Ellison, 2011), and responses of incumbents airlines in on-time performance measures (e.g., Prince and Simon, 2015).[2] [3] To the best of my knowledge, there has not been an attempt to empirically detect preemptive motives behind the location choices of incumbents in terms of the space of possible attributes of the product.

I study this question in the context of the airline industry, by analyzing how incumbent airlines adjust their flight schedules (i.e., location of departure times for non-stop flights) in response to a threat of entry by Southwest Airlines. I examine this issue within the framework of a horizontal product differentiation and spatial model, where the space on which airlines locate their flights is a circle (i.e., 24 hour clock). Passengers have a distribution of most preferred departure times (MPDT) around the clock, and airlines set their flight schedules (or departure times) taking into account this distribution and the schedules of competitors. Then, passengers not only obtain utility from the price paid

[2] Airlines' measures of on-time performance can be interpreted as a dimension of product quality for air travel, and thus, as a vertically differentiated feature of the product.

[3] Snider (2009) also studies price cuts and capacity investment as an entry deterrence strategy in the market Dallas-Fort Worth to Wichita, one of the markets in which the Department of Justice alleged predation against American Airlines in 2000. Unlike other papers that look at preemptive actions, Snider (2009) studies incumbent responses when the competitor enters the market.

and vertical attributes of product, but also from the schedule delay, which is the difference between the passengers' most preferred departure time and the flights' departure times.

Theoretical models of spatial product differentiation stress two opposite incentives that firms face when deciding their locations. On the one hand, firms have an incentive to minimize differentiation in order to steal business or customers from competitors. On the other hand, there is an incentive to maximize differentiation in order to reduce price competition. Different assumptions on the elasticity of demand, number of stores or outlets to be located, distribution of consumers around the space, or nature of transport costs (i.e., schedule delay costs in this case) can cause one or the other of these forces to dominate, resulting in a tendency towards either minimal or maximal differentiation.[4] The empirical evidence on tests of theoretical models of spatial product differentiation is scarce. A notable exception is Borenstein and Netz (1999) who study the effects of competition in location patterns for the airline industry.[5] They analyze, for example, the difference in the locational pattern between a market characterized by two firms each locating three outlets, and a market characterized by six firms each locating one outlet. They find a negative effect of competition on differentiation at the market level. However, reductions in exogenous scheduling constraints increase differentiation, implying that firms may be differentiating their products where possible to reduce price competition.[6]

[4] See Borenstein and Netz (1999) or Loertscher and Muehlheusser (2011) for a survey on theoretical models of spatial product differentiation.

[5] Examples of other papers that study this topic are Mazzeo (2002) or Seim (2006).

[6] As mentioned by Borenstein and Netz (1999), the airline industry is a complicated setting for testing the predictions of the theoretical models, since many of the assumptions of these models do not hold in this industry. More specifically, airlines not only compete on schedules and prices, but also on other dimensions such as quality of their products or the routing network. In addition, passengers are distributed non-uniformly in their most preferred departure times and face schedule delay costs which vary over consumers. Lastly, airline scheduling decisions are the solution of a problem where each flight is integrated into the network. In this sense, airlines attempt to schedule flight departures and arrivals into short periods of time in order to facilitate connections. By doing this, they must trade off benefits from

In this chapter I examine a different question, not only because I look at the effects of a threat of entry on incumbent responses, but also because I look at the location pattern responses from the incumbent perspective, instead of looking at the location patterns at the market level (i.e., characterization of the distribution of all departure times in the market). The chapter contributes to and builds on the literature on airline competition. Despite the importance of understanding the strategic effects of product positioning within a market, such as the departure times of flights in a market, most of this literature has focused on other sources of market power in the industry (such as an airline's scale of operation at an airport), or the effects of entry on market outcomes after entry occurs.[7]

In addition, the chapter provides an empirical setting for testing the theoretical work on strategic entry deterrence and accommodation linked to location choices, which typically offer a rationale for preemptive action. This theoretical work includes Hay (1976), Prescott and Visscher (1977), and Schmalensee (1978), whose "proliferation strategy" stories indicate that a threat of entry might induce incumbent firms to produce a larger amount of products than they would otherwise. By crowding the space of possible attributes of the product, this strategy has the effect of forcing out potential entrants.

more convenient connections against congestion costs and revenue losses from locating around times with less dense demand.

[7] The exceptions are Goolsbee and Syverson (2008), Goetz and Shapiro (2012), and Prince and Simon (2015). Examples of papers on the airline competition literature include Borenstein (1989), Reiss and Spiller (1989), Borenstein (1991), Berry (1990), Berry (1992), Peters (2006), Ciliberto and Tamer (2009), Benkard, Bodoh-Creed and Lazarev (2010), Aguirregabiria and Ho (2012), Ciliberto, Murry and Tamer (2015), or Li, Mazur, Roberts and Sweeting (2016) among others.

Bonanno (1987) shows that entry deterrence need not be achieved through product proliferation, and in some cases, the incumbent firm resorts to an entry deterring stage based on location choice (or product specification strategy) rather than product proliferation.[8]

To answer the question of interest, I follow an empirical strategy similar to the one used by Goolsbee and Syverson (2008), who previously studied incumbent airlines responses when Southwest threatens entry into a market. They define as an exogenous threat of entry situations where Southwest begins operating in the second endpoint airport of a market (i.e., directional airport pair), but before it starts flying non-stop flights in the market itself. Using a within market regression model of an airline's schedule differentiation decision over time, I look at how the differentiation in departure times for non-stop flights of an incumbent airline is affected when Southwest threatens entry. I focus my analysis on the markets between the 93 airports out of which Southwest operated flights at any point between January, 1993 and November, 2016.

Goolsbee and Syverson (2008) show that Southwest presence at both endpoint airports of a market is a strong predictor of Southwest entering the market with non-stop flights in the future. This allows us to identify preemptive actions by measuring how incumbents respond to Southwest presence at both endpoints of the market. In this particular case, since Southwest is likely to enter the market with non-stop flights in the near future, the incumbent may change the degree of differentiation in departure times as an attempt to either deter or accommodate entry. For example, as an attempt to deter entry, an incumbent might change the degree of product differentiation by concentrating its flights

[8] Other papers that offer a rationale for preemptive action in decisions other than location choices are Dixit's (1979) capacity commitment model, Spence's (1981) strategic learning-by-doing model, Milgrom and Roberts' (1982) cost-signaling model, Aghion and Bolton's (1987) long-term contracting model, and Klemperer's (1987) and Farrell and Klemperer's (2007) switching costs model.

around peaks of demand or around times when there is an expectation that Southwest will place its flights. Conversely, if there is an expectation that Southwest will enter the market no matter what, the incumbent might respond by increasing the degree of differentiation in departure times as an attempt to soften price competition when entry takes place. In any case, the identification strategy is based on the fact that there is little reason to expect demand or cost driven motives for re-scheduling of flights to be any stronger or weaker in the face of such a threat. In other words, if revenue gains or cost savings are to be had by changing the schedule, then incumbents should be re-scheduling their flights regardless of the presence or absence of threats from Southwest, which do not affect these variables. Then, any preemptive action in response to a threat must be a strategic response.

My main set of results indicate that incumbent airlines respond to the threat of entry by increasing the degree of differentiation in departure times when Southwest threatens a market. My estimates also show that when a carrier is threatened in a market by Southwest, both the incumbent's range in departure times (i.e., difference in minutes between the last and first flight of the day) and the incumbent's interquartile range of the distribution of departure times increase. I do not find evidence of incumbents trying to schedule their flight closer to the peaks of demand.

In addition, I analyze heterogeneities on incumbent responses by characteristics of the market and the incumbent. In particular, I study incumbent responses by dividing the sample either according to market share levels or by whether the flight departs from a hub or arrives to a hub. I find that higher market share is a strong determinant of the strength of the carrier's response to a threat of entry by Southwest. The response in terms of product differentiation is more pronounced when the incumbent has higher market share. Hub at a destination airport (as opposed to flights departing from a hub) is also a strong determinant of the incumbent's response.

I also present evidence on the explanation for these preemptive actions. Consistent with a deterrence motive, I find that in large markets where Southwest's entry is guaranteed, and consequently entry deterrence is not possible, incumbents do not appear to change the degree of product differentiation. Similarly, I do not find evidence of incumbents changing their degree of product differentiation in those markets where Southwest begins non-stop service between two endpoint airports of the market either in the same or the following month that it starts operating in the second endpoint airport (i.e., instances where entry is likely to be preannounced). Finally, and also consistent with the deterrence motive, I find suggestive evidence of incumbents placing their flights closer to times when there is an expectation that Southwest will schedule its departures.

The chapter is organized as follows. Section 2.2 describes the airline scheduling decision problem. It also introduces some terminology related to the schedule development that is useful for the remaining sections of the chapter. Section 2.3 describes the data and some summary statistics. The estimation and identification strategies are presented in Section 2.4. Section 2.5 discusses the main results, and Section 2.6 presents evidence on the explanation for the preemptive actions. Finally, Section 2.7 concludes.

2.2. The Scheduling Decision Problem

Airlines compete for passengers and market share based on the price charged, the quality of service (e.g., airport and in-flight service amenities), products offered (e.g., restrictions on discount fare products), and other dimensions such as the frequency of service and departure schedule on each route served. The airline scheduling development process is a component of an airline's strategic plan that involves decisions on frequency plans, timetable development, and other elements such as fleet assignment and the aircraft rotation planning.[9] The frequency of service is usually established first. Decisions are made a year or more in advance, and are based on the routes to be flown (i.e., airline's network) and fleet capabilities. Timetables and aircraft rotations are decided between 2 and 6 months in advance, and after frequency decisions have been made. The process typically continues with final revisions until the flight departs.[10]

Frequency of flights on a route is typically driven by demand forecasts and competition. It involves not only estimates of total demand between origin and destination cities, but also of the potential for additional traffic and profits from connecting flights. It also comprises estimates of the expected market share on the route, determined to a great extent by frequency share relative to competitors.[11] The number of departures, as well as

[9] Schedule development is one of the parts of an airline's strategic plan. The airline economics literature usually classifies the airlines' planning and strategic decisions into five different components of interacting decisions: 1) fleet planning; 2) network and route planning; 3) schedule development; 4) pricing; and 5) revenue management. The first three are considered long run strategic decisions, since they typically require a long lead time before implementation as well as a considerable investment. Additionally, they are expected to have a significant impact on the configuration of the airline in the long run. Examples of these include fleet sizing (i.e., what aircraft to acquire/retire, when and how many of them); the type of network structure to operate (i.e., hub and spoke system or point to point), hub locations and city-pairs to be served; and how often, at what times and with which aircraft to operate on each route. The last two components, pricing and revenue management, are usually decided or adjusted in a daily basis, with the objective of maximizing airlines' revenue. They involve decisions on prices as well as inventory control for each different fare type. See Barnhart (2009), Belobaba (2009) or Jacobs, Garrow, Lohatepanont, Koppelman, Coldren and Purnomo (2012) for an exhaustive discussion of the airline planning and scheduling process.

[10] Barnhart (2009), Belobaba (2009) and Jacobs et al. (2012) provide a comprehensive discussion of the airline scheduling decision problem.

[11] The airline economics and transportation economics literature recognizes that the frequency of departures on a route improves the "convenience" of air travel for passengers, which in turn increases market share in the route. This relationship is usually known as the "S-curve" effect (see for instance Wei and

aircraft size decisions, are also affected by "load consolidation" (i.e., consolidation on the ratio between passengers and seats). The goal of load consolidation is easier to achieve when airlines operate a hub and spoke network, since it allows them to operate higher frequency and/or larger aircraft, given that a single flight can provide service to several origin-destination markets at the same time.

After choosing a given number of departures on a each route, airlines define a specific timetable of flight departures. One of the goals is to provide departures at peak times (usually early morning and late afternoon) that are most attractive to a larger proportion of travelers in many markets. Although proximity to passengers' most preferred travel times is one of the primary goals when defining a timetable of flight departures, airlines usually take into account, and trade off, other factors that affect demand for air travel. One of these factors is represented by airlines' strategic incentives in the selection of departure times in response to competitors times on the same route. In particular, airlines weigh two opposite forces when choosing location times: locate closer to competitor times for business stealing or further apart to create differentiation and weaken price competition. Borenstein and Netz (1999) study the relationship between competition in a market and the degree of product differentiation in departure times. They find that reductions in exogenous scheduling constraints increase differentiation, implying that firms may be differentiating their products where possible to soften price competition.

Hansen, 2005; or Hansen and Liu, 2015). In particular, higher frequency reduces schedule displacement or wait time between flights, reducing thus travel inconvenience. This is specially important for capturing time sensitive business travelers. Even though it is much more important in short-haul markets than for long-haul routes where actual flight time dominates wait time, the literature indicates that in some cases it can be as important as path quality (e.g., non-stop service vs. one-stop service).

Air carriers also select schedules in order to enable one-stop city-pair market service by creating potential connections.[12] The value or quality of these connections is usually described by the layover time as well as the itinerary distance relative to the non-stop distance between the origin and destination airports. To achieve this goal, airlines seek to coordinate connections at their hubs at a few points in time by scheduling their flights into periods of time which comprise a high number of arrivals and departures, something denominated as banks. Figure 2.1 shows departures and arrival banks for American Airlines at the Dallas- Fort Worth airport, where American holds one of its hubs. We observe how departure banks follow arrival banks in order to facilitate connections with layover times as short as possible.

The network benefits associated with the facilitation of connections (or the hub and spoke system) come, however, at the costs of rising marginal congestion costs due to more traffic, as well as longer connecting times and greater delays. Hub carriers want to maximize the number of possible connecting markets for passengers, but also want to minimize operational costs related to congestion and passengers' travel time spent on congestion delays or layover times. Thus, they must trade off the benefits from scheduling banks of flights against all costs associated with congestion. Although hub airlines can partially offset the increased congestion by smoothing scheduled flight arrival times, it comes at the expense of increasing the length of connections for some passengers (potentially decreasing profits). Mayer and Sinai (2003a) analyze the two commonly mentioned factors that might explain air traffic congestion: network benefits due to scheduling bank

[12] Domestic flights in the U.S. are required a minimum time for connection. Additionally, the maximum connection time for two domestic flights to be eligible as a connection in a single ticket is 4 hours.

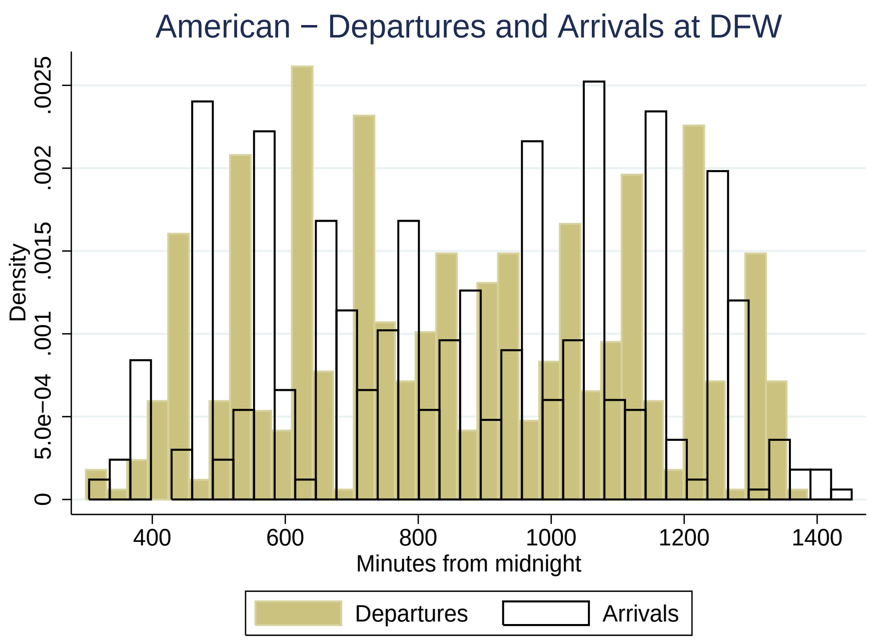

Figure 2.1. American Airlines - Arrivals and Departures at Dallas-Fort Worth.
Notes: The figure shows, for October 5th 2015, the distribution of arrivals and departures of American Airlines (AA) at Dallas-Fort Worth (DFW). Data come from the On Time Performance database (OTP).

of flights and congestion externalities.[13] They find that although both factors impact congestion, the first effect dominates empirically, implying that hub carriers incur most

[13] The congestion externality hypothesis, also known as the tragedy of the commons, states that congestion occurs because airlines schedule flights without internalizing the true marginal cost of adding a flight, which leads to congestion at airports, and consequently to flight delays and higher travel time for other airlines. This is consistent with the fact that most airports in the U.S. allow unlimited landings and takeoffs. A few exceptions to this in the United States are slot controlled airports, where airlines hold slots or permissions on the number of takeoffs and landings that the carrier can schedule over a given time period. To schedule a commercial flight between two airports in non-slot controlled airports, air carriers only need to pay user and landing fees and to have access to gates and other airport (on-ground) services. Access to runway, either for arrivals or departures, is allocated by air traffic controllers according to a first-come, first-serve basis. Thus, flights obtain runway access by queuing on the airport's taxiways or airspace, and as a consequence, any flight is subject to the possibility of delay for those periods of the day in which scheduled demand exceeds runway capacity. See Odoni (2009) for additional details on this.

of the additional travel time and congestion costs from hubbing.[14] Daniel (1995), Daniel and Harback (2008) and Molnar (2013) study other reasons why an airline may find it profitable to schedule the departure and arrival of flights in short periods of time. In particular, these authors analyze the case in which an airline may find it profitable to schedule flights at a hub airport in a way that causes runway congestion if this action deters competitor entry. This airline strategy can be profitable to a carrier by deterring competitor entry by raising their costs, allowing the airline to preserve market power at the hub airport.

There are other sets of factors that airlines take into account when scheduling flights. One of them is the cannibalization of demand for other flights in the airline's route or network that serve the same city-pairs. Others are related to schedule development constraints such as minimum turnaround times (i.e., minimum time required to clean and refuel the plane), time zone differences that set limits in feasible departure times, airport

[14] It seems to be the case that the benefits created by tighter connections outweigh the cost generated by higher congestion. Anecdotal evidence suggests the same outcome. For example, American Airlines depeaked its Chicago hub in 2002, and applied later the same strategy to its remaining hubs. The depeaking of its hubs, known in the airline industry as "rolling the hub", consisted in spreading out operations and lengthening of layover times with the goal of saving costs and raising profits by reducing congestion and improving operational performance. Delta and United Airlines also followed a depeaking strategy of their hubs after American's adoption of rolling hubs. In recent years, however, there has been a reversal of this trend, where network carriers have mostly rebanked their hubs. The explanation for this phenomenon has to do with the fact that in the early 2000's airlines needed a different business model. Air carriers were struggling financially and cost reduction in the industry was critical. Moreover, the high level of competition meant that there was less incentive to schedule flights into periods of time which comprise a high number of arrivals and departures, since airlines had less pricing power to extract fare premiums for shorter connections. Nowadays, the situation is different. There is less competition and air carriers have more pricing power, being worth to rebank hubs accepting the resulting higher costs of congestion and lower asset utilization. Managers in the industry have stated that although the depeaking strategy has lowered operating costs, the lost revenue outweighed the savings, with the revenue losses apparently attributed to the lower number and timeliness of possible connections. See Brueckner and Lin (2015) for additional details on this.

slot times and noise curfews that limit scheduling flexibility, or crew scheduling and routine maintenance requirements. These constraints, and the consequent schedule choice, affect airlines' operational costs since they determine the extent of efficient utilization of fleet, crew and ground installations.

Finally, any flight flying non-stop in a given route has not only a departure time associated with it, but also an arrival time. Airlines schedule arrival times to include a schedule buffer in excess of the minimum time required to move the aircraft from gate to gate in standard weather conditions and in the absence of congestion. This schedule buffer is aimed to control for runway or airspace congestion, or any other sources of delay (such as expected weather conditions or mechanical problems). Both high values and low values of the schedule buffer are costly for airlines. Pilots are paid for the maximum of scheduled time and the duration of a flight from gate to gate. Then, higher flight times increase airlines operation costs. Additionally, since higher schedule buffer times increase flight time, it reduces aircraft productivity and potentially passenger demand, since longer flight times are supposed to decrease passengers' utility from air travel. On the other hand, short buffer times leaves little room for dealing with any unexpected problems, such as mechanical problems or weather delays. This decreases airlines' profits to the extent that flight delays reduce demand. In practice, the empirical evidence suggests that airlines choose scheduled travel times which are very close to the minimum allowed under federal regulations. The likeliest explanations for this behavior are labor cost minimization at passengers' expenses, and airlines trying to maintain greater aircraft utilization.[15]

[15] These are findings reported by Mayer and Sinai (2003b). See Mayer and Sinai (2003b) for additional details about this.

2.3. Data

The goal of this chapter is to empirically test whether the threats of entry in given markets are determinants of airline's flight location decisions and differentiation in departure times decisions. To study this, it is necessary to measure both location decisions and threats of entry with the data. The data come from two main sources. Information on scheduled departure and arrival times comes from the On Time Performance (OTP) database, which contains domestic airline segment data. Certificated U.S. air carriers, that account for at least one percent of domestic scheduled passenger revenues, report monthly air carrier scheduled and actual arrival and departure times for flights. These data also provide information on the number of scheduled and actual departures, departure and arrival delays, origin and destination airports, canceled or diverted flights, taxi-out and taxi-in times, air time, and non-stop distance between airports. These data are collected daily and span from the first month of 1993 to November of 2016. I restrict the data for my analysis to Mondays.

Information on capacity (i.e., available seats), enplaned passengers, load factors (i.e., ratio of enplaned passengers to available seats), market presence (e.g., number of destinations served out from an airport and number of total departures performed from an airport), and airport entry decisions come from the Air Carrier Statistics (T-100 Domestic Segment) database. These data are collected monthly and span from the first month of 1993 to November of 2016. Both sources of data are maintained and published by the U.S. Department of Transportation (DOT).

Table 2.1 reports summary statistics of the data on scheduling decisions, for all Mondays of 2015. In column (1) I show information for the whole sample, while in columns (2) to (5) I report the same information for each of the four main airlines: American (AA), United (UA), Delta (DL), and Southwest (WN). We observe that the mean departure time locates at around 13:30pm for the pooled sample, while the mean value for the arrival time is 15:10pm. Since the distribution of departure and arrival times is usually not uni-modal, the mean does not provide rich information about it. Figure 2.2 plot the distribution of arrival and departure times for all airlines in the sample. Both distributions exhibit several peaks around the clock. We observe that the distribution of departure times contains more mass around early times in the day than the distribution of arrival times. The opposite is true for late times in the day. Figures B.1 to B.4 in Appendix B.1 plot the distribution of departure times around the clock for each of the big four airlines (i.e., American, United, Delta, and Southwest).

Table 2.1 also shows information on aircraft utilization. Southwest airlines is, among the big four airlines, the one that reports (on average) the lowest scheduled and actual flight times. The typical flight duration for Southwest is of 2 hours. All network carriers report longer average flight times, which possibly reflects the selection of routes that they fly, with higher non-stop distances. Additionally, we observe that Southwest is the airline with higher aircraft utilization among the four. In a typical day, the average aircraft employed by Southwest flies for approximately 670 minutes, performs 6 departures, spends around 43 minutes on the ground before departing again, and its flight duration contains only 22 minutes in excess of the minimum impeded time. These numbers differ considerably from those exhibited by network carriers, which display lower aircraft utilization. This is consistent with the empirical evidence reporting higher productivity levels for Southwest compared to major airlines.

