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Demand Volatility, Adjustment Costs, and Productivity: An Examination of Capacity Utilization in Hotels and Airlines[†]

By R. Andrew Butters*

Measures of productivity reveal large differences across producers even within narrowly defined industries. Traditional measures of productivity, however, will associate differences in demand volatility to differences in productivity when adjusting factors of production is costly. I document this effect by comparing the influence of demand volatility on capacity utilization in a high (hotels) and low (airlines) adjustment cost industry. Differences in annual demand volatility explain a large share of the variation in occupancy rates of hotels at the metro area–segment-year level. In contrast, differences in annual demand volatility have no effect on load factors of airlines at the destination-airline-year level. (*JEL* D24, L83, L93)

Measures of productivity reveal large differences across producers even within narrowly defined industries (Bartelsman and Doms 2000, Syverson 2011). Syverson (2004b) finds within the average US manufacturing industry a plant in the ninetieth percentile is nearly *twice* as productive as a plant in the tenth percentile. These large productivity differences are neither specific to the United States nor shortlived. Hsieh and Klenow (2009) document productivity differences across producers in China and India that are even larger than those in the United States, while Foster, Haltiwanger, and Syverson (2008) find that the productivity-level differences of US manufacturing plants are persistent.

A considerable amount of work from academics and the popular press has tried to "put a face on" the variation in productivity (Syverson 2011). Examples include factors internal to the firm such as the use of better management practices (Bloom and Van Reenen 2007, Gibbons and Henderson 2012, *The Economist* 2014), the

* Kelley School of Business, Indiana University, 1309 East Tenth St., Bloomington, IN, 47405 (email: rabutter@indiana.edu). John Asker was coeditor for this article. The work in this paper is drawn from chapter 3 of my PhD dissertation at Northwestern University under the supervision of Meghan Busse, Michael Mazzeo, Daniel Spulber, and Yi Qian. An earlier version of this paper was circulated as "Demand Volatility, Adjustment Costs, Temporal Aggregation and Productivity." I thank three anonymous referees for many useful comments. I also would like to thank Scott Brave, Jeffrey R. Campbell, Matthias Doepke, Shane Greenstein, Thomas Hubbard, Benjamin F. Jones, Alejandro Justiniano, Mauricio Romero, Valerie Smeets, and seminar participants at the 13th Annual International Industrial Organization Conference, the 85th Southern Economic Association Annual Meeting, Northwestern University, Federal Reserve Bank of Chicago, University of Georgia, Indiana University, and the Bureau of Economic Analysis, as well as the generous funding of the Kellogg School of Management and Kelley School of Business.

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utilization of information technology (Hubbard 2003; *The Economist* 2007; Bloom, Sadun, and Van Reenen 2012), the investment in R&D (Bøler, Moxnes, and Ulltveit-Moe 2015), the decision to export (Van Biesebroeck 2005; De Loecker 2007, 2013) or import (Halpern, Koren, and Szeidl 2015), and differences in organizational structure (Hortaçsu and Syverson 2007, Braguinsky et al. 2015). Similarly, several factors external to the firm, such as the strength of competition in output markets (Syverson 2004a), size of entry costs (Collard-Wexler 2011), and the regulatory environment (Knittel 2002; Fabrizio, Rose, and Wolfram 2007), have also been offered.

Generally speaking, the factors internal to the firm tend to paint a picture of "the haves" versus "the have-nots." Some managers, establishments, and firms are figuring things out, while others are not. Typically, these investigations must also reconcile why not all firms or businesses adopt such an activity. On the other hand, most of the explanations involving factors external to the firm commonly take the underlying variation in productivity as given and instead focus on the mechanism that allows these differences to persist and not be competed away. While these two types of investigations lead to varied policy and welfare implications, they both have left a large amount of variation in productivity left unexplained.

This paper offers an alternative explanation that might account for some of the productivity differences. When adjusting (and storing) production is costly, increases in demand volatility increase the unit costs of otherwise identical producers. Put simply, two producers with the same technical productivity (and facing identical input prices) but different demand volatilities will have different unit costs, even if both use resources efficiently. In the most straightforward case, and the one documented here, the differences in demand volatility will be reflected in different utilization rates of the inputs facing adjustment costs. Furthermore, even large differences in demand volatility may be difficult to observe at some frequencies of observation (e.g., variation in seasonality in annual surveys). Consequently, variation in *measured* productivity might not reflect variation in *technical* productivity if differences in demand volatility and adjustment costs are present. In other words, differences in measured productivity might not reflect differences in the competitive advantages or capabilities of producers but instead differences in their demand environments.

This sort of explanation for the observed productivity differences across firms leads to substantially different inferences as well as policy and welfare implications. This explanation does not require any inferior behavior on the part of the managers, establishments, or firms that accompany most of the investigations of factors internal to the firm. Moreover, this explanation offers a factor external to the firm—demand volatility together with adjustment costs—that generates the differences in productivity across firms as opposed to taking them as given. Consequently, this explanation exposes a critical dimension that needs to be accommodated before aggregate welfare calculations are made on the basis of firm- or establishment-level productivity differences.

I find this explanation has support empirically. To arrive at this assessment, I conduct a comparison of two industries: hotels and airlines. I leverage several characteristics of the hotel and airline industries for the investigation. First, both industries produce a perishable good across many isolated markets. Additionally, each industry exhibits considerable variation in the volatility of sales (within a year) across locations that I observe at a monthly frequency. Despite the two industries being similar in many ways, they *differ* in one critical aspect—the size of adjustment costs in capital. Hotels face considerable costs when adjusting the available number of rooms, while airlines face smaller costs when adjusting the number of available seats to any particular destination in their network because of the mobility of aircraft.

Each characteristic mentioned above makes the comparison between hotels and airlines ideal for my study. The large amount of variation in demand volatility (within the hotel and airline industries) and adjustment costs (across the hotel and airline industries) increases the power of my hypothesis test. Because of the isolated geographic markets, I am able to treat different metro areas