Table 2.1. Descriptive Statistics

Variable	(1) **All**	(2) **American**	(3) **Delta**	(4) **United**	(5) **Southwest**
Departure Time	807.950	795.382	811.190	798.612	808.341
	(292.575)	(296.903)	(292.787)	(296.949)	(292.652)
Arrival Time	907.166	917.167	919.581	902.917	902.697
	(306.306)	(307.822)	(297.881)	(323.008)	(315.332)
Scheduled Flight Time	141.034	170.988	147.052	197.939	126.425
	(74.898)	(77.581)	(73.922)	(88.392)	(57.312)
Actual Flight Time	136.559	165.666	140.023	189.409	120.489
	(73.935)	(77.308)	(73.198)	(87.593)	(55.678)
Aircraft Use	586.373	549.006	576.361	582.838	671.759
	(220.087)	(232.977)	(216.069)	(248.415)	(162.231)
Departures per Aircraft	5.290	4.070	4.842	3.642	6.162
	(1.959)	(1.482)	(1.538)	(1.207)	(1.519)
Turn around Times	61.191	77.311	66.978	77.544	42.758
	(77.179)	(93.822)	(83.027)	(92.909)	(42.662)
Buffer Time	25.612	30.687	28.137	34.397	22.040
	(10.828)	(11.216)	(10.392)	(10.850)	(9.282)

Note: The table reports the mean and standard deviation (in parentheses) of variables characterizing scheduling decisions for all Mondays of 2015. All variables except "Departures per Aircraft" are measured in minutes. Departure and Arrival Times are measured in minutes from midnight. Data come from the On Time Performance database (OTP).

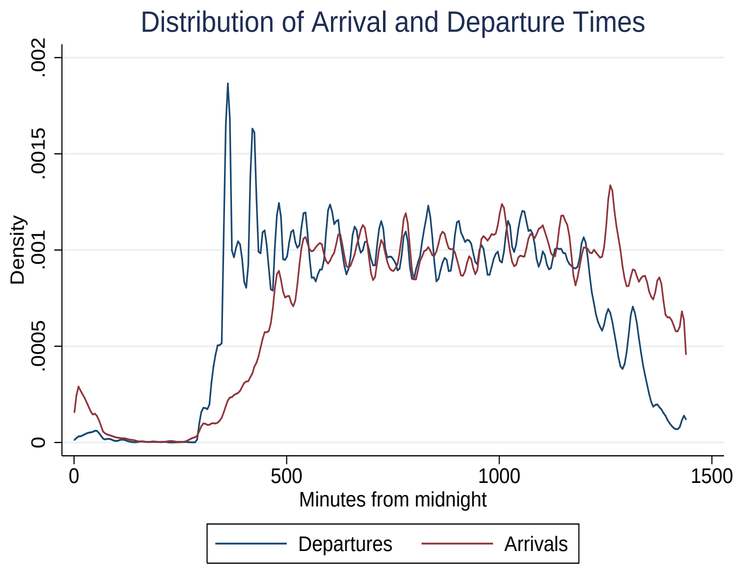

Figure 2.2. Distribution of Scheduled Arrival and Departure Times.
Notes: The figure shows, for all Mondays of 2015, the distribution of arrival and departure times, measured in minutes from midnight. Data come from the On Time Performance database (OTP).

To select the sample for studying incumbent responses in location times when Southwest threatens entry, I restrict the sample to those markets between the 93 airports out of which Southwest operated flights at any point between January, 1993 and November, 2016. A market in this case, is defined as a directional trip between an origin and destination airport. This definition is the same as in Borenstein (1989), Ciliberto and Tamer (2009) or Berry and Jia (2010); and similar to the ones used by Berry (1992), Berry, Carnall and Spiller (1996), or Aguirregabiria and Ho (2012), with the only difference that they consider city-pairs instead of airport-pairs.[16] A product, in a given market, is defined

[16] Goolsbee and Syverson (2008) define a market as a non-directional airport pair. In the current setting, the directionality of the market matters, since several factors which depend on the direction of travel

as a combination of airline and departure time. I only look at those products offered by incumbents airlines that comprise non-stop flights. Figure 2.3 shows the evolution over time in the number of airports in which Southwest established presence.

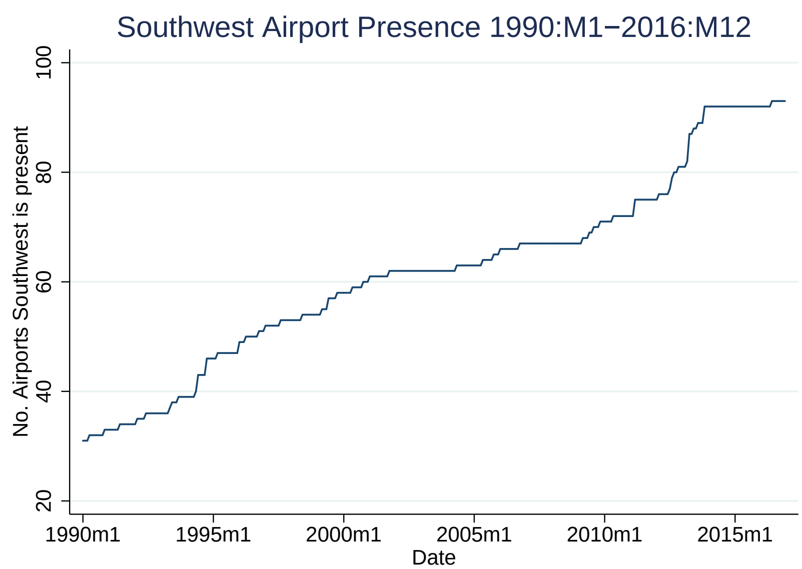

Figure 2.3. Airport Presence Over Time - Southwest Airlines.
Notes: The figure shows, for the period 1990:M1-2016:M11, the evolution over time in the number of airports in which Southwest Airlines (WN) established presence. Data come from the Air Carrier Statistics (T-100 Domestic Segment).

The empirical strategy follows closely the one used by Goolsbee and Syverson (2008). For each market in the sample, I look at incumbents' location responses once that Southwest begins operating in the second endpoint airport of a market (i.e., threatens entry), but before it starts flying non-stop flights in the market itself.[17] I capture these responses

affect the scheduling decision problem. Examples include time zones, hub or airport presence status, or airport regulations on take-offs and landings such as noise curfews, among others.

[17] Note that this definition for a threat of entry is only appropriate for low cost carriers, due to the way in which these airlines are willing to fly routes between two non-hub airports. In fact, Goolsbee and

using dummies in the 73-month window surrounding the month in which Southwest establishes a presence in both endpoints of a market (36 months before to 36 months after). Southwest's actual entry is defined as occurring when it establishes direct non-stop service between the two airports. I control for this event using dummies during and after Southwest starts flying the market. The data contain 525 instances of Southwest threatening entry into markets, 265 of which Southwest had actually entered with direct flights by the end of 2016.[18] This yields around 37,000 market-carrier-month observations of average logged differentiation in departure times measures for incumbent airlines' direct flights on threatened markets.

To measure incumbent airlines' location decisions, I construct measures of differentiation in departure times for each airline-market-time, using information on scheduled departure times from the OTP database. These measures take into account the differentiation between every pair of flights in a market own by a given airline. This means, for instance, that when looking at the differentiation in departure times for airline i in market m, the measure will only contain information on the relative distance of airline i's flights in market m, telling us nothing about the distance of flights belonging to i relative to flights own by competitor airlines in the market (if any). To formalize these measures, consider the case of airline i in market m, with n daily departures scheduled at times $d_1, ..., d_k, ..., d_n$, and expressed as minutes after midnight. Differentiation in departure times for flight k belonging to airline i in market m is then calculated as in Borenstein

Syverson (2008) find that when Southwest threatens a market according to this definition, it was 18.5% more likely to enter the market with a non-stop flight in the next quarter.

[18] I also follow Goolsbee and Syverson (2008) in eliminating from the sample any routes that are truncated by the end of the sample, and those routes where Southwest establishes a second endpoint airport presence simultaneously with actually flying the route, since in those cases it is not possible to identify the threat of entry separately from actual entry.

and Netz (1999):

$$Diff_{imk} = \frac{1}{n-1} \sum_{l \neq k} [\min\{| \ d_l - d_k \ |, 1440 - | \ d_l - d_k \ |\}]^{\alpha}$$

where $\alpha \in (0, 1)$ is a parameter that captures the sensitivity of the differentiation index to flights that are farther away. When α is close to zero, this measure is more sensitive to changes in the time between flights that are close together to begin with. If α is close to 1, then this measure is equally affected by changes in the time between flights that are close together or far apart to begin with. It is also very close to the average distance between flights. I arbitrarily set $\alpha = 0.5$, but also try alternative values such as 0.25 and 0.75. Note also that the above index is minimized at zero, when all flights exhibit the same departure time. On the other hand, it is maximized when the n flights are equally spaced around the 24-hour clock. Finally, the reason why the number 1440 appears in the definition of the index is because we are measuring distance between flights located in a circle (i.e., 24-hour clock), and 1440 is the number of minutes in a day.

Average differentiation in departure times for airline i in market m is then given by:

$$AvgDiff_{im} = \frac{1}{n(n-1)} \sum_{k=1}^{n} \sum_{l \neq k} [\min\{| \ d_l - d_k \ |, 1440 - | \ d_l - d_k \ |\}]^{\alpha}, \qquad 0 < \alpha < 1$$

where this index measures the average of the absolute time difference between each pair of i's flights in the market raised to the α power. I follow Borenstein and Netz (1999) and normalize the above index by the maximum possible time difference ($MaxDiff_{im}$), given the number of scheduled flights. This maximum possible time difference is simply the value of the average differentiation in departure times that would result if the flights were equally spaced around the clock. This normalization allows for comparisons of differentiation in departure times across airlines-markets with different numbers of scheduled flights. Then, the measure I use to quantify the degree of product differentiation for an incumbent airline in a market is:

$$D_{im,\alpha} = \frac{AvgDif_{im}}{MaxDiff_{im}} \tag{2.1}$$

This variable ranges between 0 and 1, measuring the proportion of the maximum possible differentiation in departure times. The closer to 1, the closer the flights are to being evenly distributed over a 24-hour clock.

Besides the differentiation in departure times variable, I characterize the distribution of departure times using a set of alternative measures. The list includes the departure times of the first and last flights of the day, the range (i.e., difference between the departure time of the last and first flights of the day), percentiles 25th and 75th of the distribution of departure times, the interquartile range, the fraction of flights scheduled during the morning and afternoon peaks of demand, and measures of correlation between scheduled departure times and passengers' most preferred departure times. To construct these correlation measures, I use information on scheduled departures from the OTP database. Information on passengers' most preferred departure times comes from Garrow, Jones and Parker (2007) and Brey and Walker (2011), who construct these measures based on a 2004 on-line survey conducted by the Boeing Company.[19] I create these variables using the uncentered correlation coefficients between the firms' scheduled departure profiles and

[19] See Garrow et al. (2007) and Brey and Walker (2011) for more details about the survey design.

passengers' most preferred departure times.[20] Appendix B.2 formalizes these correlation measures and provides details on their construction.

I also create measures of departure and arrival banks, for each airline-airport-time in the data, using information on scheduled departure and arrival times from the On Time Performance database. Departure and arrival banks are constructed using kernel estimates of the probability of departing or arriving from/to an airport at certain times of the day. I use these variables for two different purposes. First, I use them to check the robustness of the results when studying the distance of scheduled departures to the banks. Second, I use the departure and arrival banks variables to create measures of differentiation in departure and arrival banks using equation (2.1). Then, these variables are included as control variables in the main regression equation.

Finally, I construct other variables at the carrier-market-time level, such as the number of destinations served out from an airport, the total number of departures scheduled from an airport, the incumbent's market share of passengers in the market, and variables denoting the hub status of the incumbent at the endpoint airports of the market. Some of these variables are interacted with the threat proxy to assess heterogeneities in an incumbent's response as a function of market or incumbent characteristics.

Table 2.2 reports summary statistics for the final sample. The standard deviation for the logged value of differentiation in departure times ($\alpha = 0.5$) is 0.142, and for the logged number of departures is 0.545.

[20] Uncentered correlation measures have already been used in other applications. Jaffe (1986), for example, uses it to measure the degree of technology closeness between firms. Bloom et al. (2013b) use it to measure the proximity in technology and product market space between firms.

Table 2.2. Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
$D_{0.25}$	37206	0.918	0.059	0.352	1
$D_{0.5}$	37206	0.854	0.102	0.124	1
$D_{0.75}$	37206	0.804	0.136	0.043	1
$\ln(D_{0.25})$	37206	-0.088	0.070	-1.045	0
$\ln(D_{0.5})$	37206	-0.167	0.142	-2.091	0
$\ln(D_{0.75})$	37206	-0.237	0.214	-3.136	0
$\ln(flights)$	37206	1.413	0.545	0.693	3.016
$\ln(seats)$	37176	9.619	0.744	5.011	11.550
$\ln(Diff.\ Arrival\ Banks)$	37206	-0.253	0.188	-2.196	-0.001
$\ln(Dif.\ Departure\ Banks)$	37206	-0.254	0.200	-2.226	0.000
$\ln(Total\ passengers\ Dest.\ Airport)$	37206	13.585	1.000	9.705	15.235
$\ln(Total\ passengers\ Origin\ Airport)$	37206	13.575	1.003	9.705	15.235
$\ln(Airports\ served\ from\ Dest.\ Airport)$	37206	2.548	1.494	0	4.868
$\ln(Airports\ served\ from\ Origin\ Airport)$	37206	2.520	1.499	0	4.868
$\ln(Departures\ from\ Dest.\ Airport)$	37188	7.209	1.634	0	9.996
$\ln(Departures\ from\ Origin\ Airport)$	37188	7.179	1.644	0	9.996

Note: The table reports summary statistics of variables in the final sample. Data come from the On-Time Performance database (OTP) and the Air Carrier Statistics (T-100 Domestic Segment).

2.4. Estimation

The empirical specification follows closely the model used by Goolsbee and Syverson (2008). It measures the impact of the threat of entry (i.e., Southwest establishing a presence in both endpoints of a market) around the time of the event (by looking at the periods before, during, and after this event), exploiting the time-series variation in location decisions and threats of entry for a specific incumbent-market. The regression equation is as follows:

$$\begin{aligned} y_{imt} &= \gamma_{im} + \mu_{it} + \sum_{\tau=-8}^{3+} \beta_\tau SW\_Threat_{m,t_0+\tau} \\ &+ \sum_{\tau=0}^{3+} \varphi_\tau SW\_Entry_{m,t_e+\tau} + X'_{imt}\alpha + \epsilon_{imt} \end{aligned}$$

where y_{imt} is the outcome of interest (e.g., incumbent's degree of product differentiation in terms of departure times) for incumbent carrier i, flying market m, in month t. γ_{im} and μ_{it} are carrier-market and carrier-time fixed effects, respectively.[21] The periods in which Southwest establishes a presence in both endpoints of a market and starts flying the market are denoted by t_0 and t_e, respectively. Therefore, variables $SW\_Threat_{m,t_0+\tau}$ and $SW\_Entry_{m,t_e+\tau}$ are dummies surrounding the period when Southwest establishes a presence in both endpoints of a market but without flying the market, and dummies that begin in the period when Southwest actually starts flying the market. To measure the impact of threatened entry on incumbents' outcomes, the coefficients of interest are those corresponding to the $SW\_Threat_{m,t_0+\tau}$ dummies. These are quarterly dummies that comprise the 24 months prior to the month when Southwest establishes presence at the two endpoints of the threatened market, a dummy for the month in which Southwest establishes presence at both endpoints of a market, quarterly dummies for the 6 months after presence is established, and a single dummy for the period 7 or more months after t_0. These post establishment dummies take a value of one only if Southwest has not yet entered the market with non-stop flights. Given that the regression equation include

[21] To clarify this, carrier-market effects γ_{im} are fixed effects at the level of the incumbent airline and directional airport-pair. Similarly, carrier-time effects μ_{it} are represented by dummies at the airline-year-month level.

carrier-market fixed effects, the coefficients for these dummies measure the relative size of the dependent variable in the dummy period relative to its average value in the excluded period (i.e., between two and three years prior to establishing presence in both endpoints of a market).

In most of the specifications I include in the regression equation a vector of control variables, X_{imt}, containing the (log of) total number of passengers flying through the origin and destination airports of the market, the (log of) the number of destinations served by the incumbent airline out of the origin and destination airports of the market, and measures of differentiation for departure and arrival banks at the origin and destination airports, respectively. Finally, ϵ_{imt} is an error term. In order to account for intertemporal correlation in the error term, I cluster the standard errors at the market-carrier level.

I measure the impact of Southwest threatening entry on different outcomes which summarize incumbents' location decisions. The baseline specifications use as dependent variable the degree of product differentiation in terms of departure times, where differentiation in departure times is measured by equation (2.1). Since the differentiation index $D_{im,\alpha}$ is bounded between zero and one, I also report results using as dependent variable the log-odds ratio of the index, given by $D^{odds}_{im,\alpha} = \ln[D_{im,\alpha}/(1 - D_{im,\alpha})]$, which produces an unbounded statistic.[22] Other specifications look at the locations of the first and last flights of the day, the range of the locations (i.e., difference between the departure times of the last and first flights of the day), the interquartile range of the distribution of departure times, and the locations of flights relative to peaks of demand (i.e., 7am-10am and 5pm-8pm) and own arrival banks.

[22] One might be worried about the limited range of the differentiation index $D_{im,\alpha}$, since the assumption of a normally distributed error term may not be justifiable.

The identification of the effect exploits variation in location decisions and threats on a given airline and market over time. Identification of airlines' motives for relocating their flights originates from the manner in which a threat will impact an airline's decision to supply flights at different departure times in a particular market at a given time. Since airlines schedule their flights not only in response to competing flights, but also taking into consideration the distribution of demand over the day as well as network effects (i.e., connections), identification of the effect relies on the fact that the incentive for improved service though connections or from matching higher densities of demand from relocating their flights should not be affected one way or another by a new threat from Southwest. As the threat is generated from Southwest starting non-stop service in a market whose one of its endpoints is also the endpoint of the threatened market, it is unlikely to be correlated with any supply or demand related factors that would make the threatened market more efficient for the incumbent airline to change the location of its flights.

There are different threats to the identification strategy. The identification assumption behind any strategic effect is that the entry threats are exogenous to demand and supply side factors that might affect the location of flights in a given market. In other words, Southwest's decision to enter a market must be uncorrelated with cost or demand factors in the market in which the incumbent is currently operating (and shares one of its endpoints with the market in which Southwest enters) that would make it more suitable for the incumbent to relocate its flights. An endogeneity problem would arise if changes in the location of an incumbent' flights and an initiation of a threat of entry are simply the responses to changes in demand conditions at an endpoint airport. Similarly, responses to changes in aggregate supply at an endpoint airport (such as hubbing, de-hubbing, or changes in the level of concentration) might also confound the effects of a threat of entry. I attack these issues by controlling for the overall airport-level demand in the time period, as well as for the degree of differentiation in arrival and departure banks at the origin and destination airports, respectively. To further control for supply side factors, I include in the regressions the total number of destinations served by the incumbent airline out of the origin and destination airports of the market.

Another threat to the identification strategy may arise if both threats and schedule changes are responses made primarily to compete for passengers on one-stop service to one of the endpoint airports. For instance, consider the case where American Airlines is offering one-stop service from Cincinnati, OH to Austin, TX through its hub in Dallas, TX. Similarly, Southwest offers non-stop service from Phoenix, AZ to Austin, TX, from Dallas, TX to Austin, TX, and now enters the route Cincinnati, OH-Phoenix, AZ, threatening non-stop service on the route Cincinnati, OH-Dallas, TX. However, in this scenario, American and Southwest start competing over stop passengers in the market Austin, TX-Cincinnati, OH. Then, rather than a preemptive action to a threat of entry, the co-movement between an entry threat and schedule changes may be explained by a competitive response to recently established competition for one-stop passengers. For instance, in the above example, American Airlines may change its schedule in the Dallas, TX- Cincinnati, OH market to compete with Southwest's one-stop Austin-Phoenix-Cincinnati service, by reducing its layover time for its own one-stop service from Austin to Cincinnati through Dallas.

The aforementioned type of competition would create a positive correlation between entry threats and schedule changes if Southwest's new connecting service encourages the incumbent airline to provide a different set of connecting times that it had no intention in offering before Southwest established a presence at both endpoint airports of the market. Even though competition for connecting service may be a motive for changing the location of flights in a market, I disregard its importance for explaining the identification of any effect. In particular, most of incumbent airlines in the data are hub-and-spoke carriers, which unlike point-to-point airlines, create one-stop service by building connections at their hub locations. The one-stop flights formed by the entry threat and those belonging to incumbent airlines using the non-stop threatened market are serving completely different sets of passengers. More specifically, the threatened non-stop market can be used by passengers from many origin cities other than passengers from the origin city of the new one-stop product added by Southwest, as well as non-stop passengers. This makes unlikely that a change in the schedule would be made primarily for the purpose of competing over a specific one-stop product that a low-cost competitor is entering. Moreover, it is unrealistic that the new Southwest' one-stop product created by the entry threat is a good substitute for incumbents' service through their hubs.

2.5. Results

Column (1) of Table 2.3 reports the results where the dependent variable measures the (log of) degree of differentiation in departure times for the incumbent carrier in the market. The coefficients of interest for determining the impact of an entry threat on incumbents' flight schedules are the β_τ's. These are the coefficients for dummies for the 36 months prior to the month when Southwest establishes presence at both endpoints of the threatened market, for the establishment month (i.e., t_0) itself, for the 6 months after

t_0, and a single dummy for the period 7 or more months after t_0. All these dummies take a value of one only if Southwest has not yet entered the market. The distribution of incumbents' departure times change significantly before Southwest begins flying non-stop flights in the market, with incumbents shifting the distribution of flight locations towards times where the distribution of departure times is more equally spaced around the clock. Since all specifications include market-carrier fixed effects, reported coefficients show the relative sizes of the dependent variable in the dummy period relative to its average value in the excluded period between 25 and 36 months prior to t_0. By the time Southwest establishes a presence at both endpoint airports of the market (period t_0), the differentiation in departure times measure is 3.3% higher than in the excluded period. Moreover, the differentiation index in departure times increases slightly further as time passes without Southwest entering the market with non-stop flights.

The aforementioned index is also higher in months before t_0 than in the excluded period. The patterns suggest that it begins to increase around fourth quarters before t_0 (i.e., between 10 and 12 months before the month in which Southwest establishes presence in both endpoints of the market).[23] The differentiation index increases to 2.8% above the average of the baseline period once Southwest actually enters the market with non-stop flights at time t_e. The increasing trend in the outcome variable continues by the periods

[23] As Goolsbee and Syverson (2008) mention, it is not surprising to observe a preemptive action before the month in which Southwest establishes presence at both endpoints of the market. This preemptive action should take place when incumbents realize that Southwest's chances of entering a market have risen. Since advertising, selling tickets and hiring decisions have to be made several months before the entry actually occurs, airlines typically announce entry several months in advance. Moreover, as Goolsbee and Syverson (2008) note, industry insiders are likely to find out about entries before the public announcement, as airlines must negotiate gate leases and airport facilities with the airport authority. In their study, Goolsbee and Syverson (2008) find statistically significant differences in incumbents prices (relative to the excluded period) as far as seven quarters before t_0.

following entry (increasing to 3.3% above the average of the baseline period). To provide an intuition for the size of the effect, in the case of a market with two flights (and assuming that flight frequency does not change with the entry threat), the value of the index for the excluded period would correspond to a schedule with one departure at 8am and another departure at 4:45pm. The entry threat would imply moving the second flight to 5:20pm if the first flight remained at 8am.

Demand and supply shocks may also be an alternative explanation for the results reported in column (1). For instance, if Southwest chooses to enter airports where aggregate demand is growing faster, or de-hubbing at some of the endpoint airports of the market is taking place, this will lead to a spurious correlation between the entry threat and the change in incumbents' departure times. To account for these confounding effects, I control in the regressions for the (log of) total number of passengers flying through the origin and destination airports of the market, the (log of) number of destinations served by the incumbent airline out of the origin and destination airports of the market, and (log of) measures for the degree of time differentiation in arrival and departure banks at the origin and destination airports, respectively. Column (2) of Table 2.3 reports the results of a specification that controls for the potential role of demand and supply shocks. Most of the control variables have significant and positive coefficients. More specifically, when either the demand for air-travel, or the differentiation in departure and arrival banks increases, the differentiation in departure times also rises. The coefficients related to the threat of entry and entry variables remain similar to those reported in column (1), and still statistically significant and economically substantial. These results imply that the change in the differentiation measure due to Southwest's actual entry is the difference

Table 2.3. Incumbent Responses to a Threat of Entry

	(1)	(2)	(3)	(4)	(5)
Variables	$\ln(D_{0.5})$	$\ln(D_{0.5})$	$\ln(flights)$	$\ln(seats)$	$\ln(D_{0.5})$
$SW\_Threat\_t_{0-8}$	0.0057	0.0027	-0.0049	-0.0141	0.0016
	(0.0067)	(0.0061)	(0.0126)	(0.0161)	(0.0055)
$SW\_Threat\_t_{0-7}$	0.0008	0.0030	-0.0013	-0.0141	0.0003
	(0.0078)	(0.0073)	(0.0141)	(0.0202)	(0.0068)
$SW\_Threat\_t_{0-6}$	0.0123	0.0118	-0.0047	-0.0041	0.0089
	(0.0096)	(0.0090)	(0.0146)	(0.0178)	(0.0084)
$SW\_Threat\_t_{0-5}$	0.0150	0.0140	-0.0089	0.0129	0.0101
	(0.0103)	(0.0096)	(0.0167)	(0.0211)	(0.0090)
$SW\_Threat\_t_{0-4}$	0.0300***	0.0270***	-0.0053	0.0242	0.0219**
	(0.0105)	(0.0100)	(0.0190)	(0.0226)	(0.0095)
$SW\_Threat\_t_{0-3}$	0.0325***	0.0295***	0.0097	0.0177	0.0220**
	(0.0105)	(0.0096)	(0.0205)	(0.0257)	(0.0089)
$SW\_Threat\_t_{0-2}$	0.0318***	0.0281***	0.0197	0.0268	0.0179*
	(0.0115)	(0.0106)	(0.0210)	(0.0269)	(0.0098)
$SW\_Threat\_t_{0-1}$	0.0303***	0.0282***	0.0079	0.0219	0.0197**
	(0.0115)	(0.0106)	(0.0228)	(0.0281)	(0.0099)
$SW\_Threat\_t_{0}$	0.0330***	0.0240**	0.0068	0.0164	0.0163
	(0.0127)	(0.0119)	(0.0253)	(0.0323)	(0.0112)
$SW\_Threat\_t_{0+1}$	0.0330***	0.0286***	0.0042	0.0164	0.0217**
	(0.0122)	(0.0108)	(0.0253)	(0.0306)	(0.0101)
$SW\_Threat\_t_{0+2}$	0.0308**	0.0248**	-0.0119	-0.0147	0.0205*
	(0.0128)	(0.0118)	(0.0268)	(0.0325)	(0.0111)
$SW\_Threat\_t_{0+3}$	0.0423***	0.0399***	0.0143	0.0249	0.0281**
	(0.0136)	(0.0128)	(0.0291)	(0.0353)	(0.0122)
$SW\_Entry\_t_{e}$	0.0283*	0.0318**	-0.0095	-0.0043	0.0234*
	(0.0155)	(0.0152)	(0.0329)	(0.0381)	(0.0142)
$SW\_Entry\_t_{e+2}$	0.0329**	0.0415***	0.0025	0.0073	0.0301**
	(0.0149)	(0.0143)	(0.0338)	(0.0399)	(0.0133)
$SW\_Entry\_t_{e+3}$	0.0334*	0.0457***	-0.0222	-0.0010	0.0365**
	(0.0181)	(0.0170)	(0.0374)	(0.0443)	(0.0155)
Observations	37,206	37,206	37,170	37,176	37,206

Notes: all specifications, except column (1), include as control variables the (log of) total number of passengers flying through the origin and destination airports of the market, the (log of) number of destinations served by the incumbent airline out of the origin and destination airports of the market, and (log of) measures for the degree of time differentiation in arrival and departure banks at the origin and destination airports, respectively. Column (5) includes as an additional control the (log) number of departures performed by the incumbent carrier in the market. Standard errors are in parentheses and are clustered by market-carrier. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

between the preemptive (2.4%) and ultimate (4.1%) increase. These results indicate that preemptive actions in terms of flight location decisions are important. Approximately 60% of the differentiation in departure times effect that Southwest has on incumbents' flight locations takes place before Southwest begins non-stop flights operations in the market itself.

One possibility that might explain the previous findings is that, under the threat of entry, incumbents might be adjusting the frequency of departures in the market, and consequently the changes in location patterns observed in the data might be the response to this action. This would confound the distinction between the location choice mechanism and the product proliferation strategy if, for instance, incumbents increase flight frequency under a threat of entry, and as a consequence relocate their flights more equally spaced around the clock as a response to it.[24] Columns (3) and (4) of Table 2.3 report the results where the dependent variables are the (log of) average number of departures per day in the market and the (log of) number of seats per month, respectively. All of the dummies surrounding the threat event are not statistically significant at conventional levels, and in many instances they change signs over time. This suggests at least that the increase in differentiation in departure times is not always accompanied by an increase in the number of flights or capacity.[25] In column (5) I run the baseline specification

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[24] For example, Dixit's (1979) capacity commitment model offers a rationale for investments in capacity as a preemptive motive. Investments in capacity, in the case of the airline industry might be achieved through a higher flight frequency.

[25] The result related to flight frequency is robust to other sources of data as well as the distinction between departures performed and scheduled. Results for departures scheduled and performed based on information from the Air Carrier Statistics (T-100 Domestic Segment) are available from the author upon request. In both cases, the results are qualitatively and quantitatively similar to those reported in column (2) of Table 2.3, confirming the preemptive actions by incumbent firms in terms of location decisions of flights within a market-day, instead of number of departures.

including as an additional control variable the (log of) average number of departures per day in the market. The results are almost identical to those reported in column (2). This set of results would support the hypothesis that airlines use as a preemptive action a product specification strategy, by relocating their flights or capacity decisions across different departure times.

I augment this analysis in several ways. First, I consider alternative measures of differentiation in departure times by taking into account different values of α, the parameter that captures the sensitivity of the differentiation index to flights that are located farther away. Columns (2) and (3) of Table 2.4 report the results for alternative differentiation in departure times measures that were computed using values of α of 0.25 and 0.75, respectively. The results are qualitatively identical to those reported in column (1) for α equal to 0.5 (i.e., baseline specification). The magnitudes of the coefficients, however, are different. In particular, there is a monotonic relationship between the values of α and the estimates of the coefficients associated with any of the dummy variables surrounding the threat and entry events. These results might suggest, that the relocation of flights takes place by re-scheduling flights that are more far away to begin with. Columns (4) to (6) of the table report results using as dependent variable the log-odds ratio of the index. The results are qualitatively similar to those reported in columns (1) to (3). The coefficients, however, are in most of the cases not statistically significant at conventional levels. This is likely driven by the fact that the constant marginal effect of the right-hand side variables on the log-odds ratio variable implies that as the differentiation measures approaches either limit (i.e., 0 or 1), the right-hand side variables have less and less impact on the differentiation index.[26]

A second expansion in the baseline results looks at different moments of the distribution of departure times, such as, the departure times of the first and last flights of the day, the range (i.e., difference between the departure times of the last flight of the day and first flight of the day), percentiles 25th and 75th of the distribution of departure times, and the interquartile range. Column (1) of Table 2.5 shows the estimation of the model where the dependent variable is the (log of) range. The threat of entry has a positive and significant effect on the range, increasing the time difference between the first and last flights of the day in approximately 6% above the average of the baseline period. This coefficient implies an average increase in the range of approximately 25 minutes. The trend continues in the periods following entry, where the range rises to approximately 9% above the average of the baseline period. One might be wondering if this increase in the range is a consequence of first flights of the day departing earlier, or last flights of the day departing later. Columns (2) and (3) of Table 2.5 show incumbent responses in terms of departure times of first and last flights of the day. The estimates are imprecise, but the point estimates suggest that departure times of the first and last flights of the day decrease and increase, respectively, on threatened routes in the period before and around when Southwest enters the second endpoint airport of the market. The lack of precision of the estimates, joint with the fact that the coefficients for the dummies of interest in the range regression are greater in magnitude than the difference between the coefficients for these dummies in the last and first flights of the day regressions, might suggest that

[26] The mean values for the differentiation measures are 0.918, 0.854, and 0.804 for α equal to 0.25, 0.5 and 0.75, respectively

Table 2.4. Incumbent Responses to a Threat of Entry - Robustness

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	$\ln(D_{0.5})$	$\ln(D_{0.25})$	$\ln(D_{0.75})$	$\ln(D_{0.25}^{odds})$	$\ln(D_{0.5}^{odds})$	$\ln(D_{0.75}^{odds})$
$SW\_Threat\_t_{0-8}$	0.0027	0.0011	0.0045	0.0002	0.0039	0.0083
	(0.0061)	(0.0030)	(0.0093)	(0.0380)	(0.0422)	(0.0485)
$SW\_Threat\_t_{0-7}$	0.0030	0.0013	0.0050	-0.0246	-0.0225	-0.0221
	(0.0073)	(0.0036)	(0.0111)	(0.0463)	(0.0505)	(0.0567)
$SW\_Threat\_t_{0-6}$	0.0118	0.0061	0.0175	0.0128	0.0138	0.0136
	(0.0090)	(0.0045)	(0.0136)	(0.0534)	(0.0579)	(0.0644)
$SW\_Threat\_t_{0-5}$	0.0140	0.0068	0.0216	0.0366	0.0421	0.0447
	(0.0096)	(0.0048)	(0.0146)	(0.0550)	(0.0601)	(0.0678)
$SW\_Threat\_t_{0-4}$	0.0270***	0.0131***	0.0418***	0.0830	0.1010	0.1210
	(0.0100)	(0.0049)	(0.0151)	(0.0598)	(0.0659)	(0.0756)
$SW\_Threat\_t_{0-3}$	0.0295***	0.0144***	0.0453***	0.0839	0.1008	0.1198
	(0.0096)	(0.0048)	(0.0146)	(0.0621)	(0.0686)	(0.0788)
$SW\_Threat\_t_{0-2}$	0.0281***	0.0138***	0.0431***	0.0911	0.1084	0.1285
	(0.0106)	(0.0053)	(0.0160)	(0.0674)	(0.0743)	(0.0850)
$SW\_Threat\_t_{0-1}$	0.0282***	0.0140***	0.0429***	0.0899	0.1062	0.1247
	(0.0106)	(0.0053)	(0.0161)	(0.0705)	(0.0779)	(0.0895)
$SW\_Threat\_t_{0}$	0.0240**	0.0123**	0.0360**	0.0501	0.0588	0.0678
	(0.0119)	(0.0059)	(0.0179)	(0.0776)	(0.0856)	(0.0980)
$SW\_Threat\_t_{0+1}$	0.0286***	0.0144***	0.0432***	0.0685	0.0779	0.0870
	(0.0108)	(0.0054)	(0.0164)	(0.0771)	(0.0851)	(0.0978)
$SW\_Threat\_t_{0+2}$	0.0248**	0.0122**	0.0379**	0.0801	0.0934	0.1095
	(0.0118)	(0.0059)	(0.0179)	(0.0799)	(0.0879)	(0.1006)
$SW\_Threat\_t_{0+3}$	0.0399***	0.0196***	0.0612***	0.1350	0.1581*	0.1847*
	(0.0128)	(0.0064)	(0.0194)	(0.0865)	(0.0957)	(0.1104)
$SW\_Entry\_t_{e}$	0.0318**	0.0156**	0.0487**	0.1158	0.1357	0.1578
	(0.0152)	(0.0076)	(0.0230)	(0.0962)	(0.1065)	(0.1223)
$SW\_Entry\_t_{e+2}$	0.0415***	0.0205***	0.0633***	0.1376	0.1582	0.1796
	(0.0143)	(0.0071)	(0.0216)	(0.0948)	(0.1046)	(0.1197)
$SW\_Entry\_t_{e+3}$	0.0457***	0.0227***	0.0689***	0.1218	0.1352	0.1448
	(0.0170)	(0.0084)	(0.0256)	(0.1024)	(0.1135)	(0.1300)
Observations	37,206	37,206	37,206	37,199	37,199	37,199

Notes: All specifications include airline-market fixed effects and airline-time fixed effects. All specifications include as control variables the (log of) total number of passengers flying through the origin and destination airports of the market, the (log of) number of destinations served by the incumbent airline out of the origin and destination airports of the market, and (log of) measures for the degree of time differentiation in arrival and departure banks at the origin and destination airports, respectively. Standard errors are in parentheses and are clustered by market-carrier. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

incumbents might be re-scheduling either the first or last flight of the day (but not necessarily both) depending on the characteristics of the market. Columns (4), (5), and (6) report the results from the estimation of the model where the dependent variables are the interquartile range of the distribution of departure times, and percentiles 25th and 75th of this distribution, respectively. The results for the interquartile range and percentile 25th are qualitatively and quantitatively similar to those obtained for the range and first flight of the day, respectively. In all three cases the estimates are imprecise. We do not observe a clear pattern in the case of percentile 75th. Overall, these results imply that the higher level of differentiation in departure times is not only driven by changes in schedules of flights at the extremes of the day, but also by flights located closer to the center of the distribution.

I also check if the preemptive actions correspond to incumbents trying to schedule some of its flights closer to peaks of demand, or more specifically, if there is an effort for trying to place flights around times with a higher density of passengers that prefer to flight at those times. To this end, I look first at the fraction of flights scheduled during the morning (i.e., 7am-10am) and afternoon (i.e., 5pm-8pm) peaks, respectively. Columns (1) and (2) of Table 2.6 report the results from the estimation of these models. Although the coefficients are positive in both columns, they tend to be small and and in all cases they are not statistically significant. To further explore this issue, I look at the response in measures of correlation between scheduled departure times and passengers' most preferred departure times when Southwest threatens entry. Columns (3) to (6) of Table 2.6 show the estimates for these models. Column (3) reports the results for a model where passengers would only obtain utility if they flew at their most preferred departure

Table 2.5. Incumbent Responses to a Threat of Entry - Alternative Outcomes

Variables	(1) ln($range$)	(2) ln($first\ flight$)	(3) ln($last\ flight$)	(4) ln(iqr)	(5) ln($pctile\ 25th$)	(6) ln($pctile\ 75th$)
$SW\_Threat\_t_{0-8}$	0.0123	-0.0080	0.0060	0.0098	-0.0024	0.0030
	(0.0144)	(0.0090)	(0.0053)	(0.0142)	(0.0088)	(0.0055)
$SW\_Threat\_t_{0-7}$	0.0070	-0.0014	0.0018	0.0045	0.0023	0.0009
	(0.0166)	(0.0126)	(0.0064)	(0.0169)	(0.0134)	(0.0066)
$SW\_Threat\_t_{0-6}$	0.0240	0.0041	0.0106	0.0215	0.0038	0.0105
	(0.0198)	(0.0162)	(0.0073)	(0.0197)	(0.0159)	(0.0075)
$SW\_Threat\_t_{0-5}$	0.0324	-0.0071	0.0098	0.0229	-0.0037	0.0063
	(0.0214)	(0.0180)	(0.0080)	(0.0210)	(0.0173)	(0.0082)
$SW\_Threat\_t_{0-4}$	0.0581***	-0.0092	0.0167**	0.0500**	-0.0112	0.0127
	(0.0223)	(0.0175)	(0.0085)	(0.0226)	(0.0169)	(0.0089)
$SW\_Threat\_t_{0-3}$	0.0651***	-0.0099	0.0148	0.0512**	-0.0115	0.0109
	(0.0221)	(0.0199)	(0.0094)	(0.0216)	(0.0199)	(0.0095)
$SW\_Threat\_t_{0-2}$	0.0662***	-0.0216	0.0152	0.0292	-0.0115	0.0055
	(0.0241)	(0.0230)	(0.0100)	(0.0234)	(0.0228)	(0.0101)
$SW\_Threat\_t_{0-1}$	0.0638***	-0.0235	0.0127	0.0322	-0.0146	0.0040
	(0.0242)	(0.0246)	(0.0106)	(0.0250)	(0.0241)	(0.0109)
$SW\_Threat\_t_{0}$	0.0533**	-0.0208	0.0091	0.0040	-0.0069	-0.0060
	(0.0270)	(0.0267)	(0.0120)	(0.0275)	(0.0259)	(0.0123)
$SW\_Threat\_t_{0+1}$	0.0662***	-0.0209	0.0124	0.0229	-0.0158	-0.0011
	(0.0255)	(0.0252)	(0.0114)	(0.0263)	(0.0243)	(0.0118)
$SW\_Threat\_t_{0+2}$	0.0496*	-0.0184	0.0072	0.0372	-0.0225	0.0034
	(0.0274)	(0.0270)	(0.0121)	(0.0273)	(0.0260)	(0.0119)
$SW\_Threat\_t_{0+3}$	0.0919***	-0.0282	0.0196	0.0565*	-0.0201	0.0089
	(0.0293)	(0.0303)	(0.0125)	(0.0297)	(0.0282)	(0.0128)
$SW\_Entry\_t_{e}$	0.0657*	-0.0240	0.0178	0.0609*	-0.0234	0.0144
	(0.0345)	(0.0349)	(0.0145)	(0.0354)	(0.0292)	(0.0148)
$SW\_Entry\_t_{e+2}$	0.0959***	-0.0253	0.0220	0.0637*	-0.0246	0.0118
	(0.0332)	(0.0335)	(0.0145)	(0.0336)	(0.0304)	(0.0146)
$SW\_Entry\_t_{e+3}$	0.1080***	-0.0300	0.0162	0.0592	-0.0237	0.0022
	(0.0394)	(0.0357)	(0.0158)	(0.0392)	(0.0320)	(0.0162)
Observations	37,206	37,206	37,206	37,206	37,206	37,206

Notes: All specifications include airline-market fixed effects, airline-time fixed effects. All specifications include as control variables the (log of) total number of passengers flying through the origin and destination airports of the market, the (log of) number of destinations served by the incumbent airline out of the origin and destination airports of the market, and (log of) measures for the degree of time differentiation in arrival and departure banks at the origin and destination airports, respectively. Standard errors are in parentheses and are clustered by market-carrier.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

times. Columns (4) to (6) relax this assumption, allowing passengers to derive utility from flying at times which are not necessarily their most preferred. I allow consumers to derive utility from flying within 60, 240, and 1440 minutes of their most preferred departure times (columns (4), (5) and (6), respectively). There are no significant effects in the results. Coefficients on the time dummies tend to be small and negative, and in all cases they are not statistically significant. The results seem to suggest that the increase in differentiation in departure times originated by a threat of entry is not accompanied by an effort of trying to schedule flights around times with a higher density of demand.

Finally, I check whether my results are somehow being driven by a price and cost cutting strategy. Goolsbee and Syverson (2008) find that incumbents' market prices generally fall in the face of a threat of entry by Southwest. Then, a concern here is that when Southwest threatens entry into a market, incumbent airlines respond not only by cutting prices but also costs in these markets in order to sustain profitability, and that this cost cutting behavior is performed through scheduling decisions. The feasibility of this price and cost cutting strategy through scheduling decisions depends on the extent to which scheduling of departure times impacts costs.[27] Airlines' operational costs linked to scheduling decisions are typically determined by two factors: 1) the extent of efficient utilization of fleet, crew and ground installations; 2) costs derived from congestion.

While airlines can re-schedule their flights in order to avoid congestion and reduce costs, this strategy also involves a revenue loss or leakage. Hub carriers want to maximize the number of possible connecting markets for passengers, but also want to minimize passenger travel time spent on congestion delays or layover times. Thus, they must trade off all costs associated with congestion against the benefits from scheduling banks of flights. Although airlines can partially offset the increased congestion by smoothing

[27] It also depends on the extent to which passengers are more sensitive to price than to departure times, something that is presumably the case.

Table 2.6. Incumbent Responses to a Threat of Entry - Alternative Outcomes

Variables	(1) Fraction of flights in morning peak	(2) Fraction of flights in afternoon peak	(3) $\rho_{(schd,mpdt)}$	(4) $\rho^{k1h}_{(schd,mpdt)}$	(5) $\rho^{k4h}_{(schd,mpdt)}$	(6) $\rho^{k24h}_{(schd,mpdt)}$
$SW\_Threat\_t_{0-8}$	0.0063	0.0089	0.0001	-0.0042	-0.0196	-0.0451
	(0.0078)	(0.0061)	(0.0030)	(0.0109)	(0.0317)	(0.0684)
$SW\_Threat\_t_{0-7}$	0.0166	0.0158*	-0.0024	-0.0098	-0.0305	-0.0857
	(0.0102)	(0.0086)	(0.0037)	(0.0133)	(0.0385)	(0.0777)
$SW\_Threat\_t_{0-6}$	0.0067	0.0150	-0.0053	-0.0232	-0.0612	-0.1236
	(0.0109)	(0.0099)	(0.0041)	(0.0148)	(0.0429)	(0.0788)
$SW\_Threat\_t_{0-5}$	0.0007	0.0114	-0.0024	-0.0138	-0.0285	-0.0420
	(0.0116)	(0.0098)	(0.0044)	(0.0161)	(0.0474)	(0.0916)
$SW\_Threat\_t_{0-4}$	-0.0006	0.0105	-0.0015	-0.0134	-0.0309	-0.0314
	(0.0127)	(0.0104)	(0.0048)	(0.0169)	(0.0503)	(0.1010)
$SW\_Threat\_t_{0-3}$	0.0025	0.0101	-0.0029	-0.0166	-0.0355	-0.0440
	(0.0137)	(0.0113)	(0.0051)	(0.0179)	(0.0548)	(0.1119)
$SW\_Threat\_t_{0-2}$	0.0006	0.0164	-0.0008	-0.0131	-0.0390	-0.0679
	(0.0149)	(0.0119)	(0.0056)	(0.0200)	(0.0598)	(0.1184)
$SW\_Threat\_t_{0-1}$	0.0109	0.0182	0.0026	-0.0051	-0.0071	-0.0582
	(0.0152)	(0.0134)	(0.0059)	(0.0211)	(0.0640)	(0.1285)
$SW\_Threat\_t_{0}$	0.0109	0.0180	0.0008	-0.0112	-0.0174	-0.0532
	(0.0167)	(0.0143)	(0.0064)	(0.0230)	(0.0711)	(0.1426)
$SW\_Threat\_t_{0+1}$	0.0187	0.0125	-0.0002	-0.0161	-0.0280	-0.0766
	(0.0170)	(0.0142)	(0.0061)	(0.0218)	(0.0675)	(0.1413)
$SW\_Threat\_t_{0+2}$	0.0142	0.0169	-0.0000	-0.0156	-0.0359	-0.1657
	(0.0181)	(0.0150)	(0.0068)	(0.0240)	(0.0720)	(0.1443)
$SW\_Threat\_t_{0+3}$	0.0113	0.0213	0.0013	-0.0052	0.0171	-0.0170
	(0.0194)	(0.0160)	(0.0074)	(0.0256)	(0.0764)	(0.1532)
$SW\_Entry\_t_{e}$	0.0168	0.0227	-0.0032	-0.0264	-0.0589	-0.1732
	(0.0204)	(0.0172)	(0.0081)	(0.0283)	(0.0851)	(0.1765)
$SW\_Entry\_t_{e+2}$	0.0172	0.0197	-0.0027	-0.0230	-0.0424	-0.1003
	(0.0211)	(0.0172)	(0.0083)	(0.0292)	(0.0883)	(0.1850)
$SW\_Entry\_t_{e+3}$	0.0291	0.0123	-0.0070	-0.0396	-0.0901	-0.1817
	(0.0236)	(0.0187)	(0.0090)	(0.0323)	(0.0982)	(0.2121)
Observations	37,206	37,206	37,206	37,206	37,206	37,206

Notes: All specifications include airline-market fixed effects, airline-time fixed effects. All specifications include as control variables the (log of) total number of passengers flying through the origin and destination airports of the market, the (log of) number of destinations served by the incumbent airline out of the origin and destination airports of the market, and (log of) measures for the degree of time differentiation in arrival and departure banks at the origin and destination airports, respectively. Standard errors are in parentheses and are clustered by market-carrier.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

scheduled arrival times, it comes at the expense of increasing the length of connections for some passengers (potentially decreasing profits). In fact, Mayer and Sinai (2003a) find that airlines incur most of the congestion costs from hubbing, implying that congestion is the price they are willing to pay for network benefits associated with the hub and spoke system.[28] Then, the empirical evidence does not provide support to the cost cutting strategy motivated by decreasing congestion costs. In any case, I examine how the average distance to the closest bank is affected by a threat of entry by Southwest. Column (1) of Table 2.7 look at the average distance to the closest bank of incumbents' flights in threatened markets. The results show that there are no significant patterns in the distance to the closest bank. The coefficients tend to be small, implying average changes in distance to the banks of no more than seven minutes. In all cases the coefficients are not statistically significant, and the coefficients of the time dummies change signs over the event study. In column (2) of Table 2.7 I empirically analyze the response on the utilization of fleet, in order to understand if incumbents are trying to increase aircraft productivity in threatened markets. The dependent variable I look at is (log of) turnaround time (i.e., time required to unload an airplane after its arrival at the gate and to prepare it for departure again). There are no effects of the threat of entry on this variable. All coefficients are small and not statistically significant.

Taken together, the results suggest that incumbents do engage in preemptive scheduling behavior when Southwest threatens entry into a market. In Section 2.6 I present some evidence regarding the motivation for this preemptive action. Before that, in the next section I explore heterogeneous effects by market characteristics.

[28] See footnote 14 of this chapter for more details about this.

Table 2.7. Incumbent Responses to a Threat of Entry - Price/Cost Cutting Strategy

Variables	(1) ln(distance to closest bank)	(2) ln(turnaround)
$SW\_Threat\_t_{0-8}$	-0.0391	-0.0106
	(0.0239)	(0.0153)
$SW\_Threat\_t_{0-7}$	0.0383	-0.0056
	(0.0274)	(0.0198)
$SW\_Threat\_t_{0-6}$	-0.0010	0.0027
	(0.0304)	(0.0182)
$SW\_Threat\_t_{0-5}$	0.0246	0.0189
	(0.0318)	(0.0197)
$SW\_Threat\_t_{0-4}$	0.0462	0.0176
	(0.0324)	(0.0211)
$SW\_Threat\_t_{0-3}$	0.0034	0.0110
	(0.0347)	(0.0224)
$SW\_Threat\_t_{0-2}$	-0.0008	0.0231
	(0.0381)	(0.0243)
$SW\_Threat\_t_{0-1}$	0.0033	0.0222
	(0.0401)	(0.0269)
$SW\_Threat\_t_{0}$	-0.0183	0.0029
	(0.0443)	(0.0301)
$SW\_Threat\_t_{0+1}$	0.0516	0.0225
	(0.0426)	(0.0293)
$SW\_Threat\_t_{0+2}$	0.0740	-0.0025
	(0.0474)	(0.0313)
$SW\_Threat\_t_{0+3}$	0.0798	0.0095
	(0.0507)	(0.0334)
$SW\_Entry\_t_{e}$	0.0888	-0.0175
	(0.0570)	(0.0366)
$SW\_Entry\_t_{e+2}$	0.0909	-0.0081
	(0.0552)	(0.0375)
$SW\_Entry\_t_{e+3}$	0.1101*	0.0027
	(0.0579)	(0.0407)
Observations	37,205	34,307

Notes: All specifications include airline-market fixed effects and airline-time fixed effects. All specifications include as control variables the (log of) total number of passengers flying through the origin and destination airports of the market, the (log of) number of destinations served by the incumbent airline out of the origin and destination airports of the market, and (log of) measures for the degree of time differentiation in arrival and departure banks at the origin and destination airports, respectively. Standard errors are in parentheses and are clustered by market-carrier. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

2.5.1. Subsample Analysis

In this section I study how market and incumbent characteristics interact with an incumbent's response in terms of differentiation in departure times when Southwest threatens entry into a market. More specifically, I study if preemptive actions in departure times vary according to the incumbent's market power and the hub status of the endpoint airports of the market.

In the first subsample analysis, I study the incumbent's response as a function of its market share, measured in terms of passengers transported. Presumably, one should expect a stronger incumbent's response in those markets where the incumbent has a greater market share, not only because it has more at stake, but also because it is less constrained by competition. To test this hypothesis, I divide the sample into three mutually exclusive subsamples: (1) those cases where the incumbent's average market share was below the 25th percentile (46.1%), (2) those cases which lied between the 25th and 75th percentile (90.3%), and (3) those cases where the incumbent's average market share was above the 75th percentile.[29] Columns (1) to (3) of Table 2.8 report the results of the analysis, showing that the effect of a threat of entry on the differentiation index is largest on those incumbents in the upper 25th percentile of market share (i.e., those instances where the incumbent is essentially a monopolist). On instances where the incumbent's market power is low (those in the bottom 25th percentile), the effect of a threat of entry on the differentiation index is small and statistically insignificant. Overall, the results seem to confirm

[29] The incumbent's average market share is computed over the period before Southwest establishing presence at both endpoints of the market.

the hypothesis that the incumbent's response should be monotone increasing in market share.

In a second subsample analysis, I divide the sample according to the hub status of the incumbent at the origin and destination airports of the market in question. In particular, I run separate models for flights departing from a hub, and flights arriving to a hub.[30] The effect of a threat of entry on an incumbent's response as a function of the hub status at the origin or destination airports is not trivial. The literature has established that an airline's operation at a given airport significantly affects its competitive position on routes flown out of that airport.[31] The mechanisms behind this phenomenon might include greater market power, lower costs and better service through the use of a hub-and-spoke network, or product differentiation. According to the market power story, we should observe stronger incumbent responses in flights departing from a hub than in the case of flights arriving to a hub. On the other hand, adjusting the schedule of departures at a hub airport seems to be a much more complicated task than doing the same at a non-hub airport, since it would involve rescheduling a higher number of flights (in order to account, for instance, for gate availability and connections). Similarly, if airport presence is an important component for product differentiation, an incumbent airline might not need to resort to a product specification strategy in location times in order to further differentiate (horizontally in this case) its products, since an alternative strategy to soften

[30] For simplicity I do not distinguish by size of the hub. I define a hub as an airport from which the incumbent airline serves at least 20 different destination airports.
[31] See, for instance, Levine (1987); Borenstein (1989), Morrison, Winston, Bailey and Kahn (1989), Berry (1990), or Berry (1992) among others.

price competition could potentially be achieved in a different and more effective way.[32] Columns (4) and (5) of Table 2.8 show the results of the hub subsample analysis. We observe that the positive coefficients on the threat variables are much more pronounced when the destination airport is a hub than in the case when the origin airport is a hub. In the sample of markets where the destination airport is a hub the effect of a threat of entry by Southwest on the differentiation index is 0.029 (at t_0), compared to 0.0038 when the sample includes only incumbents-markets where the origin airport is a hub. Overall, these results are indicative of an incumbent reacting more aggressively when the origin airport of the market is not a hub, something that would be consistent with the stories mentioned above about product differentiation or schedule adjustment costs at a hub.

[32] For instance, when firms compete in several non-price dimensions, Irmen and Thisse (1998) show that if one dimension is sufficiently dominant, firms will maximally differentiate along that dimension and minimally differentiate along all others.

Table 2.8. Incumbent Responses to a Threat of Entry: Subsample Analysis

Variables	(1) $\ln(D_{0.5})$ Avg. Mkt Share $< 25th$ pctile	(2) $\ln(D_{0.5})$ Avg. Mkt Share $> 25th$ & $< 75th$ pctile	(3) $\ln(D_{0.5})$ Avg. Mkt Share $> 75th$ pctile	(4) $\ln(D_{0.5})$ To Hub	(5) $\ln(D_{0.5})$ From Hub
$SW\_Threat\_t_{0-8}$	-0.0284	0.0221**	0.0042	0.0008	-0.0045
	(0.0176)	(0.0091)	(0.0144)	(0.0095)	(0.0081)
$SW\_Threat\_t_{0-7}$	-0.0259	0.0021	0.0144	-0.0000	-0.0030
	(0.0216)	(0.0118)	(0.0154)	(0.0113)	(0.0098)
$SW\_Threat\_t_{0-6}$	-0.0252	0.0230	0.0123	0.0136	0.0032
	(0.0264)	(0.0145)	(0.0153)	(0.0157)	(0.0117)
$SW\_Threat\_t_{0-5}$	-0.0134	0.0167	0.0211	0.0238	-0.0072
	(0.0274)	(0.0165)	(0.0154)	(0.0157)	(0.0136)
$SW\_Threat\_t_{0-4}$	0.0017	0.0204	0.0353*	0.0368**	0.0053
	(0.0294)	(0.0162)	(0.0192)	(0.0176)	(0.0137)
$SW\_Threat\_t_{0-3}$	-0.0064	0.0223	0.0297	0.0365**	0.0110
	(0.0284)	(0.0139)	(0.0210)	(0.0167)	(0.0132)
$SW\_Threat\_t_{0-2}$	-0.0231	0.0138	0.0370*	0.0342*	0.0081
	(0.0299)	(0.0160)	(0.0210)	(0.0176)	(0.0156)
$SW\_Threat\_t_{0-1}$	-0.0204	0.0140	0.0536**	0.0311*	0.0095
	(0.0297)	(0.0156)	(0.0215)	(0.0183)	(0.0165)
$SW\_Threat\_t_{0}$	-0.0053	-0.0040	0.0599**	0.0290	0.0038
	(0.0306)	(0.0172)	(0.0230)	(0.0198)	(0.0189)
$SW\_Threat\_t_{0+1}$	-0.0179	0.0152	0.0601***	0.0334*	0.0055
	(0.0302)	(0.0162)	(0.0230)	(0.0184)	(0.0166)
$SW\_Threat\_t_{0+2}$	-0.0183	0.0129	0.0453*	0.0300	-0.0029
	(0.0364)	(0.0163)	(0.0248)	(0.0204)	(0.0172)
$SW\_Threat\_t_{0+3}$	0.0084	0.0264	0.0494*	0.0476**	0.0180
	(0.0380)	(0.0190)	(0.0251)	(0.0217)	(0.0181)
$SW\_Entry\_t_{e}$	-0.0250	0.0132	0.0367	0.0301	0.0109
	(0.0421)	(0.0218)	(0.0318)	(0.0260)	(0.0214)
$SW\_Entry\_t_{e+2}$	0.0056	0.0207	0.0433	0.0472*	0.0219
	(0.0397)	(0.0217)	(0.0310)	(0.0248)	(0.0200)
$SW\_Entry\_t_{e+3}$	0.0231	0.0262	0.0284	0.0555*	0.0265
	(0.0420)	(0.0240)	(0.0332)	(0.0293)	(0.0246)
Observations	8,867	19,152	9,187	16,885	16,535

Notes: All specifications include airline-market fixed effects and airline-time fixed effects. All specifications include as control variables the (log of) total number of passengers flying through the origin and destination airports of the market, the (log of) number of destinations served by the incumbent airline out of the origin and destination airports of the market, and (log of) measures for the degree of time differentiation in arrival and departure banks at the origin and destination airports, respectively. Standard errors are in parentheses and are clustered by market-carrier. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

2.6. Entry Deterrence or Accommodation?

A natural question is whether the preemptive actions taken by incumbent airlines when Southwest threatens entry into a market respond to an entry deterrence strategy, or instead, to a strategy followed to try to soften competition once entry occurs (i.e., accommodation strategy).

To detect this, I conduct different tests. First, following the insights of Dafny (2005) and Ellison and Ellison (2011), I compare the preemptive behavior in markets in my sample where entry is unlikely, entry is uncertain, and in markets where entry is very likely. If entry deterrence is the motivation, we should not observe a preemptive action where deterrence is impossible. Southwest business model, based on aircraft productivity and density of the market, implies that market size is a good proxy for assessing the likelihood of entry, conditional on presence at both endpoints of the market. Then, we should not observe a preemptive action in very small markets, since either entry deterrence (or accommodation) is unnecessary. On the other hand, if entry deterrence is impossible in very large markets, we should not observe any preemptive action in these markets if entry deterrence is the motivation. To test this hypothesis, I divide the sample into three mutually exclusive subsamples: (1) those markets where average market size was below the 25th percentile, (2) those markets with average market size laying between the 25th and 75th percentile (i.e., interquartile range), and (3) those markets where the average market size was above the 75th percentile. Columns (1) to (3) of Table 2.9 report the results of the analysis, showing that the effect of a threat of entry on the differentiation index is largest in those markets in the interquartile range of market size (i.e., those instances where Southwest entry is uncertain). On instances where the average market size is low (those in the bottom 25th percentile), the effect of a threat of entry on the differentiation index is small and statistically insignificant. A similar result is found for those cases in which the average market size is high (i.e., those in the upper 25th percentile). In this later case, point estimates are not statistically significant at conventional levels, but they are slightly higher than those corresponding to the lower quartile of average market size. Thus, when there is no such possibility of deterrence, as on the upper quartile markets, incumbents take, at best, modest actions. These results suggest that incumbents' responses are motivated by their goal of deterring Southwest from entry.

To further investigate the strategic motives behind the preemptive actions, I follow an analysis similar to the one performed by Goolsbee and Syverson (2008) by looking at those markets in which Southwest begins direct service between two endpoint airports of the market either in the same or the following month that it starts operating in the second endpoint airport. These are instances where entry is likely to be preannounced, and therefore the deterrence motive is very unlikely since it seems impossible to deter entry. Column (4) of Table 2.9 shows the results from the estimation of this model. All coefficients are negative, but they are all imprecisely estimated (and not statistically significant at conventional levels of significance). It seems that in this exercise the data are too sparse to speak to preemptive motives.

The way through which the deterrence action, higher incumbent levels of differentiation in departure times in this case, might operate is not clear. A possible mechanism through which the deterrence behavior could operate involves business stealing, by placing flights around times which would constitute niches of the market for a potential entrant.

Then, a possible explanation for the observed preemptive action is that it reflects efforts by incumbents to reduce displacement costs (i.e., difference between the departure time and passengers' most preferred departure times) among existing valuable customers, making them less likely to switch to Southwest should it enter. Another possible explanation for the observed preemptive behavior is that it reflects efforts by incumbents to place flights close to Southwest expected departure times. The mechanism here is the same as before: business stealing effects. In order to test this hypothesis, I construct measures of expected departure times for Southwest, in the threatened markets. These measures are created using the departure and arrival banks at the airport of the market in which Southwest established presence first. If the endpoint airport of the market in which Southwest established presence first is the origin airport, then the expected departure times for Southwest in this market are given by the arrival banks plus 45 minutes (where 45 minutes represents the average turnaround time for Southwest Airlines). If the endpoint airport of the market in which Southwest established presence first is the destination airport, then the expected departure times for Southwest in this market are given by the departure banks at the destination airport, minus 45 minutes, minus the median flight time in the market, plus any time difference between the origin and destination airports in the market. These expected departure times would coincide with those chosen by Southwest if the airline wanted to maximized the connectivity of its flights as well as minimize the layover times of its passengers at the connections. To study if incumbents react to a threat of entry by scheduling their flights closer to Southwest expected departure times I compute the average distance to the closest expected departure time by Southwest. The results for this entry deterrence motive are shown in column (5) of Table 2.9. Although noisy, the point estimates from the regression suggest that when Southwest threatens entry into a market, incumbents respond by placing their flights closer to Southwest's expected departure times. I cannot definitively confirm this deterrence behavior given the point estimates and the coefficients' precision, but there is an indication at conventional significance levels that flights are scheduled closer to Southwest's expected departure times once presence at both endpoints of the markets has been established.

Table 2.9. Incumbent Responses to a Threat of Entry: Entry Deterrence or Accommodation?

Variables	(1) $\ln(D_{0.5})$ Small Mkt. Size	(2) $\ln(D_{0.5})$ Medium Mkt. Size	(3) $\ln(D_{0.5})$ Large Mkt. Size	(4) $\ln(D_{0.5})$ Preannounced Entry	(5) log avg. Distance to closest expected departure time by SW
$SW\_Threat\_t_{0-8}$	-0.0195	0.0096	0.0023	-0.0135	-0.0351
	(0.0203)	(0.0100)	(0.0084)	(0.0241)	(0.0268)
$SW\_Threat\_t_{0-7}$	-0.0082	0.0035	0.0087	-0.0463	-0.0105
	(0.0216)	(0.0117)	(0.0122)	(0.0322)	(0.0309)
$SW\_Threat\_t_{0-6}$	-0.0114	0.0198	0.0230	-0.0511	-0.0045
	(0.0262)	(0.0121)	(0.0179)	(0.0342)	(0.0347)
$SW\_Threat\_t_{0-5}$	0.0056	0.0193	0.0169	-0.0560	0.0220
	(0.0245)	(0.0146)	(0.0176)	(0.0440)	(0.0358)
$SW\_Threat\_t_{0-4}$	0.0135	0.0391***	0.0217	-0.0276	-0.0110
	(0.0274)	(0.0142)	(0.0200)	(0.0644)	(0.0385)
$SW\_Threat\_t_{0-3}$	0.0172	0.0489***	0.0308	-0.0338	-0.0349
	(0.0241)	(0.0146)	(0.0196)	(0.0632)	(0.0419)
$SW\_Threat\_t_{0-2}$	0.0166	0.0489***	0.0291	-0.0469	-0.0064
	(0.0264)	(0.0162)	(0.0177)	(0.0633)	(0.0426)
$SW\_Threat\_t_{0-1}$	0.0194	0.0524***	0.0258*	-0.0371	-0.0530
	(0.0271)	(0.0166)	(0.0154)	(0.0717)	(0.0418)
$SW\_Threat\_t_{0}$	0.0027	0.0548***	0.0278		-0.0832*
	(0.0336)	(0.0192)	(0.0170)		(0.0466)
$SW\_Threat\_t_{0+1}$	0.0142	0.0623***	0.0199		-0.0786*
	(0.0301)	(0.0164)	(0.0174)		(0.0452)
$SW\_Threat\_t_{0+2}$	-0.0067	0.0544***	0.0310		-0.0802*
	(0.0316)	(0.0181)	(0.0202)		(0.0476)
$SW\_Threat\_t_{0+3}$	0.0057	0.0742***	0.0383		-0.1205**
	(0.0381)	(0.0185)	(0.0259)		(0.0537)
$SW\_Entry\_t_{e}$	-0.0041	0.0527**	0.0396*	-0.0636	-0.1445**
	(0.0404)	(0.0259)	(0.0240)	(0.0497)	(0.0623)
$SW\_Entry\_t_{e+2}$	-0.0023	0.0720***	0.0477*	-0.0485	-0.1104*
	(0.0419)	(0.0214)	(0.0245)	(0.0776)	(0.0595)
$SW\_Entry\_t_{e+3}$	-0.0214	0.1017***	0.0462*	-0.0565	-0.1310**
	(0.0457)	(0.0270)	(0.0273)	(0.0889)	(0.0636)
Observations	6,914	18,435	11,857	3,056	34,626

Notes: All specifications include airline-market fixed effects and airline-time fixed effects. All specifications include as control variables the (log of) total number of passengers flying through the origin and destination airports of the market, the (log of) number of destinations served by the incumbent airline out of the origin and destination airports of the market, and (log of) measures for the degree of time differentiation in arrival and departure banks at the origin and destination airports, respectively. Standard errors are in parentheses and are clustered by market-carrier. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

2.7. Conclusions

This chapter studies the response of incumbent airlines to a threat of entry by Southwest Airlines, which is initiated when Southwest starts operating in both endpoint airports of a market but before it starts flying non-stop flights in that market. I examine whether entry threats by Southwest cause incumbent airlines to change the degree of product differentiation in the market, measured by differentiation in departure times, in an effort to either deter or accommodate entry.

The results indicate that incumbents do indeed take preemptive actions as a response to Southwest's entry threat. In particular, an incumbent airline reacts by increasing the degree of differentiation in departure times before entry takes place. The results also reveal that this response is typically accompanied by an increase in the incumbent's range in departure times (i.e., difference in minutes between the last and first flights of the day) as well as in the interquartile range of the distribution of departure times. The preemptive action does not seem to be related to incumbents trying to schedule their flights closer to the peaks of demand. Moreover, the response does not appear to be driven by efficiency motives, or airport specific supply or demand shocks. I also find that higher market share is a strong determinant of the strength of the carrier's response to a threat of entry by Southwest. The response in terms of product differentiation is more pronounced when the incumbent has higher market share. Hub at a destination airport (as opposed to flights departing from a hub) is also a strong determinant of the incumbent's response.

The chapter also presents evidence on the explanation for these preemptive actions. Consistent with a deterrence motive, I find that in markets where Southwest's entry is guaranteed, and consequently entry deterrence is not possible, incumbents do not appear to change the degree of product differentiation. Additionally, and also consistent with the deterrence motive, I provide suggestive evidence that the preemptive action takes the form of incumbents scheduling their flights closer to times when there is an expectation that Southwest will schedule its departures.

Overall, the findings of the chapter suggest that, in addition to pricing and quality, schedule planning is an important tool for competition in the U.S. passenger airline industry. The chapter demonstrates the importance of considering the role of scheduling decisions not only in terms of integrating the carriers' networks, but also as a strategic response to the competitive environment.

CHAPTER 3

Airport Access and Market Structure in the Airline Industry

3.1. Introduction

This chapter estimates a static oligopoly model of airline competition to study the effects of an airline's scale of operation at an airport (airport presence hereafter) and airport constraints on market structure. The model is a static complete information game, where players first decide on the type of products to be offered in the market, and then, conditional on entry, the prices for their products. Thus, an important feature of the model is that it allows for market structure (number and identity of players that enter the market, the type of product offered by each entrant, and the prices charged) to be endogenous and to react to counterfactual scenarios.

A very well established fact in the literature on airline economics is that an airline's operation at a given airport significantly affects its competitive position on routes flown out of that airport.[1] The most common explanations for this effect rely on demand and cost factors.[2] The demand side story suggests that passengers might value certain characteristics that are associated with airport presence, such as in-airport amenities,

[1] Borenstein (1989) finds that airport dominance and route dominance significantly affect the fares in markets where a carrier is dominant at the originating hub airport. Borenstein (1991) shows that an airline with a dominant position at an airport has a larger share of the overall originating traffic, and thus also has a larger share of any market originating at the dominated hub. Berry (1992), using a structural model, also finds evidence consistent with the large literature that indicates an important role for airport presence in determining airline profitability.

[2] In fact, some literature also emphasizes the role of strategic factors. In particular, this literature argues that airport presence can be an effective strategy to deter the entry of competitors (see for instance Hendricks, Piccione and Tan, 1997).

frequent flyer miles, more convenient check-in, etc. On the other hand, the supply side story establishes that higher airport presence leads to lower costs (either variable or fixed), not only because it reduces the number of round-trips necessary to carry a given number of passengers on a given set of itineraries (if a hub and spoke system is used), but also because it might decrease the cost per passenger on a route if economies of scale on plane size are sufficiently large. In addition, the fixed costs of entering a market or route may also decline if the airline already operates at both endpoint airports of the market. These cost savings may be achieved, for example, by sharing certain inputs in production across flights that serve different destinations from an origin airport. They might include the costs of getting access to airport facilities, staff re-location, new sales offices, etc. A natural question is whether or not airport presence can act as a barrier to entry for other firms, given its role on the demand and supply side of the market. Consumers view products as imperfect substitutes for a number of reasons, one of them being airport presence in the airline industry. If introducing a new product is connected with significant fixed costs, product differentiation may well lead to persistent entry barriers.

Another cause of entry barriers in the airline industry may be airport constraints. Airports operating at full capacity constrained the mode of competition in the market, preventing entry and making it too costly or even impossible for incumbents to re-gain market share or compete in dimensions other than price.[3] Airport constraints, such as number of runways, gates, or Air Traffic Control systems not only influence entry into a

[3] An established fact in the economic airline literature is the S-curve relationship between market share and frequency share. This suggests that there is a region of increasing returns to market share when increasing the frequency share. Airport capacity constraints impose restrictions in this mode of competition.

market, but also airlines' choices of aircraft size, service frequency and routing network.[4] By affecting airlines' incentives on routing network, frequency and aircraft size, these constraints affect the equilibrium variety of products offered by airlines in the market. In fact, the role of airport capacity (or operating barriers) hindering competition has been a topic of debate among researchers and policy makers. For instance, the U.S. Government Accountability Office (GAO) has raised concerns in reiterated opportunities regarding the effects of airport constraints on competition (GAO, 1996; GAO, 1997b; GAO, 1997a; GAO, 1998; GAO, 1999; GAO, 2012). In these documents, the GAO sustains that the operating limits in the form of slot controls, restrictive gate leasing arrangements, perimeter rules, and growing capacity constraints (because of congestion and limited facilities) continue to block entry at key airports, especially in the East and upper Midwest where slot controls and perimeter rules are in place.[5] [6] Likewise, the GAO states that opportunities for establishing new or expanded service are limited at different airports by restrictive gate leases. These leases grant an airline exclusive rights to use most of an airport's gates over a long period of time. Such long-term, exclusive-use gate leases prevent nonincumbents from securing necessary airport facilities on equal terms with incumbent airlines. To gain access to an airport in which most gates are exclusively leased, a nonincumbent must sublet gates from the incumbent airlines, often

[4] Government regulations, such as landing fee policies, also influence these airlines' choices.

[5] The Federal Aviation Administration (FAA) has since 1969 set limits on the number of operations (takeoffs and landings) that can occur during certain periods of the day at a few airports with the goal of minimizing congestion and reducing flight delays. The authority to conduct a single operation during those periods is commonly referred to as a "slot". Currently, there are four slot controlled airports: Washington National, New York Kennedy, Newark and La Guardia.

[6] Perimeter rules governing operations at New York's La Guardia and Washington's National airports prohibit flights to and from those airports that exceed a certain distance.

at non-preferred times and at a higher cost than the incumbent.[7] Ciliberto and Williams (2010) study the effect of limited access to airport facilities on creating market power in the airline industry. They find that control of an airport's resources appears to be an important source of the dominant carriers' market power (for example, the control of gates is a crucial determinant of the hub premium).[8] In a related paper, Snider and Williams (2015) investigate the effects of Congressional mandates aimed at increasing competition in the industry, which required highly concentrated major U.S. airports to increase the availability of scarce facilities to all carriers. They find a significant decrease in fares resulting in airports covered by the legislation. This fare reduction is mostly driven by decreases in dominant carriers' fares at hub airports and by the entry of low-cost carriers into new markets.

To study the effects of airport presence and airport constraints on market structure I rely on the estimation of a static complete information game. The model incorporates the dependence of demand and costs to airport presence and constraints that I have described above. In this model, airlines decide first what markets (directional city-pairs) to enter, the type of product to provide conditional on entry (i.e., non-stop flights vs stop-flights), and then the fares for each market-product they serve. A key feature of the model is that it allows me to recover an estimate of the fixed costs of serving a market, and its dependance on airport constraints and airport presence. This enables me to estimate

[7] Although the development, maintenance, and expansion of airport facilities is essentially a local responsibility, most airports are operated under federal restrictions that are tied to the receipt of federal grant money from the FAA. The GAO suggested that one way to alleviate the barrier created by exclusive-use gate leases would be for the FAA to add a grant restriction that ensures that some gates at an airport would be available to nonincumbents.

[8] In this sense, reduction in airport constraints might create opportunities for incumbent and non-incumbent airlines to re-establish their competitive position at an airport, by bargaining and getting access and control over new resources and facilities.

the relative contribution of airport presence on demand and costs to explain price-cost margins in the industry. The goal of this chapter is then characterized by the following questions: (1) What are the fixed costs of entering into a market? (2) How do airport presence and airport constraints affect these fixed costs? (3) How do airport presence and airport constraints affect market structure (equilibrium entry, product offerings and prices)?

The chapter adds to the extensive empirical literature on the airline industry, contributing more specifically to the topics of entry and determinants of market power.[9] The closest paper in terms of this research question is Berry (1992), who investigates the importance of airport presence in determining the profits of operating in a given market. He relies on a structural model of equilibrium outcomes where airlines' profit function is modeled in reduced form. This assumption implies that airlines have homogeneous products and variable costs. In my model, products are differentiated and variable costs are heterogeneous across airlines. My specification of demand and variable costs follows a random coefficient logit model as in Berry, Levinsohn and Pakes (1995), where product characteristics comprise an indicator for non-stop flight and measures of market presence at origin and destination airports, among other characteristics. Perhaps most importantly, the model I use accounts for the decision of whether or not to enter the market as well as the type of products to be offered. Considering this stage is necessary to recover an estimate of fixed entry costs, which are relevant for learning about their implications

[9] Previous work on the airline industry has mainly focused on the determinants of the hub premium (e.g., Borenstein, 1989; Borenstein, 1991; Berry, 1992), the effects of mergers (e.g., Borenstein, 1990; Kim and Singal, 1993; Peters, 2006; Benkard et al., 2010; Li et al., 2016), and the effects of entry on market outcomes (Sinclair, 1995; Reiss and Spiller, 1989; Ciliberto and Tamer, 2009; Goolsbee and Syverson, 2008; Boguslaski, Ito and Lee, 2004; Benkard et al., 2010; Aguirregabiria and Ho, 2012).

on market structure. In particular, the differentiated effects of airport presence on profits through its influence on demand and supply allow us to separate, for example, the price-cost margins into the component that is due to product differentiation and the one that is due to costs.

This chapter builds on a significant literature on structural models of firm product repositioning. Prior work on firm product repositioning has either relied on cross-sectional variation provided by multiple geographic markets (e.g., Mazzeo, 2002; Seim, 2006; Fan, 2013; Draganska et al., 2009; Ciliberto et al., 2015; Li et al., 2016) or on the times series or panel feature of the data to recover fixed costs measures of repositioning the product (e.g., Eizenberg, 2014; Nosko, 2014; Wollmann, 2015; Sweeting, 2013; and Aguirregabiria and Ho, 2012). In this chapter I follow the first approach to recover the fixed costs of entry. The model used in this chapter is similar to a set of closely related models used in three different recent papers. The first one is Eizenberg's (2014) model of entry and competition in the personal computer industry. He assumes that firms do not know the error terms of the demand and marginal costs equation before entry. This limits the amount of entry selection captured by the model to only selection in observables. Li et al. (2016) and Ciliberto et al. (2015) estimate a model of entry and competition for the airline industry, with the goal of studying the effects of the recent wave of mergers. Unlike Eizenberg's (2014) model, these papers allow for selection on entry both on observable and unobservable characteristics of demand and marginal costs. Differences between these two papers rely on equilibrium selection rules and correlation in unobservables.[10]

[10] More specifically, the model estimated by Li et al. (2016) imposes an equilibrium selection rule in the entry stage and does not allow for correlation in the unobservables. Then, this model can be thought of as a private case of the model estimated by Ciliberto et al. (2015), which does not rely on that assumptions for estimation.

In this chapter, estimation relies on the timing assumption that firms do not observe the error terms for product quality or marginal costs before entry (similar to the model by Eizenberg, 2014), as well as on equilibrium selection rules and stronger assumptions about the correlation of unobservables (like in the model estimated by Li et al., 2016).

I estimate the model using data from the Airline Origin and Destination Survey (DB1B) for the second quarter of 2014, 2015 and 2016. I focus on markets between the 55 largest U.S. cities (2,970 markets or directional city-pairs), and on the behavior of six carriers: American, United, Delta, Southwest, Other network carriers, and Other low cost carriers. The results indicate that an airline's scale of operation at an airport measured by the number of non-stop destinations that the airline serves from the airport is an important factor for consumers' willingness to pay as well as for the fixed costs of entering a market. I find that the effect of airport presence on the fixed costs of serving a market is substantial, especially for non-stop products. Additionally, my results indicate that the fixed costs of offering service in a market in which any of its endpoint airports is either a slot controlled airport or classified as capacity constrained by the Federal Aviation Administration are considerably higher than in non-capacity constrained or non-slot controlled airports. I use the estimated model and counterfactual experiments to study the effects of airport constraints and airport presence on market structure and pricing. The results of these experiments suggest that both airport constraints and airport presence affect pricing and market structure significantly. Elimination of airport constraints or changes in airport regulation affecting airport presence significantly encourage entry into markets and, as a consequence, tend to drive prices down.

This chapter is organized as follows. Section 3.2 introduces the model. Section 3.3 presents the data and some summary statistics. Section 3.4 describes the estimation strategy, and Section 3.5 reports the results. I study the effects of airport presence and airport constraints on market structure in Section 3.6 using counterfactual analysis. Finally, Section 3.7 concludes.

3.2. Model

The industry is configured by N airline companies, C cities, $M = C \times (C-1)$ local markets, and $Q = M/2$ city-pairs. A local market is a particular directional origin-destination city-pair. At any given period t the industry contains a set of network (or legacy) carriers $\mathcal{N}$ and low cost carriers $\mathcal{L}$. Any airline can only be described or characterized by one of these types (i.e., network carrier, or low cost carrier (LCC)). Low cost carriers, as opposed to network carriers who provide service using their hubs, fly point-to-point.

For my analysis, I take airlines hubs as given, focusing primarily on the determination of entry decisions into local markets and prices charged.[11] Each period t, airlines solve a two-stage game, where they first make decisions sequentially on entry (i.e., no entry, stop entry, or non-stop entry) on each city pair (and thus, their product offerings); and then maximize profits competing on prices in each market given the current state. The timing of the game is as follows:

[11] Low cost carriers do not operate hubs but focus cities.

1- Network and LCC carriers realize sunk costs shocks of entry using stop and non-stop products (η^s, η^{ns}), and sequentially make their decisions on entry in each segment. I aasume that at the entry stage, airlines do not observe the shocks to preference and marginal costs (ξ, ζ). The entry decision is characterized by the three possible actions: no entry, entry with connecting service, or entry with non-stop service. I assume that players only choose one of these options.

2- Given legacy and LCC carriers entry decisions, these two type of airlines observe the shocks to preference and marginal costs (ξ, ζ) and compete in prices, setting prices according to a model of Nash-Bertrand competition.

I assume that airlines solve the problem by working backwards from the second stage. They first compute the expected equilibrium profits that will obtain under any possible set of product offerings (i.e., entry decisions) and then choose the products (i.e., no entry, stop entry, or non-stop entry) that maximize those profits. For this reason, I describe first the demand system and static profit maximization problem, to turn attention then to the airlines' entry decision problem.

3.2.1. Demand

A market is defined as directional round-trip air travel between an origin and destination city during a given time period. The assumption that markets are directional implies that round-trip air travel from Chicago to Miami is a distinct market as compared to round-trip air travel from Miami to Chicago. Furthermore, this directional assumption allows for the possibility that origin city characteristics may influence market demand.

A flight itinerary (r) is defined as a specific sequence of airport stops in traveling from the origin to destination city. Products are defined as a unique combination of airline and flight itinerary. For instance, a United non-stop flight from Miami to Chicago and a United stop flight from Miami to Chicago with a stop in New York are two different products in the same market. A set of J_{mt} products is offered in quarter t and market m. Each consumer chooses among one of these products or chooses the outside option of not purchasing any of them, which may include other means of transportation such as train or auto travel, or the use of phone.

I follow Berry et al. (1995) and model demand as a random-coefficient logit specification. The demand model is also similar to the one used in Berry et al. (1996) and Berry and Jia (2010). Every time (t) consumers decide whether to purchase a ticket for market m, which airline to patronize (a), and the type of product (j). The indirect utility function of a consumer who purchases product (j, m) is:

$$u_{ijmt} = x_{jmt}\beta - \alpha p_{jmt} + \xi_{jmt} + \mu_{ijt} + \varepsilon_{ijmt} \tag{3.1}$$

where β is a $K \times 1$ vector of taste for product characteristics; and x_{jmt} is a K dimensional vector of product characteristics, including a constant term, market distance and the squared value of it, a binary indicator for one-stop itinerary, variables measuring the scale of operation or airport presence of the airline in the origin and destination airports of the route, a dummy for a tourist destination, the number of slot controlled airports in the route, market size fixed effects, and airline and time (year) fixed effects.[12] I allow some of

[12] I follow Ciliberto and Tamer (2009) and measure airport presence as a carrier's ratio of markets served by an airline out of an airport over the total number of markets served out of an airport by at least one carrier.

the parameters associated with these characteristics to vary by type of carrier (i.e., legacy or low cost). This heterogeneity in carrier-type in the parameters is aimed to capture the different amenities and type of services between low cost and legacy carriers. Price is denoted by p_{jmt}, and its coefficient is denoted by α.

The variable ξ_{jmt} is a demand shifter or a measure of differences in product quality that are unobserved by the researcher, but observed by consumers and firms. These unobserved characteristics might include factors such as the quality of the food and the service, departure times, or tickets restrictions such as advanced purchase Saturday night stayover fares or advanced purchase fares with no stayover restrictions.[13] Since prices are likely to be correlated with ξ_{jmt} (e.g., refundable tickets are generally more expensive than nonrefundable ones), I will instrument for prices allowing for any arbitrary correlation between these unobserved product attributes and prices.

Note that utility is the sum of a mean-utility (across consumers) component $\delta_{jmt} = x_{jmt}\beta - \alpha_m p_{jmt} + \xi_{jmt}$ obtained from consuming product j, and a consumer specific deviation $\mu_{ijt} + \varepsilon_{ijmt}$. The term $\mu_{ijt} = \sigma_p p_{jmt} \nu_{ip} + \sum_{k=1}^{K} \sigma_k x_{jtk} \nu_{ik}$ is a consumer-specific deviation from the mean utility level which depends on the consumers' taste for each product characteristic, where $\sigma = (\sigma_p, \sigma_1, ..., \sigma_K)$ is a set of parameters that measure variation (across consumers) in random taste shocks for respective product characteristics, and $\nu_i = (\nu_{ip}, \nu_{i1}, ..., \nu_{iK})$ is a set of consumer i's random taste shocks for respective product characteristics. Finally, ε_{ijmt} is the logit error random component of utility, distributed *i.i.d.* (across consumers and products) as a Type-I Extreme Value.

[13] Although the data allows to distinguish between restricted and unrestricted fares, it is still not possible to learn about the different kinds of restrictions. See Section 3.3 for further discussion about the data.

The utility from the outside option is given by:

$$u_{iot} = \varepsilon_{iot}$$

where ε_{iot} is another logit error term. Therefore, coefficients of variables that vary at the market level and enter the utility for inside the market goods are interpreted as being relative to the outside good.

The demand specification described above allows the taste of consumers who purchase a product to vary systematically with x_{jmt} and p_{jmt}. In particular, it allows consumers' taste towards a product characteristic $k \in 1, 2, ..., K$ to shift around its mean, β^k, with the consumer-specific term $\sigma_k \nu_{ik}$. Traditional random coefficient models, as in Berry et al. (1995), assume that the individual taste for product characteristics and prices (β_i, α_i) are distributed *i.i.d.* normal across consumers, with correlation of tastes across these characteristics assumed to be zero for simplicity. As noted by Berry et al. (1996) and Berry and Jia (2010), there are reasons to believe that this assumption does not hold true in the airline industry. In particular, there is not only a group of travelers for whom the price of a ticket is not an important consideration in their decision to fly (business travelers), and another group of consumers for whom the price of a ticket is an important factor; but moreover, business travelers may have systematically different tastes for observed x's, such as non-stop itineraries, flight frequencies or airport presence.[14] This observation suggests that tastes are correlated across characteristics. For computational reasons, I

[14] Berry et al. (1996) and Berry and Jia (2010) assume two different type of consumers (i.e., business and tourist travelers). Berry et al. (1996) allow for correlation in tastes across price, connection in the itinerary, hub size, flight frequency in the route, and difference between origin and destination mean January temperatures. Berry and Jia (2010) allow for correlation in tastes across price, connection in the itinerary, and the constant term.

restrict the correlation of tastes across characteristics and some of the σ_k to be zero in the empirical application. However, I allow for heterogeneity in price sensitivity, in the taste for stop travel, in the taste for airport presence at the origin airport, and in the taste for the outside option (via a random coefficient on the constant term). Heterogeneity along these dimensions governs firms' incentives to provide product variety.

The market share of product $j \in J_{mt}$ predicted by the model is given by:

$$d_{jmt} = \int \frac{e^{\delta_{jmt}+\mu_{ijt}}}{1+\sum_{l=1}^{J_{mt}} e^{\delta_{lmt}+\mu_{ilt}}} dF(\nu)$$

where $F(.)$ is the joint distribution of taste shifters ν_i. Then, market shares are defined as the share of a given product out of all potential trips between the two endpoint cities. Since the number of potential trips is not observed, I follow the standard practice in the economic airline literature of assuming that it is proportional to the population of the origin and destination cities.[15]

3.2.2. The Firm's Problem

At any given period t, airlines solve a two-stage game. In the first stage, airlines choose sequentially whether or not to enter in a local market and their product offerings (i.e., stop or non-stop service). In the second stage, air carriers maximize profits by setting prices a la Nash-Bertrand for each product in each market; taken as given the current entry decisions, and the knowledge of demand. Additionally, consumers make purchase decisions.

[15] In the empirical application, it is assumed to be proportional to the geometric mean of the population of the origin and destination cities.

I assume that airlines solve the problem by working backwards from the second stage. They first compute the expected equilibrium profits that will obtain under any possible set of product offerings and then choose the products (i.e., no entry, stop service, or non-stop service) that maximize those profits. For this reason, I start describing the second stage of the game (i.e., pricing stage), to turn attention then to the first stage (i.e., entry stage).

3.2.2.1. Second Stage: Pricing. In the second stage of the game, upon observing shocks to demand and marginal costs, air carriers maximize profits by setting prices according to a static Nash-Bertrand equilibrium, conditioning in own and rival's observed entry decisions.

In this second stage, the variable profit function for airline a in local market m at time t is given by:

$$R_{amt} = (p_{jmt} - mc_{jmt})q_{jmt} \qquad for \quad j \in \Omega = \{Stop, Non-stop\} \tag{3.2}$$

where mc_{jmt} is the constant marginal cost of providing the services necessary to offer product j (or the cost per passenger of product j), $q_{jmt} = d_{jmt} \times M_{mt}$ represents the number of enplaned passengers (equal to market share times the size of the market M_{mt}), and $\Omega = \{Stop, Non-stop\}$ is the set of product offerings that an airline can offer in a market. As it was previously mentioned, I assume that players only choose one type of product (e.g., stop vs non-stop service) conditional on entry.

Marginal costs for product j in market m are represented by:

$$\ln mc_{jmt} = w'_{jmt}\gamma + \zeta_{jmt} \tag{3.3}$$

where w_{jmt} is a vector of observed cost-shifters for product j in market m, γ is a vector of parameters to be estimated, and ζ_{jmt} is an unobserved cost shock at the product level. The vector of cost-shifters w_{jmt} include a constant term, itinerary round-trip distance (in 1,000 of miles) and the squared value of it, a dummy for a connection in the itinerary, the number of destinations served out by the air carrier from the origin and destination airports, dummies of ticketing carriers, and time (year) effects. These cost-shifters are aimed to capture those costs that vary with the number of passengers, such as certain inflight amenities (e.g., food), baggage handling and processing costs, ticketing costs, security screening costs, and airport passenger facility charges, among others.

Prices are set according to a static Nash-Bertrand equilibrium. Following Berry et al. (1995), equilibrium markups $b_{jmt}(d_{mt}, x_{mt}, p_{mt}, \theta_d)$ are computed from the knowledge of the demand data and parameters. Thus, the pricing equation for product j in market m is given by:

$$p_{jmt} = mc_{jmt} + b_{jmt}(d_{mt}, x_{mt}, p_{mt}, \theta_d) \tag{3.4}$$

where θ_d is the vector of parameters that enter in the demand equation.

3.2.2.2. First Stage: Entry. As mentioned in previous sections, the industry is configured by N airlines, which are potential entrants in each of the M local markets (directional round-trip between two cities). In the entry stage, each carrier observes the realizations of fixed entry costs, but not the demand and marginal cost realizations. The fixed costs realizations are known by all potential entrants in the game (i.e., complete information game). Upon observing these realizations, air carriers decide sequentially on entry into the market and the type of service to provide. The strategy space is then characterized by the following three possible actions: no entry, entry with connecting service, or entry with non-stop service. I assume that players only choose one of these options.[16] Note that the information assumption on observability of demand and cost shocks allows airlines to be selected only on observed characteristics of demand and marginal costs, and therefore it rules out entry selection on unobserved variation in qualities and costs.

Airlines make entry decisions sequentially. I assume that airlines with the highest average presence at the endpoint cities move first. The sequential move assumption, together with the single product assumption, ensures that the game has a unique pure-strategy equilibrium (provided that there is a unique equilibrium in the pricing stage of the game). Additionally, the assumptions of the game imply that even though the entry decision and product offerings are endogenous, the airlines' hub status are taken as exogenous.

Airline a's expected profit in market m at time t is given by:

$$\begin{aligned}\pi_{amt} &= \int_{\xi,\zeta} R_{amt}(\sigma_{amt}, \sigma_{-amt}; \hat{\theta}_d, \hat{\gamma}, x, p^*, w, \xi, \zeta) dF_\xi dF_\zeta \\ &- 1_{[\sigma_{amt}=Non-stop]} \times FC^{NS}_{amt} - 1_{[\sigma_{amt}=Stop]} \times FC^{S}_{amt}\end{aligned}$$

where $\sigma_{amt} \in \{No-entry, Stop, Non-stop\}$ represents the strategy profile, and where the fixed costs of non-stop and stop service are represented by:

[16] This means that an airline offering non-stop service does not offer connecting service.

$$FC^{NS}_{amt} = \gamma^{ns}_0 + \gamma^{ns}_1 Avg\_NDS_{amt} + \gamma^{ns}_2 LCC_a + \gamma^{ns,s}_3 CONST_{mt} + \eta^{ns}_{amt}$$

$$FC^{S}_{amt} = \gamma^{s}_0 + \gamma^{s}_1 Avg\_NDS_{amt} + \gamma^{s}_2 LCC_a + \gamma^{ns,s}_3 CONST_{mt} + \eta^{s}_{amt}$$

Fixed costs of offering service represent those costs that do not vary with the number of passengers flown in the market. These costs represent, for example, the cost of leasing gates, office space, or hiring personnel for aircraft operations at the airports (in order to enplane and deplane flights, for example). I assume that fixed costs of offering non-stop and stop service depend on an airline's network (i.e., economies of density) measured by the average number of non-stop routes that an airline serves out of the origin and destination airports of the market (Avg_NDS_{amt}), the type of carrier (where LCC_a is a dummy for low cost carrier), and on whether the market contains a constrained airport at any of its endpoints.[17] The marginal effect of $CONST$ on fixed costs is assumed to be the same across the two type of fixed costs (i.e., the coefficient for this variable is the same across fixed cost equations). $\{\eta^{ns}_{amt}, \eta^{s}_{amt}\}$ are shocks to the fixed costs functions observed by airlines when making its entry decisions. I assume that $\eta^j \sim N(0, \sigma^j_f)$ for $j \in \{ns, s\}$, and that η^j_{amt} is independent across airlines and city-pairs.[18] Finally, I assume that non-entrants make zero profit.

[17] The set of constrained airports is comprised by slot controlled airports and airports classified as capacity constrained by the Federal Aviation Administration (FAA). The list of slot controlled airports include Washington Reagan (DCA), Newark (EWR), John F. Kennedy (JFK), and La Guardia (LGA). The list of capacity constrained airports, as classified by the FAA, include Newark (EWR), John F. Kennedy (JFK), La Guardia (LGA), San Francisco (SFO), O'Hare Chicago (ORD), Atlanta (ATL), Philadelphia (PHL), Charlotte (CLT), and Fort Lauderdale-Hollywood (FLL).

[18] I also assume independence among η^{ns}, η^{s}, ξ, and ζ.

3.3. Data

The data come from two main sources. The Origin and Destination Survey (DB1B), which is a 10 percent random sample of airline tickets from U.S. reporting carriers, provides information on flight itineraries (origin, destination and connecting airports), itinerary fare, ticketing and operating carriers for each segment of the itinerary, distance flown on each itinerary in a directional market, and the number of passengers traveling on a given itinerary in each quarter and year. These data are collected quarterly and span from the first quarter of 1993 to the third quarter of 2016. Airport presence data comes from the Air Carrier Statistics database, also known as the T-100 data bank, which contains domestic airline market and segment data. Certificated U.S. air carriers report monthly air carrier traffic information using Form T-100. Segment data provides information on the number of departures performed, departures scheduled, passengers, freight, mail, cargo and aircraft hours. These data are collected monthly and span from the first month of 1993 to the last month of 2016. Both sources of data are maintained and published by the U.S. Department of Transportation (DOT). For my analysis, I use data from the second quarter of 2014, 2015, and 2016.

I focus on the the 55 largest metropolitan areas ("cities"), which comprise a total of 67 airports.[19] A market, then, is a directional round-trip between and origin and destination city. This implies that there are 2,970 markets in the model. These definitions are the

[19] This selection criterion is similar to others papers in the literature. For instance, Berry (1992) who selects the 50 largest cities, and uses city-pair as definition of market. Ciliberto and Tamer (2009) select airport pairs within the 150 largest Metropolitan Statistical Areas. Borenstein (1989) considers airport-pairs within the 200 largest airports. Aguirregabiria and Ho (2012) focus on the 55 largest metropolitan areas, using directional city-pairs as definition of the market. Berry and Jia (2010) focus on airports located in medium to large metropolitan areas with at least 850,000 people in 2006, defining the market as a directional round-trip travel between and origin and destination airport.

same as in Berry (1992), Berry et al. (1996), and Aguirregabiria and Ho (2012); and similar to the ones used by Borenstein (1989), Ciliberto and Tamer (2009) or Berry and Jia (2010) with the only difference that they consider airport-pairs instead of city-pairs. In the estimation of the model, I include markets that are temporarily not served by any carrier (i.e., markets where the number of observed entrants is equal to zero). Market size is defined as the geometric mean of the total population of the origin and destination cities.[20] Table 3.1 presents the list of metropolitan areas with their respective airports.

To construct the estimation sample, I keep only round-trip tickets within the continental U.S., with at most four segments. I eliminate tickets cheaper than $20, those containing ground transportation as a part of the itinerary, those with multiple ticketing carriers, and tickets with fare credibility questioned by the Department of Transportation. Additionally, I consider that a product of an airline is active in the market if during the quarter the product has at least 270 passengers per quarter (approximately 21 passengers per week) or if the share of the product on the total number of passengers enplaned by the airline in the market is at least 5%. Other papers have used similar criteria and thresholds to help eliminate idiosyncratic product offerings that are not part of the normal set of products offered in a market.[21] Service in the market is defined by the ticketing carrier in the DB1B data. This implies that passengers carried by regional affiliates (such as American Eagle, Delta connection, or United Express) count as if they were carried by the associated major carrier.

[20] These data come from the Population Estimates Program of the US Bureau of Statistics, which produces annually population estimates based upon the last decennial census.
[21] See for example Berry (1992), Ciliberto and Tamer (2009) or Aguirregabiria and Ho (2012).

Table 3.1. Metropolitan Areas and Airports

City	**Airports**	**City**	**Airports**
New York, NY	LGA, JFK, EWR	Las Vegas, NV	LAS
Los Angeles-Long Beach, CA	LAX, BUR, LGB	Portland, OR	PDX
Chicago, IL	ORD, MDW	Oklahoma City, OK	OKC
Dallas, TX	DAL, DFW	Tucson, AZ	TUS
Phoenix, AZ	PHX	Albuquerque, NM	ABQ
Houston, TX	HOU, IAH, EFD	New Orleans, LA	MSY
Philadelphia, PA	PHL	Cleveland, OH	CLE, CAK
San Diego, CA	SAN	Sacramento, CA	SMF
San Antonio, TX	SAT	Kansas City, MO	MCI
San Jose, CA	SJC	Atlanta, GA	ATL
Detroit, MI	DTW	Omaha, NE	OMA
Denver, CO	DEN	Tulsa, OK	TUL
Indianapolis, IN	IND	Miami, FL	MIA, FLL
Jacksonville, FL	JAX	Colorado Spr, CO	COS
San Francisco-Oakland, CA	SFO, OAK	Wichita, KS	ICT
Columbus, OH	CMH	St Louis, MO	STL
Austin, TX	AUS	Santa Ana, CA	SNA
Memphis, TN	MEM	Raleigh-Durham, NC	RDU
Minneapolis, MN	MSP	Pittsburg, PA	PIT
Baltimore, MD	BWI	Tampa, FL	TPA
Charlotte, NC	CLT	Cincinnati, OH	CVG
El Paso, TX	ELP	Ontario, CA	ONT
Milwaukee, WI	MKE	Buffalo, NY	BUF
Seattle, WA	SEA	Lexington, KY	LEX
Boston, MA	BOS	Norfolk, VA	ORF
Louisville, KY	SDF	Orlando, FL	MCO
Washington, DC	DCA, IAD	Salt Lake City, UT	SLC
Nashville, TN	BNA		

To estimate the model, I restrict the analysis to the entry decisions of six carriers. Some of the carriers are modeled as individual carriers: American Airlines (AA), Delta (DL), United Airlines (UA), and Southwest (WN). From this list, Southwest Airlines is defined as a low cost carrier, while the remaining airlines are considered legacy carriers. I aggregate the service of all remaining carriers in the data into two different groups:

"Other Legacy Carriers" (e.g., Alaska Airlines or Virgin America) and "Other Low Cost Carriers" (e.g., JetBlue, Spirit Airlines, or Frontier). I consider an airline as a potential entrant if it is serving at least one market out of both of the endpoint airports.[22]

I construct measures of airport presence at the origin and destination cities of a market following the definition used by Ciliberto and Tamer (2009), who measure airport presence as a carrier's ratio of markets served by an airline out of an airport over the total number of markets served out of an airport by at least one carrier. Airport presence is allowed to affect both demand for air travel and costs. This is aimed to capture product differentiation through in-airport amenities or frequent flyer programs, but also the fact that airlines with high airport presence have a different cost structure than other carriers (e.g., economies of density).[23] I assume that it is the airline's presence at the origin and destination airports (separately) what affects demand. I allow the effect of airport presence on product quality to be different for legacy and low costs carriers. On the other hand, marginal costs are assumed to be affected by the number of destinations served out from the origin and destination airports of the market (i.e., a different measure of airport presence than the one that is allowed to affect demand). I use the airport presence measures to construct hub indicator variables for airlines, which are then used to instrument for the demand equation. I defined an airline having a hub in a given city if it serves at

[22] Variation in the number of potential entrants can play an important role in the identification of the parameters in entry models. See for instance Berry and Tamer (2006). Variation in market size, like in Ciliberto and Tamer (2009), has also been proven to help identification of the model.

[23] Hub and spoke networks reduce the number of trips necessary to carry a given number of passengers on a given network of cities. Then, economies of scale in plane size allow airlines to lower total costs by using a hub and spoke network. In addition, high airport presence at an airport allow carriers to lower market specific fixed cost, given that some resources, such as gates and personnel, can be used by flights from different origin and destination cities.

least 20 destinations and the airline has at least 25% of airport presence (according to the definition by Ciliberto and Tamer, 2009).

I conduct the empirical analysis using data from the second quarter of 2014, 2015, and 2016. As mentioned in Section 3.2, a product in a given market and time is a unique combination of airline and flight itinerary. The sample contains 53,207 products or observations for a total of 8,309 market-year combinations. On average, there are approximately 6.4 observations per market-year.

3.3.1. Descriptive Statistics

Table 3.2 reports summary statistics of my sample, pooling all of the years together (i.e., 2014- 2016). The table shows the mean, standard deviation, minimum, and maximum values for some of the variables used in the analysis and estimation. The average fare is estimated at around $502. This represents an increase with respect to values reported for previous years by the empirical literature. For example, Berry and Jia (2010) estimate the average fare for 2006 at around $451. This numbers would imply a 11.3% increase in the average fare between 2006 and 2014- 2016. We also observe that the average itinerary distance is approximately 1,500 miles, and around 18% of the products in the sample are non-stop products.

The average value of airport presence for the products in the sample is estimated at around 38%.[24] Approximately 32% of the products have a hub or focus city at the origin or destination airport, while 74% have one at a connecting airport. Moreover, 94% of the products in the sample have a hub or focus city on route. This numbers speak to the

[24] Airport presence is defined as a carrier's ratio of markets served by an airline out of an airport over the total number of markets served out of an airport by at least one carrier.

important role of hub airports and focus cities in the provision of air travel. Finally, the table also provides information on the share of products by carriers. American accounts for 17% of the products in the sample. Delta and United account for similar numbers: 22% and 15%, respectively. Southwest, on the other hand, accounts for the highest proportion, holding approximately 32% of the products in the sample.

Table 3.2. Summary Statistics - Product Level

Variable	Mean	Std. Dev.	Min	Max
Product Share	0.020	0.044	3.34E-04	0.364
Fare ($100)	5.026	1.251	1.503	13.710
Distance (1,000 miles)	1.541	0.657	0.129	3.774
Non Stop	0.178	0.382	0	1
Stop Inconvenience	0.959	0.486	0	2.242
Presence Origin	0.388	0.284	0.016	1
Presence Destination	0.387	0.285	0.016	1
Hub Origin	0.325	0.461	0	1
Hub Connection	0.739	0.384	0	1
Hub Destination	0.325	0.460	0	1
Hub on Route	0.938	0.191	0	1
No. of Connections	1.535	0.763	0	2
American	0.171	0.376	0	1
Delta	0.222	0.415	0	1
United	0.155	0.362	0	1
Southwest	0.323	0.468	0	1
US Airways	0.069	0.254	0	1
Other Major Carriers	0.015	0.120	0	1
Other Low Cost Carriers	0.045	0.208	0	1
Obs.	53207			

Table 3.3 shows some summary statistics at the market-year level for the full sample (i.e., years 2014, 2015, and 2016). It complements the information provided in the previous table by reporting information on the level of competition within a market-year. The

average number of products in a market-year is estimated at around 6.4. On average, 60% of the products in a market-year are rival products. The average number of carriers in a market-year is approximately 3.5, and on average, 20% of the products in a market are rival non-stop products. The table also reports the average number of passengers flying non-stop and connecting flights. As expected, the average number of passengers flying non-stop is considerable higher than the average number of passengers flying connecting flights.

Table 3.3. Summary Statistics - Market Level

Variable	Mean	Std. Dev.	Min	Max
No. of Products	6.404	4.278	1	30
No. of Carriers	3.491	1.383	1	9
% Rival Products	0.600	0.201	0	0.875
% Rival Routes Non-Stop	0.201	0.288	0	1
No. Passengers Direct Flights	594.151	1251.395	0	18061
No. Passengers Connecting Flights	124.961	125.367	0	1304
No. Market-Year	8309			

Tables 3.4 and 3.5 report summary statistics for the probability of entry by airline and type of product, and for the distribution of entrants in the markets. Table 3.4 shows that American enters in 49% of the markets, United in 28% and Southwest in 57%. Southwest is the airline with the highest probability of entering with non-stop service (29%). The average number of entrants across markets is approximately 2. Finally, Table 3.5 indicates that in 20% of the markets there are no airlines offering service (of any kind). Similarly, in 17.5% of the markets there is only one airline offering service.

Table 3.4. Probability of Entry by Airline and Type of Entry

Airline	(1) Probability of Entry	(2) Probability of Non-Stop Entry	(3) Probability of Stop-Entry
American	0.493	0.196	0.297
Delta	0.467	0.166	0.304
United	0.281	0.164	0.117
Southwest	0.569	0.289	0.280
Other Legacy	0.061	0.054	0.006
Other LCC	0.150	0.141	0.008
Avg. No. Entrants	2.023		
Avg. No. Non-stop Entrants	1.010		
Avg. No. Stop Entrants	1.013		

Table 3.5. Distribution of Entrants by Type of Entry

No. Airlines in Market	Any Product	Non-stop Products	Stop Products
0 Airlines	0.2067	0.483	0.434
1 Airline	0.1754	0.232	0.271
2 Airlines	0.2397	0.153	0.178
3 Airlines	0.1987	0.075	0.083
4+ Airlines	0.1795	0.057	0.034
Total	1	1	1

3.4. Estimation

The estimation strategy requires recovering from the data the parameters of the demand (θ_d, σ), marginal cost (γ), and fixed cost functions $(\gamma^s, \gamma^{ns}, \sigma_f^s, \sigma_f^{ns})$. Even though the number of parameters is large (i.e., 49), the assumption of the model on that selection in the entry stage is only characterized by selection on observables (i.e., firms make entry decisions base only on fixed cost and observable characteristics of demand and marginal costs, but not on the unobservable characteristics of these two elements) allows for a two-stage approach in the estimation of the parameters. The estimation strategy is then characterized by the following two stages. The first stage recovers an estimate for demand and marginal costs parameters. This provides information on variable profits associated with product configurations. The second stage provides an estimate for the fixed costs parameters. The equilibrium and assumptions of the model place restrictions on fixed cost parameters. I describe first the estimation of the first stage parameters (i.e., demand and marginal costs parameters), and then the procedure followed to estimate the fixed costs parameters of the model.

3.4.1. First Stage: Demand and Marginal Costs Parameters

Identification of demand parameters comes from the joint distribution of prices, market shares, and observed product characteristics. Marginal costs are identified from the pricing equation (3.4), as the difference between observed prices and equilibrium markups. Then, the joint distribution of marginal costs and cost shifters identifies the marginal costs parameters.

It is important to emphasize, that the timing assumptions of the model rule out entry selection on unobservable characteristics of the demand or marginal costs functions. The intuition for this assumption is that firms do not observe (ξ, ζ) until after they have made their entry and product offerings decisions. Consequently, selection on entry does not depend on these unobservable variables.[25] This timing assumption of the model implies that selection on (ξ, ζ) can be ignored, and that demand and marginal costs parameters

[25] The timing assumption not only rules out observability of (ξ, ζ) at the entry stage, but also implies that airlines cannot forecast these variables, even though they know their distribution.

can be consistently estimated following the Berry et al. (1995) method, and are still point-identified.

The estimation of the demand and supply parameters is performed using the Generalized Method of Moments (GMM). I minimize the following loss function by choosing the parameter vector $(\theta_d, \sigma, \gamma)$:

$$\min_{\theta_d,\sigma,\gamma} \upsilon' Z \Phi^{-1} Z' \upsilon \tag{3.5}$$

where $\upsilon = (\xi \;\; \zeta)'$ is a column vector of demand (ξ) and supply (ζ) residuals with:

$$\begin{aligned} \xi_{jmt} &= \delta_{jmt} - x_{jmt}\beta - \alpha p_{jmt} \\ \zeta_{jmt} &= \ln mc_{jmt} - w'_{jmt}\gamma \end{aligned}$$

Z is a matrix containing the instruments for the demand (Z_d) and supply (Z_s) equation,

$$Z = \begin{bmatrix} Z_d & 0 \\ 0 & Z_s \end{bmatrix} \tag{3.6}$$

and Φ^{-1} is a positive definite weighting matrix given by

$$\Phi^{-1} = \begin{bmatrix} [\frac{1}{n} Z_d' \xi \xi' Z_d]^{-1} & 0 \\ 0 & [\frac{1}{n} Z_s' \zeta \zeta' Z_s]^{-1} \end{bmatrix} \tag{3.7}$$

where n is the number of observations.

Estimation exploits the fact that the demand and marginal costs parameters enter linearly in the loss function. This implies that, in practice, the minimization of the loss function can be performed by searching only over σ. Thus, I follow Berry et al. (1995)

nested fixed point algorithm in the estimation of these parameters, where conditional on a parameter vector σ, the remaining parameters can be obtained as:

$$\theta_d = \left(X_d' Z_d \Phi_d^{-1} Z_d' X_d\right)^{-1} X_d' Z_d \Phi_d^{-1} Z_d' \delta \tag{3.8}$$

$$\gamma = \left(W' Z_s \Phi_s^{-1} Z_s' W\right)^{-1} W' Z_s \Phi_s^{-1} Z_s' \ln mc \tag{3.9}$$

where X_d and W are matrices of regressors in the demand model (x_{jmt} and p_{jmt}) and supply model respectively, δ is a vector of mean utilities, and Φ_d^{-1} and Φ_s^{-1} are the portion of Φ^{-1} that corresponds to the demand and supply moments respectively.

In the estimation, I assume that the set of consumers' random taste shocks for product characteristics $\nu = (\nu_p, \nu_1, ..., \nu_K)$ are independent and identically distributed according to a standard normal distribution.[26]

According to the demand specification (3.1), demand is affected by the following product attributes: a constant term, fares, an indicator for a stop itinerary, airport presence at the origin and destination cities, the interaction between a dummy for low cost carrier and airport presence at the origin and destination cities, a dummy for a tourist destination, the number of slot controlled airports in the route, market size fixed effects, and carrier and time (year) effects. Fares are endogenous, since they are set in the second stage after airlines observe the realized errors. I instrument for fares using variables that help to predict the markup (and thus the fare) as well as variables that affect costs but do not affect the demand. The first set of instruments used to identify the fare coefficient include a mix of variables related to product rival attributes, the competitiveness of the

[26] In practice I use 50 draws for each product characteristic.

market environment and route level characteristics. The list of instruments for the demand equation includes the number of carriers in the market, the percentage of products in the market that are offered by competitors, and the percentage of rival routes that offer direct flights. A potential concern here is that, product attributes of rivals might be correlated with unobserved demand variables. The typical example is ticket restrictions. If ticket restrictions respond to rival product attributes, then the use of this variable as an instrument would be problematic. This concern is mitigated, however, by the fact that airlines typically offer all levels of restrictions in all markets. This means, for example, that both refundable and non-refundable tickets are available in all markets (see for example Berry and Jia, 2010). Some other components of ξ_{jmt} capture the frequency and time of departures, the fleet composition and in-flight amenities, etc., which we would expect to be exogenous in the short run.

Another set of instruments is comprised by those variables that affect costs but do not affect demand. The list of these variables includes itinerary distance and its squared value, interactions between these two variables and a dummy for low cost carrier, and a dummy for hub (or focus city) at a connection.

Finally, all exogenous variables that enter into the demand equation (3.1) are also used as instruments.

The instruments for the supply equation (3.3) include all the exogenous cost shifters (w), as well as some of the exogenous demand side instruments that help to predict the markup term.

3.4.2. Second Stage: Fixed Costs Parameters

In a second stage, I use the simulated method of moments (SMM) to estimate the parameters on the fixed cost function $\gamma^F = (\gamma^s, \gamma^{ns}, \sigma_f^s, \sigma_f^{ns}) \in \Gamma \subset \Re^P$, where P is the dimensionality of the parameter space. For each market, and any guess of $\gamma^F \in \Gamma$, I solve a large number (S) of games.

I assume that the following moment condition holds at the true parameter value γ_0^F:

$$E[g(X, \gamma_0^F)] = 0$$

where $g(X, .) \in \Re^L$ with $L \geq P$ is a vector of moment functions that specifies the differences between the observed equilibrium moments ($m(X)$) and those predicted by the model ($m^s(X, \gamma^F)$).

A SMM estimator $\hat{\gamma}^F$ minimizes a weighted quadratic form in $\hat{g}(X, .)$ given by:

$$\hat{\gamma}^F = \arg\min_{\gamma^F \in \Gamma} \quad \left[\hat{m}(X) - \hat{m}^s(X, \gamma^F)\right]' W \left[\hat{m}(X) - \hat{m}^s(X, \gamma^F)\right] \tag{3.10}$$

where $\hat{m}(X) - \hat{m}^s(X, \gamma^F)$ is a simulated estimate of the true moment function, and W is an $L \times L$ positive semidefinite weighting matrix. I use the optimal weighting matrix given by the inverse of the variance covariance matrix of $g(X, \gamma^F)$.[27] Since $m(x)$ and $m^s(X, \gamma^F)$ are independent by construction, the optimal weighting matrix is equal to $W = [(1 + \frac{1}{S})\Omega]^{-1}$, where Ω denotes the variance covariance matrix of the data (observed) moments, the first term in the inner brackets represents the randomness in the actual

[27] Pakes and Pollard (1989) and McFadden (1989) showed that the SMM estimator is consistent. Moreover, under the optimal weighting matrix, the SMM estimator is asymptotically efficient relative to estimators which minimize a quadratic norm in $g(.)$.

data, and the second term represents the randomness in the simulated data.[28] I compute Ω by block bootstrap with replacement on the actual data.[29] Note that the asymptotic variance of the efficient estimator $\hat{\gamma}^F$ is proportional to $(1 + \frac{1}{S})$. Since I use S = 50, this implies that the standard error of $\hat{\gamma}^F$ is increased by 2% by using simulation estimation. Standard errors are computed numerically (see Appendix C.1 for details on this).

Element l of moment function $g(X, .)$ is denoted by $g_l(X, .)$ and represented by:

$$g_l(X, .) = E[Y_l Z_l - E_s[Y_l^s(X, \gamma_0^F) Z_l]] = 0$$

where Y_l is the observed outcome of interest (e.g., number of non-stop entrants in a market), Y_l^s is the simulated outcome, and Z_l is a vector of instruments.

To create instruments, I define groups of markets that share characteristics. An indicator variable for membership in the group plays the role of an instrument. Therefore, taking means for an outcome over markets within each group creates a moment for each group. The groups are chosen to be informative about the parameters. There are 8 different groups, which are formally defined as indicators for market size (small, medium-small, medium-large, and large markets, defined by quartiles) and distance (short and long, defined as round-trip nonstop market distance of 2,000 miles or more) pairings.

Within each group, I calculate 14 outcomes of interest providing consequently 14 moments per group, and a total of 112 moments. The moments I seek to match are the total number of nonstop entrants, the total number of stop entrants, each firm nonstop entry

[28] Lee and Ingram (1991) showed that under the estimating null, the variance-covariance of the simulated moments is equal to $\frac{1}{S}\Omega$.

[29] I use 1,000 bootstrap replications on actual data to generate the variance covariance matrix of the actual moments.

decision, and each firm stop entry decision (where the potential entrants are American, United, Delta, Southwest, Other Network Carriers, and Other LCC).

The estimation procedure is as follows:

- Step 1. Start from some initial guess of the parameter values and draw independently from the normal distribution the following vectors: the fixed costs errors for both the non-stop and stop products (η^{ns}, η^{s}). At the same time, using the empirical distribution of (ξ, ζ) conditional on type of product (i.e., non-stop or stop) and airline identity, draw demand and marginal costs errors for both non-stop and stop products.
- Step 2. Obtain the simulated profits π_{am} for all airlines a and markets m, and solve for the equilibrium of the game in each market.
- Step 3. Repeat steps 1 and 2 S times and formulate $\hat{g}(X, \gamma^F)$. Search for parameter values that minimize the objective function (3.10), while using the same set of simulation and empirical draws for all values of γ^F.

Identification of the fixed cost function exploits variation in the identity and number of potential entrants across markets, as well as the amount of entry conditional on a set of potential entrants. Additionally, identification of the fixed cost function is helped by the variable Avg_NDS_{amt} (i.e., the average number of non-stop routes that an airline serves out of the origin and destination airports of the market), that shifts the fixed cost of one airline without changing the fixed costs of the competitors.

3.5. Results

3.5.1. Demand and Marginal Cost Parameters

Table 3.6 shows the parameter estimates for the demand equation. To illustrate the endogeneity problem, the first two columns report the results of ordinary least squares (OLS) and instrumental variables (2SLS) estimation, respectively. The estimates from these two columns do not incorporate into the estimation procedure the supply equation. The last column shows the results obtained from the random coefficient logit model.

Most coefficients are precisely estimated. As expected, consumers' utility decrease with the fare. The 2SLS and random coefficient logit model estimates of the coefficient for the fare are significantly smaller than the OLS estimate. This is consistent with the endogeneity of the fare variable in the OLS estimation. The estimates from the random coefficient model imply an average own price elasticity of approximately -3.9. These results are consistent with others reported by the existing literature (see for example Berry and Jia, 2010 or Li et al., 2016 among others).

Demand for air travel seem to be U-shaped in market distance. Utility increases in distance up to 4,900 miles (one-way) and then decreases.[30] An intuitive explanation for this result seems to be that demand for air travel competes with other modes of transportation (such as cars or trains) in short-haul markets. As distance increases, these modes of transportation become worse substitutes, and therefore demand for air travel also increases with distance. As distance continues increasing, travel becomes less convenient

[30] This is an out-of sample prediction, since the maximum market distance (one-way) observed in the data is 2,724 miles.

or pleasant and utility decreases (and perhaps, other options such as phone or video calls become better substitutes).

Consumers have a strong preference for non-stop itineraries (or disutility for stop service). In other words, the coefficient for the stop variable suggests that passengers prefer itineraries with less circuitous routes while traveling from the origin to destination city. The average stop semi-elasticity, or the average percentage reduction in demand when a non-stop flight becomes a stop flight is estimated at around 0.92. This means that the number of passengers on a non-stop flight would fall by approximately 90% when a stop was added to its itinerary, holding the attributes of all other products (including those of rival carriers) fixed. By dividing the mean coefficient of the stop dummy by the mean coefficient of the fare variable it is possible to obtain a dollar amount estimate of the willingness to pay for a non-stop flight. I find that, on average, the willingness to pay for a non-stop flight is $374 more than for a stop-flight.

Demand is positively affected by airport presence at both the origin and destination airport. However, the effect of airport presence on utility is lower for low cost carriers compared to legacy carriers. These results are consistent with the idea that the higher the presence at the airport, the more convenient gate access and better service that a carrier can offer at the airport. Berry and Jia (2010) suggest that this might also capture the value of frequent flier programs, since the larger the number of destination cities that can be reached from an airport, the larger the number of cities for which consumers can redeem frequent flier miles and the higher the value of these loyalty programs. Borenstein (2005) and Borenstein and Rose (2013) pointed out that the hub premium declined over the past several years. My estimates, however, suggest that airport presence is still an important dimension for product differentiation. Holding everything else constant, a one percentage point increase in airport presence at an origin airport for a legacy carrier increases, on average, the willingness to pay of the product in \$1.89.

The tourist and slot variables exhibit the expected signs on their coefficients. Tourist destinations attract more passengers, and flights through slot controlled airports have fewer passengers. The slot variable is expected to capture the potential negative effects on demand for air travel of congestion and travel inconvenience in slot controlled airports. Regarding the carrier dummies, American and Delta exhibit the highest parameter values.

Finally, the taste variation parameters for the constant term, the fare, the stop dummy, and airport presence at the origin airport are statistically significant at conventional levels of significance. This suggests that passengers are heterogeneous in terms of their taste for these product characteristics incorporated into the model.

Table 3.7 reports the parameter estimates for the supply equation. The marginal cost equation is a function of a constant term, itinerary distance and the square value of it, a dummy for connection in the itinerary, the number of destinations served out from the origin and destination airports (measured in 10), time (year) effects, and carrier dummies.

The average marginal costs for the products in the sample is estimated at around \$357. Not surprisingly, itinerary distance raises the marginal cost of the product. However, the relationship between marginal costs and itinerary distance is non-linear. The marginal effect of itinerary distance on marginal costs is decreasing in distance. This result is consistent with the fact that most of the fuel consumption is consumed during takeoffs and landings.

Table 3.6. Demand Parameter Estimates

Variables	(1) **OLS**	(2) **2SLS**	(3) **Random Coeff.**
Means			
Fare ($100)	-0.122***	-0.669***	-0.790***
	(0.004)	(0.015)	(0.011)
Distance (1,000 miles)	-0.004	0.680***	0.743***
	(0.032)	(0.041)	(0.044)
Distance^2	-0.014	-0.077***	-0.076***
	(0.011)	(0.012)	(0.013)
Stop	-3.008***	-2.938***	-2.962***
	(0.013)	(0.015)	(0.016)
Presence Orig.	0.736***	1.413***	1.494***
	(0.020)	(0.029)	(0.030)
Presence Dest.	0.038*	0.410***	0.450***
	(0.020)	(0.025)	(0.027)
Presence Orig. LCC*	-0.249***	-0.637***	-0.675***
	(0.036)	(0.043)	(0.044)
*Presence Dest.*LCC*	0.130***	-0.150***	-0.167***
	(0.035)	(0.042)	(0.043)
Slot	-0.098***	-0.139***	-0.120***
	(0.012)	(0.014)	(0.016)
Tourism	0.868***	0.590***	0.610***
	(0.014)	(0.017)	(0.019)
Delta	0.022*	0.056***	0.063***
	(0.013)	(0.015)	(0.016)
United	-0.213***	-0.238***	-0.239***
	(0.014)	(0.016)	(0.017)
Southwest	-0.253***	-0.435***	-0.458***
	(0.030)	(0.035)	(0.035)
US Airways	-0.026	-0.238***	-0.246***
	(0.018)	(0.022)	(0.022)
Other Major Carriers	0.399***	0.042	0.056
	(0.035)	(0.041)	(0.049)
Other Low Cost Carriers	-0.033	-0.765***	-0.848***
	(0.026)	(0.036)	(0.039)
Taste Variation (σ)			
Constant			0.015***
			(0.001)
Fare ($100)			0.126***
			(0.002)
Stop			0.015***
			(0.002)
Presence Orig.			0.007**
			(0.003)
Obs.	53,207	53,207	53,207
R-squared	0.661	0.543	

Notes: All specifications include a constant, year effects, and market size fixed effects. Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Products that include a connection exhibit a higher marginal cost. Controlling for other cost shifters, the marginal cost of a stop flight was 2.4% more expensive than that of a non-stop flight. The are different factors that affect the marginal cost of connecting flights. First, as it was mentioned above, most of the fuel is consumed at the takeoffs and landings. Then, we would expect higher marginal costs in connecting flights since they involve additional landings and takeoffs than non-stop flights. On the other hand, by combining passengers from different origins and to different destinations through the connecting airport, carriers can generate denser traffic, increase the load factor, and dilute costs with more passengers. Thus, the coefficient on the connection dummy reflects these two opposite channels (Berry and Jia, 2010).

Flights departing from airports with a higher number of destinations served by the airline also have a higher marginal cost. The same is found for flights arriving at airports with a higher number of destinations served by the carrier, but the coefficient for this variable in the supply equation is small. Although the same economies of scale argument for connecting flights that was discussed above also applies to flights at airports with higher market presence since they tend to have denser traffic, these airports are usually bigger airports with higher landing fees and more stringent regulations. In this sense, the coefficients on the number of destination variables reflect these two countervailing effects.

Finally, as expected, Southwest and other low cost carrier (such as JetBlue) had lower marginal costs than the legacy carriers.

Table 3.7. Marginal Costs Estimates

Variables	(1)
Distance (1,000 of miles)	0.573***
	(0.014)
Distance^2	-0.100***
	(0.004)
Stop	0.024***
	(0.006)
No. Destinations Orig. (10)	0.020***
	(0.001)
No. Destinations Dest. (10)	0.003***
	(0.001)
Year 2014	0.110***
	(0.004)
Year 2015	0.060***
	(0.004)
Delta	0.003
	(0.004)
United	-0.001
	(0.004)
Southwest	-0.164***
	(0.005)
US Airways	-0.109***
	(0.006)
Other Major Carriers	-0.248***
	(0.013)
Other Low Cost Carriers	-0.799***
	(0.015)
Constant	0.588***
	(0.015)
Observations	53,207

Notes: Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

3.5.2. Fixed Costs Estimates

Table 3.8 shows the estimation results of the fixed costs parameters. I estimate the average per-quarter fixed costs for non-stop service at around \$250,000. This value represents 30% of the mean value of quarterly variable profits for non-stop products (which is approximately \$900,000 in my sample). Presumably, the high value of the ratio between fixed costs and variable profits shows substantial economies of scale in the airline industry. Fixed costs of non-stop products are, on average, higher for low cost carriers. On average, fixed costs of non-stop service for low cost carriers are \$370,000 higher than the average value estimated for legacy carriers. Airport presence, measured as the number of non-stop destinations served out from the endpoints of a market, has also a significant effect on fixed costs. A unit increase in airport presence (i.e., an additional destination with a non-stop connection at both endpoints of the market) implies a \$63,200 reduction in fixed costs of non-stop service. The negative sign for the coefficient of this variable is what one would expect if there were economies of density. Moreover, the magnitude of this effects seems sizable. An airline with the minimum possible value for average airport presence in the market (i.e., zero non-stop destinations in the two endpoint airports of the market) would have to pay a fixed cost of approximately \$2,800,000 for serving the market with non-stop flights. On the other hand, an airline serving 20 non-stop destinations from both endpoints of a market (i.e., approximately the average number for any of the big four airlines) would pay \$1,500,000. Entry into a market containing a constrained airport is much more costly than entry into markets characterized by unconstrained airports. On average, serving a market containing a constrained airport increases fixed costs in approximately \$266,000. This magnitude is approximately equivalent to the average fixed cost for non-stop service.

Per-quarter fixed costs for stop service are estimated, on average, at around \$46,000. Similar to the case of fixed costs for non-stop service, fixed costs of stop products are, on average, higher for low cost carriers than legacy carriers. Airport presence, measured as the number of non-stop destinations served out from the endpoints of a market, plays also an important role in characterizing the value of fixed costs for stop service. A unit increase in airport presence (i.e., an additional destination with a non-stop connection at both endpoints of the market) implies a \$5,400 reduction in fixed costs of stop service. Finally, the standard deviation of the fixed costs is estimated to be very small.

Table 3.8. Fixed Costs Estimates

Fixed Costs	**Non-Stop Service**	**Stop Service**
Constant	27808.460***	789.937***
	(669.044)	(15.469)
LCC	3722.776***	867.174***
	(331.921)	(26.637)
Avg. Non-Stop Destinations	-632.226***	-54.349***
	(17.121)	(1.353)
Constrained Airport	2663.956***	2663.956***
	(82.596)	(82.596)
Fixed Cost Std. Dev.	56.570	28.664***
	(97.658)	(5.101)

Notes: Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

3.6. Counterfactual Analysis

In this section I evaluate the effects of airport constraints and airport presence on market structure and other quantities of interest, such as equilibrium prices. A typical question asked by authorities, regulators, and practitioners in the industry is whether prices would decrease significantly after the elimination of airport constraints or after encouraging entry on airports where an incumbent has a dominant position in terms of airport presence. Since I estimate a model of entry and pricing decisions of airlines, I can use the model to simulate both the pricing and market structure effects of an elimination of airport constraints or changes in airport regulation affecting airport presence.

I first consider the case of an elimination of airport constraints. In this experiment, I set $\gamma_3^{ns,s} = 0$ and solve for the equilibrium of the model leaving all other parameters unaltered. The results of this experiment are reported in Tables 3.9 and 3.10. Table 3.9 shows the probability of observing different number of airlines in a market by type of product, before and after the elimination of airport constraints. It also reports the average number of entrants and fare by type of product. We observe that the elimination of airport constraints shifts the distribution of the number of entrants to the right, shifting mass from one or less entrants to three or more. This outcome is mostly explained by changes in the probability of offering stop service, and is related to the fact that the elimination of airport constraints represents, on average, a higher proportional reduction of fixed costs for stop products than for non-stop products. This might be driven by the fact that I restricted the coefficient of the constrained airport variable to be same across the two types of fixed costs.

The results shown in Table 3.9 indicate that, after the elimination of airport constraints, all carriers increase entry into new markets using both non-stop and stop products. Non-stop entry increases between 3.6% and 8.7%, depending on the airline. Southwest is the airline that exhibits the highest percentage increase in the probability of offering non-stop service. The effects on the probability of offering stop service are sizable. The probability of offering stop services increases between 33.5% and 70.8%, depending on the airline. United is the airline that exhibits the highest percentage increase in this probability.

Next, I simulate the effects of airport presence on market structure and pricing. In particular I ask how market structure would change if airport presence at both endpoints of a market were higher than observed. As mentioned by Berry (1992), the idea behind this experiment is to think about it as a crude approximation to policies that increase airport access. Policies that make market entry less costly or improve airport access for potential entrants (either by subsidizing the entry of airlines, passing changes in airport regulation, or increasing the capacity of an airport) are typically perceived as a good strategy for reducing concentration in airline markets. I conduct this experiment by increasing in 10 the average number of destinations served by an airline out of the endpoint airports of the market. The policy change affects all firms and local markets in the industry. Given the estimates of the fixed cost function, this policy experiment is equivalent to a subsidy of \$630,000 and \$54,000 for establishing non-stop and stop service, respectively.

The results of this experiment are shown in Tables 3.11 and 3.12. Table 3.11 reports the distribution of the number of airlines in a market by type of product, before and after the policy experiment. It also reports the average number of entrants and fare by type of

Table 3.9. Counterfactual Experiment 1: Distribution of Number of Entrants by Type of Service

Panel A: Initial Situation

No. Airlines in Market	Any Product	Non-stop Products	Stop Products
0 Airlines	0.1297	0.403	0.481
1 Airline	0.3551	0.372	0.274
2 Airlines	0.2505	0.147	0.150
3 Airlines	0.1435	0.055	0.075
4+ Airlines	0.1212	0.023	0.020
Total	1	1	1
Avg. No. Entrants	1.810		
Avg. No. Non-stop entrants		0.929	
Avg. No. Stop entrants			0.880
Avg. Fare	4.173	4.600	3.917

Panel B: Counterfactual Experiment 1: Elimination of Airport Constraints

No. Airlines in Market	Any Product	Non-stop Products	Stop Products
0 Airlines	0.0836	0.390	0.299
1 Airline	0.2911	0.368	0.347
2 Airlines	0.2473	0.153	0.216
3 Airlines	0.1770	0.061	0.108
4+ Airlines	0.2010	0.028	0.030
Total	1	1	1
Avg. No. Entrants	2.197		
Avg. No. Non-stop entrants		0.975	
Avg. No. Stop entrants			1.222
Avg. Fare	4.210	4.576	4.027

Notes: The table shows the distribution of the number of entrants by type of product, before and after the policy experiment. It also reports the average number of entrants and fare by type of product.

Table 3.10. Counterfactual Experiment 1: Product Offerings Responses by Airline

Counterfactual Experiment 1: Elimination of Airport Constraints

	(1)	(2)	(3)	(4)
Airline	Non-Stop Entry at beginning	Stop-Entry at beginning	Percentage Δ in Non-Stop Entry	Percentage Δ in Stop Entry
American	0.194	0.255	7.543	34.404
Delta	0.171	0.247	3.997	33.541
United	0.159	0.117	3.618	70.849
Southwest	0.211	0.247	8.742	35.886

Notes: The table shows the probabilities of offering non-stop and stop service by airline (before the policy experiment), and the responses in these probabilities after the policy experiment.

product. We observe that encouraging airport access for potential entrants significantly changes the distribution of the number of entrants. In particular, it shifts mass from two or less entrants to four or more. Moreover, the average number of entrants increases from 1.8 to 3.2. Even though changes in the probabilities of offering non-stop service explain part of this result, most of the outcome is explained by shifts in the distribution of the number of entrants offering stop service. One possible explanation for this finding might be related to the fact that in many markets, market size is too thin to accommodate more than two firms offering non-stop service. On the other hand, stop-service seems to be a poor substitute of non-stop service, what mitigates the effects of within-market competition on the number of entering airlines. The results shown in the table also indicate that average prices charged by air carriers drop for both non-stop and stop service. The effect on fares is more pronounced for stop products, which is explained by the results discussed above regarding the probabilities of offering stop and non-stop service.

Finally, Table 3.12 shows the percentage change in the probability of offering non-stop and stop service as a consequence of the policy experiment for each of the big four airlines (i.e., American, Delta, United, and Southwest). The probability of offering non-stop service increases between 43% and 65% depending on the airline. United and Southwest are the airlines that increase their offerings of non-stop service the most. In the new equilibrium, legacy carriers offer non-stop products in approximately 25% of the markets, while Southwest does this in 35% of the markets. Entry behavior using stop products changes dramatically after the policy experiment. The probability of offering stop service increases by 115% for American and Delta, 353% for United, and 22% for Southwest.

Table 3.11. Counterfactual Experiment 2: Distribution of Number of Entrants by Type of Service

Panel A: Initial Situation

No. Airlines in Market	**Any Product**	**Non-stop Products**	**Stop Products**
0 Airlines	0.130	0.403	0.481
1 Airline	0.355	0.372	0.274
2 Airlines	0.251	0.147	0.150
3 Airlines	0.144	0.055	0.075
4+ Airlines	0.121	0.023	0.020
Total	1	1	1
Avg. No. Entrants	1.810		
Avg. No. Non-stop entrants		0.929	
Avg. No. Stop entrants			0.880
Avg. Fare	4.173	4.600	3.917

Panel B: Counterfactual Experiment 2: Increase in Airport Presence

No. Airlines in Market	**Any Product**	**Non-stop Products**	**Stop Products**
0 Airlines	0.017	0.231	0.294
1 Airline	0.152	0.423	0.077
2 Airlines	0.109	0.208	0.184
3 Airlines	0.141	0.091	0.303
4+ Airlines	0.581	0.047	0.143
Total	1	1	1
Avg. No. Entrants	3.238		
Avg. No. Non-stop entrants		1.313	
Avg. No. Stop entrants			1.925
Avg. Fare	3.876	4.567	3.623

Notes: The table shows the distribution of the number of entrants by type of product, before and after the policy experiment. It also reports the average number of entrants and fare by type of product.

Table 3.12. Counterfactual Experiment 2: Product Offerings Responses by Airline

Counterfactual Experiment 2: Increase in Airport Presence

	(1)	(2)	(3)	(4)
Airline	Non-Stop Entry at beginning	Stop-Entry at beginning	Percentage Δ in Non-Stop Entry	Percentage Δ in Stop Entry
American	0.194	0.255	43.095	115.411
Delta	0.171	0.247	46.907	114.964
United	0.159	0.117	52.365	353.187
Southwest	0.211	0.247	65.101	21.744

Notes: The table shows the probabilities of offering non-stop and stop service by airline (before the policy experiment), and the responses in these probabilities after the policy experiment.

3.7. Conclusions

This chapter estimates a static oligopoly model of airline competition to study the effects of airport presence and airport constraints on market structure. The model is a static complete information game, where players first decide on the type of products to be offered in the market, and then, conditional on entry, the prices of their products. Thus, an important feature of the model is that it allows for market structure (number and identity of players that enter the market, the type of product offered by each entrant, and the prices charged) to be endogenous and to react to counterfactual scenarios.

The results from estimating the model suggest that on average, fixed costs represent a substantial proportion of airlines' variable profits. In addition, fixed costs of serving a market decline significantly with airport presence at the origin and destination airports of the market, and increase if the market contains at least one slot controlled or capacity constrained airport in any of its endpoints.

I use the model to study the effects of airport constraints and airport presence on market structure by running counterfactual exercises. In particular, I ask how market structure would change if airport presence at both endpoints of a market were higher than observed, or if airport constraints were eliminated. The results from the counterfactual exercises indicate that both airport constraints and airport presence affect pricing and market structure significantly. Elimination of airport constraints or changes in airport regulation affecting airport presence significantly encourage entry into markets and, as a consequence, tend to drive prices down.

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APPENDIX A

Appendix to Chapter 1

A.1. Revenue Function

This section describes in detail the derivation of revenue equation (1.1). Log revenue of business unit j at time t is represented by $\tilde{y}_{ijt} = p_{ijt} + q_{ijt}$, where log output q_{ijt} is represented by the translog production function:

$$\begin{aligned} q_{ijt} = \psi_{ijt} \quad &+ \quad \alpha_{l_s} l_{ijt} + \alpha_{m_s} m_{ijt} + \alpha_{k_s} k_{ijt} + \alpha_{ll_s} l_{ijt}^2 + \alpha_{mm_s} m_{ijt}^2 + \alpha_{kk_s} k_{ijt}^2 + \\ &+ \quad \alpha_{ml_s} m_{ijt} l_{ijt} + \alpha_{mk_s} m_{ijt} k_{ijt} + \alpha_{lk_s} l_{ijt} k_{ijt} + \alpha_{mlk_s} m_{ijt} l_{ijt} k_{ijt} \end{aligned}$$

The demand function assumed implies that,

$$p_{ijt} = \frac{1}{\sigma_s} q_{s_{ij}t} - \frac{1}{\sigma_s} q_{ijt} + p_{s_{ij}t} + \frac{\sigma_s - 1}{\sigma_s} \nu_{ijt}$$

Then, log revenue can be expresses as:

$$\tilde{y}_{ijt} = \frac{\sigma_s - 1}{\sigma_s} q_{ijt} + \frac{1}{\sigma_s} q_{s_{ij}t} + p_{s_{ij}t} + \frac{\sigma_s - 1}{\sigma_s} \nu_{ijt}$$

or equivalently as,

$$\begin{aligned} \tilde{y}_{ijt} \quad &= \quad \beta_{l_s} l_{ijt} + \beta_{m_s} m_{ijt} + \beta_{k_s} k_{ijt} + \beta_{ll_s} l_{ijt}^2 + \beta_{mm_s} m_{ijt}^2 + \beta_{kk_s} k_{ijt}^2 + \\ &+ \quad \beta_{ml_s} m_{ijt} l_{ijt} + \beta_{mk_s} m_{ijt} k_{ijt} + \beta_{lk_s} l_{ijt} k_{ijt} + \beta_{mlk_s} m_{ijt} l_{ijt} k_{ijt} + \frac{1}{\sigma_s} q_{s_{ij}t} + p_{s_{ij}t} + \omega_{ijt} \end{aligned}$$

where $\beta_f = \frac{\sigma_s - 1}{\sigma_s}\alpha_f$ for $f \in \{m, l, k, mm, ll, kk, ml, mk, lk, mlk\}$, and $\omega_{ijt} = \frac{\sigma_s - 1}{\sigma_s}(\psi_{ijt} + \nu_{ijt})$.

Observed log revenue (y_{ijt}) is allowed to be measured with error (i.e., $y_{ijt} = \tilde{y}_{ijt} + \epsilon_{ijt}$) and it is also deflated by a price index at the industry level (i.e., $p_{s_{ij}t}$). Thus,

$$\begin{aligned} y_{ijt} &= \beta_{l_s} l_{ijt} + \beta_{m_s} m_{ijt} + \beta_{k_s} k_{ijt} + \beta_{ll_s} l_{ijt}^2 + \beta_{mm_s} m_{ijt}^2 + \beta_{kk_s} k_{ijt}^2 + \\ &+ \beta_{ml_s} m_{ijt} l_{ijt} + \beta_{mk_s} m_{ijt} k_{ijt} + \beta_{lk_s} l_{ijt} k_{ijt} + \beta_{mlk_s} m_{ijt} l_{ijt} k_{ijt} + \mu_{st} + \omega_{ijt} + \epsilon_{ijt} \end{aligned}$$

where $\mu_{st} = \frac{1}{\sigma_s} q_{s_{ij}t}$.

A.2. Misreporting

The misreporting of firm diversification levels might introduce bias in the parameters that govern the law of motion for productivity, affecting the estimates that characterize the productivity effects of firm diversification. To characterize the bias, I define observed diversification as true diversification level minus the degree of under-reporting:

$$div_{it} = div_{it}^{*} - u_{it}$$

where div_{it} represents the observed diversification level of firm i at time t, div_{it}^{*} the true diversification level, and $u_{it} \geq 0$ the degree of under-reporting.

For simplicity in the exposition, I consider the simplest case where the expected future productivity is represented by:

$$\omega_{ijt} = \gamma_0 + \gamma_1 \omega_{ijt-1} + \gamma_2 div_{it-1}^{*} + \xi_{ijt}$$

Then, the estimating equation can be written as:

$$\omega_{ijt} = \gamma_0 + \gamma_1 \omega_{ijt-1} + \gamma_2 div_{it-1} + \xi_{ijt} + \gamma_2 u_{it-1}$$

The GMM estimate of γ_2 is described by the following equation:

$$\begin{aligned}
\hat{\gamma}_2 &= \frac{cov(\omega_{ijt}, div_{it-1})var(\omega_{ijt-1}) - cov(\omega_{ijt-1}, div_{it-1})cov(\omega_{ijt}, \omega_{ijt-1})}{var(div_{it-1})var(\omega_{ijt-1}) - cov(\omega_{ijt-1}, div_{it-1})^2} \\
&= \frac{cov(\gamma_1\omega_{ijt-1} + \gamma_2 div_{it-1} + \xi_{ijt} + \gamma_2 u_{it-1}, div_{it-1})var(\omega_{ijt-1})}{var(div_{it-1})var(\omega_{ijt-1}) - cov(\omega_{ijt-1}, div_{it-1})^2} \\
&\quad - \frac{cov(\omega_{ijt-1}, div_{it-1})cov(\omega_{ijt}, \omega_{ijt-1})}{var(div_{it-1})var(\omega_{ijt-1}) - cov(\omega_{ijt-1}, div_{it-1})^2}
\end{aligned}$$

where $cov(.)$ and $var(.)$ denote covariance and variance respectively.

After assuming that the misreporting error u_{it-1} is mean independent of the innovation to productivity ξ_{ijt}, and enforcing the mean independence assumption in the law of motion for future expected productivity, we can rewrite the above equation as,

$$\begin{aligned}
\hat{\gamma}_2 = \gamma_2 \quad &+ \quad \frac{var(\omega_{ijt-1})[\gamma_1 cov(\omega_{ijt-1}, div_{it-1}) + \gamma_2 cov(u_{it-1}, div_{it-1})]}{var(div_{it-1})var(\omega_{ijt-1}) - cov(\omega_{ijt-1}, div_{it-1})^2} \\
&- \quad \frac{cov(\omega_{ijt-1}, div_{it-1})[\gamma_1 var(\omega_{ijt-1}) + \gamma_2 cov(u_{it-1}, \omega_{ijt-1})}{var(div_{it-1})var(\omega_{ijt-1}) - cov(\omega_{ijt-1}, div_{it-1})^2}
\end{aligned}$$

Note that, with some algebra this can be written as:

$$\begin{aligned}
\hat{\gamma}_2 = \gamma_2 \quad &+ \quad \frac{\gamma_2[var(\omega_{ijt-1})(cov(u_{it-1}, div^*_{it-1}) - var(u_{it}))]}{var(div_{it-1})var(\omega_{ijt-1}) - cov(\omega_{ijt-1}, div_{it-1})^2} \\
&- \quad \frac{\gamma_2[cov(\omega_{ijt-1}, div_{it-1})cov(u_{it-1}, \omega_{ijt-1})]}{var(div_{it-1})var(\omega_{ijt-1}) - cov(\omega_{ijt-1}, div_{it-1})^2}
\end{aligned}$$

and therefore the asymptotic bias of the estimator will be given by,

$$\frac{\gamma_2[var(\omega_{ijt-1})(cov(u_{it-1}, div^*_{it-1}) - var(u_{it})) - cov(\omega_{ijt-1}, div_{it-1})cov(u_{it-1}, \omega_{ijt-1})]}{var(div_{it-1})var(\omega_{ijt-1}) - cov(\omega_{ijt-1}, div_{it-1})^2} \tag{A.1}$$

Note that by definition, $var(div_{it-1}) > 0$ and $var(\omega_{ijt-1}) > 0$, and additionally $var(div_{it-1}) \times var(\omega_{ijt-1}) > cov(\omega_{ijt-1}, div_{it-1})^2$, which implies that the denominator in the above equation is positive. In the data we observe that $cov(\omega_{ijt-1}, div_{it-1}) > 0$, that is, a positive covariance between observed diversification and productivity. This finding has already been documented in other studies (see, for instance, Schoar, 2002). We also expect $cov(u_{it-1}, \omega_{ijt-1}) > 0$ and $cov(u_{it-1}, div^*_{it-1}) < 0$. We should expect the first covariance to be positive since, in principle, it should be driven by what the corporate finance literature has described as strategic accounting. Under this hypothesis, high performers firms (or at least a subset of them) are less inclined to disclose financial information at the business unit level.[1] According to the literature, this strategy might be used to avoid disclosing information to potential competitors about the profitability of their operations.[2] This is also consistent with the results of some empirical studies that find evidence of managerial reporting practices matching the predictions of strategic accounting theory (see, for example, Harris, 1998; Piotroski, 1999; Berger and Hann, 2003b; Berger and Hann, 2003a; Villalonga, 2004; or Berger and Hann, 2007). Finally, we should expect a negative correlation between the true diversification level div^*_{it-1} and the

[1] This hypothesis is supported by some game theoretical models of a firm's disclosure choices. See, for instance, Darrough and Stoughton (1990), or Feltham, Gigler and Hughes (1992).

[2] For example, Ettredge, Kwon and Smith (2002) report that 86% of the firms that commented on the exposure draft for SFAS 131 were opposed to the new standard on the grounds that it would put them at competitive disadvantage.

degree of under-reporting u_{it-1}. In particular, high levels of true diversification are typically associated with operations in different, dissimilar industries. This raises the costs of hiding information, mitigating the aggregation of business activities and leading to a lower degree of under-reporting. This intuition is consistent with the findings reported by Berger and Hann (2003a), Herrmann and Thomas (2000), and Street, Nichols and Gray (2000), who show that the change in segment reporting introduced by the SFAS 131 was effective in inducing diversified firms to reveal previously hidden information about the firm's diversification strategy, mitigating the aggregation of business activities and raising the number of reported business units for many firms, especially for those who previously reported a single line of business.

Under the conditions discussed above, driven by the results and insights discussed in the literature, the sign of the asymptotic bias described by equation (A.1) would be negative. Then, we should expect the baseline estimates related to the productivity effects of corporate diversification to be asymptotically downward biased.

A.3. Production Function Estimates

Table A.1 presents the output elasticities from the revenue production function estimation. As discussed in Section 1.2, the coefficients of the production function are assumed to be industry specific, and thus they are assumed to be the same across different business units in a given industry. This means that production technology is assumed to be the same for non-diversified firms and business units belonging to diversified firms operating within the same industry. Therefore, in the estimation, the coefficients of the production function are recovered by pooling together these two types of lines of business (i.e., non-diversified firms and business units belonging to diversified firms) within the same industry. I estimate the production function coefficients by the primary industry or sector of activity, defined by the 2-digit SIC code. The industries considered in the analysis (with their respective 2-digit SIC codes) are the following: Food and Beverages (20); Textile, Apparel, and Leather (22, 23, and 31); Timber and Furniture (24 and 25); Paper and Printing (26 and 27); Chemicals (28); Pete Refining (29); Rubber and Misc. Manufacturing Industries (30 and 39); Stone, Clay, Glass, and Concrete Products (32); Primary Metal and Fabricated Metal Products (33 and 34); Machinery and Equipment (35); Electrical Machinery and Apparatus (36); Transportation Equipment (37); and Medical Instruments (38).[3]

The first two columns of Table A.1 report the 2-digit SIC industry code and the industry description respectively. Columns (3) to (5) show the estimated average revenue elasticity with respect to each factor of production (labor, materials, and capital, respectively) under the estimation strategy described in Section 1.4. Note that, since I am relying in a translog production function, each business unit may have a different revenue elasticity with respect to inputs. Unlike the Cobb-Douglas production function, revenue elasticities in the translog case are a function of input usage, and thus they are likely to vary by business units. For this reason, I report both the average and the standard deviation of the elasticities across aggregated sectors (at the 2-digit level of the industrial classification). The last two columns report the average return to scale and number of observations respectively. Labor coefficients range from 0.11 to 0.50, while the coefficients for materials range from 0.46 to 0.81. The output elasticity with respect to capital ranges

[3] Misc. Manufacturing Industries include, for example, jewelry, games and toys, musical instruments, pens, etc.

from 0.03 to 0.17. These estimates are similar and comparable to others obtained in the production function literature.[4] Standard deviations of the revenue elasticities are reported in parentheses below the means. The returns to scale coefficients are not only similar across different industries but also close to 1 in most cases.

Finally, ordinary least squares (OLS) regressions produce higher estimates for the input elasticities of variable inputs in almost all of the cases.[5] As expected, the simultaneity problem biases the estimates on the inputs upwards, and thus, when correcting for unobserved productivity shocks, the implied coefficients on the inputs drop.

[4] See for example, Doraszelski and Jaumandreu (2013), Pavcnik (2002), De Loecker (2011), or De Loecker, Goldberg, Khandelwal and Pavcnik (2016).

[5] These results are not shown in the table, but are available from the author upon request.

Table A.1. Production Function Estimates

(1) SIC code	(2) Industry	(3) Labor	(4) Materials	(5) Capital	(6) Returns to Scale	(7) Obs.
20	Food and Beverages	0.2452	0.6896	0.0701	1.005	2,636
		(0.0443)	(0.0390)	(0.0318)		
22, 23, 31	Textile, Apparel and Leather	0.2310	0.6003	0.1048	0.936	2,741
		(0.0725)	(0.0887)	(0.0485)		
24, 25	Timber and Furniture	0.3247	0.5499	0.1201	0.995	1,940
		(0.0447)	(0.0537)	(0.0401)		
26, 27	Paper and Printing	0.4490	0.4804	0.0819	1.011	3,206
		(0.0617)	(0.0498)	(0.0397)		
28	Chemicals	0.3439	0.5875	0.0537	0.985	4,961
		(0.0750)	(0.0625)	(0.0326)		
29	Pete Refining	0.1226	0.8170	0.0672	1.007	582
		(0.0788)	(0.0930)	(0.0359)		
30, 39	Rubber and Misc Manuf. Industries	0.2688	0.6613	0.0494	0.980	3,444
		(0.0298)	(0.0246)	(0.0130)		
32	Stone, Clay, Glass and Concrete Products	0.3389	0.4854	0.1058	0.930	1,270
		(0.0729)	(0.0776)	(0.0525)		
33, 34	Primary Metal Industries and Metal Products	0.2900	0.6151	0.0864	0.992	5,531
		(0.0768)	(0.0571)	(0.0296)		
35	Machinery and Equipment	0.1177	0.8141	0.0576	0.989	8,096
		(0.0385)	(0.0416)	(0.0183)		
36	Electrical Machinery and Apparatus	0.1344	0.7066	0.1754	1.016	7,445
		(0.0496)	(0.0487)	(0.0295)		
37	Transportation Equipment	0.3452	0.5249	0.1210	0.991	2,910
		(0.0627)	(0.0539)	(0.0406)		
38	Medical Instruments	0.5063	0.4667	0.0364	1.009	5,190
		(0.0545)	(0.0428)	(0.0194)		

Note: The table reports the average revenue elasticities with respect to inputs (i.e., materials, labor, and capital). Standard deviation of average revenue elasticities are in parentheses. Column (6) reports the sum of columns (3) to (5).

APPENDIX B

Appendix to Chapter 2

B.1. Distribution of Scheduled Departure Times by Airline

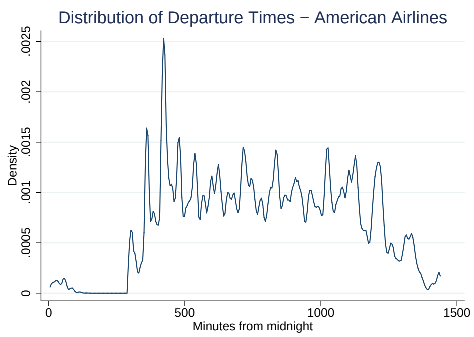

Figure B.1. Distribution of Scheduled Departure Times - American Airlines.

Note: The figure shows, for all Mondays of 2015, the distribution of scheduled departure times for American Airlines. Departure times are measured in minutes from midnight. Data come from the On Time Performance database (OTP).

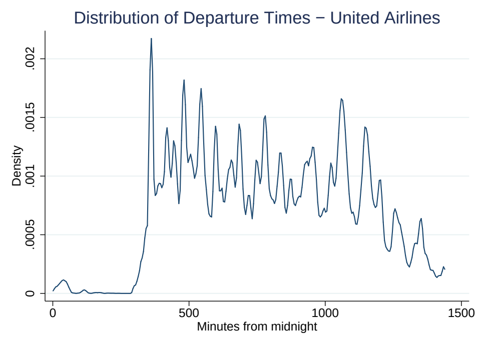

Figure B.2. Distribution of Scheduled Departure Times - United Airlines.

Note: The figure shows, for all Mondays of 2015, the distribution of scheduled departure times for United Airlines. Departure times are measured in minutes from midnight. Data come from the On Time Performance database (OTP).

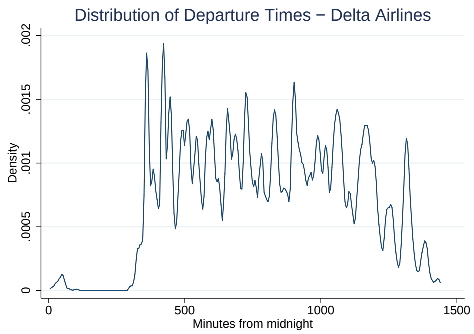

Figure B.3. Distribution of Scheduled Departure Times - Delta Airlines.

Note: The figure shows, for all Mondays of 2015, the distribution of scheduled departure times for Delta Airlines. Departure times are measured in minutes from midnight. Data come from the On Time Performance database (OTP).

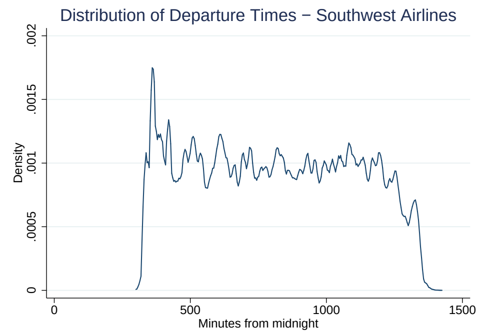

Figure B.4. Distribution of Scheduled Departure Times - Southwest Airlines.

Note: The figure shows, for all Mondays of 2015, the distribution of scheduled departure times for Southwest Airlines. Departure times are measured in minutes from midnight. Data come from the On Time Performance database (OTP).

B.2. Data Construction

This section describes the construction of correlation measures between airlines' flight scheduling decisions and passengers' most preferred departure times. To create these correlation measures, I use information on scheduled departures from the OTP database. Information on passengers' most preferred departure times comes from Garrow et al. (2007) and Brey and Walker (2011), who construct these measures based on a 2004 on-line survey conducted by the Boeing Company.[1] I create these variables using the uncentered correlation coefficients between the firms' scheduled departure profiles and passengers' most preferred departure times. Although these measures vary by the direction of travel (i.e., west to east, east to west, and south-north), I do not have information on most preferred departure times by day of the week. Therefore I assume they represent the

[1] See Garrow et al. (2007) and Brey and Walker (2011) for more details about the survey design.

preferred travel times for any day of the week. Figure B.5 plots the distribution of passengers' most preferred departure times according to the direction of travel.

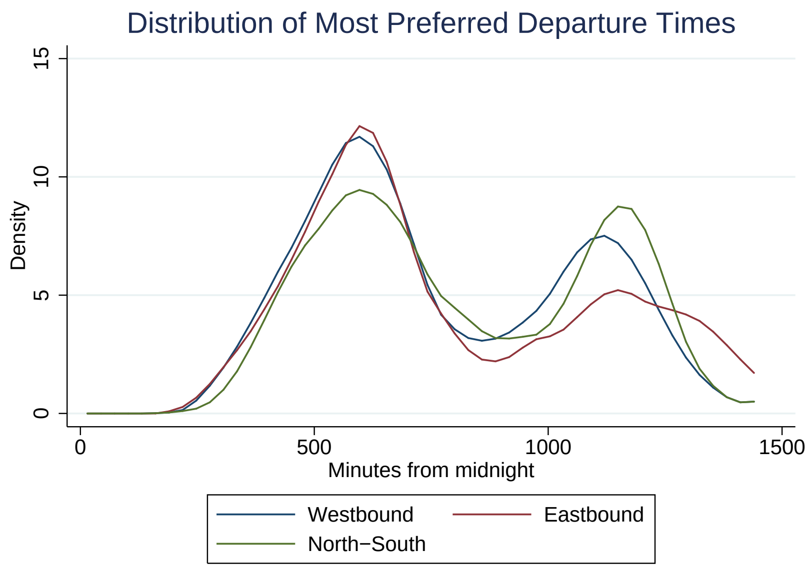

Figure B.5. Distribution of Most Preferred Departure Times.
Notes: The figure shows the distribution of passengers' most preferred departure times, measured in minutes from midnight. Data come from an online survey conducted by the Boeing Company.

To formalize these measures, consider the case of an airline i, that at time t has to allocate a fixed number of planes f_i across markets (i.e., directional airport pair), and within each market, it has to schedule departure times across K available times. In the empirical application, the space of available times is characterized by a vector with entries represented by block times (15 minute intervals). Therefore, firm i's profile of scheduled departure times at time t in segment or market m can be characterized by a vector $F_{imt} = (f_{itm1}, .., f_{itmk})$, where f_{itmk} is the number of firm i's planes allocated to time k at time t in market m. Similarly, it is possible to construct a location profile for passengers' most preferred departure times, by also discretizing the distribution into 15 minute intervals. Then, the measure of closeness between scheduled departure times and passengers' most preferred departure times for airline i at time t in market m is given by:

$$y_{imt} = \frac{F_{imt}F_p'^d}{(F_{imt}F'_{imt})^{1/2}(F_p^d F_p'^d)^{1/2}} \tag{B.1}$$

where F_p^d represents the profile for the distribution of passengers' most preferred departure times. This measure of proximity ranges between zero and one, depending on the degree of overlap between the airline scheduling decisions and passengers' preferred travel times.

The proximity measure discussed above treat available times as orthogonal to each other, since passengers' preferred travel times only match scheduled times if they coincide in the same available time. However, the assumption that available times are available to each other depend on the level of aggregation of the them. In practice, it is plausible that a passenger whose most preferred travel time is 10:30am also derive some utility from a plane scheduled, for instance, at 9am (absent a plane scheduled at her most preferred travel time). To address this, I extend the empirical analysis by estimating a model with a number of alternatives. In particular, I use a distance measure between location patterns that weights the covariance in the location profiles by their proximity, using Kernel functions to compute these weights. Formally, the proximity measure between scheduled and preferred times for a non-stop product belonging to airline i in market m at time t is given by:

$$y_{imt}^{\kappa} = \frac{F_{imt}\Omega F_p'^d}{(F_{imt}F'_{imt})^{1/2}(F_p^d F_p'^d)^{1/2}} \tag{B.2}$$

where Ω is a $k \times k$ symmetric weighting matrix with elements $\omega_{rc} = K(.)$, where $K(.)$ is a Kernel function.[2] Finally, note that equation (B.1) is equivalent to equation (B.2) when $\Omega = I$.

[2] In the empirical application, I use a quartic Kernel described by $K(u) = 15/16(1-u^2)^2 \times 1_{\{|u| \leq 1\}}$. I tried three different specifications, with different values for the bandwidth across specifications: 60 , 240, and 1440 minutes.

APPENDIX C

Appendix to Chapter 3

C.1. Standard Errors (SMM)

To obtain the standard errors of the fixed costs parameter estimates we need to compute the variance-covariance matrix of the estimator. Given the election of the optimal weighting matrix W, the SMM estimator is asymptotically normal for fixed S when $n \to \infty$:

(C.1)
$$\sqrt{N}(\widehat{\gamma}^F - \gamma_0^F) \to N(0, V)$$

where,

(C.2)
$$V = \left(1 + \frac{1}{S}\right)(J'WJ)^{-1}$$

with

(C.3)
$$J = \frac{\partial g(X, \widehat{\gamma}^F)}{\partial \gamma^F} = \begin{bmatrix} \frac{\partial g_1(X,\widehat{\gamma}^F)}{\partial \gamma_1^F} & \frac{\partial g_1(X,\widehat{\gamma}^F)}{\partial \gamma_2^F} & \dots & \frac{\partial g_1(X,\widehat{\gamma}^F)}{\partial \gamma_P^F} \\ \frac{\partial g_2(X,\widehat{\gamma}^F)}{\partial \gamma_1^F} & \frac{\partial g_2(X,\widehat{\gamma}^F)}{\partial \gamma_2^F} & \dots & \frac{\partial g_2(X,\widehat{\gamma}^F)}{\partial \gamma_P^F} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial g_L(X,\widehat{\gamma}^F)}{\partial \gamma_1^F} & \frac{\partial g_L(X,\widehat{\gamma}^F)}{\partial \gamma_2^F} & \dots & \frac{\partial g_L(X,\widehat{\gamma}^F)}{\partial \gamma_P^F} \end{bmatrix}$$

The Jacobian matrix J must be computed numerically. A practical issue connected with the estimation of this matrix is that the value of the numerical derivative, defined as $\frac{\partial g(X,\widehat{\gamma}^F)}{\partial \gamma^F} = \frac{g(X,\widehat{\gamma}^F+\epsilon)-g(X,\widehat{\gamma}^F)}{\epsilon}$, is sensitive to the exact value of ϵ in which this derivative is evaluated. As stated by Bloom (2009), this is a common problem in numerical methods with simulated data which make use of functions with potential discontinuities. To address this problem, I compute numerical derivatives following a strategy similar to the one used by Bloom (2009). In particular, I calculate four values of the numerical derivative for values of ϵ of +1%, +2.5%, +5% and -1% of the estimated parameter. Then, I take the median value of these numerical derivatives. This procedure contributes to the robustness of numerical derivatives to outliers in the function under analysis (which may arise as a consequence of potential discontinuities).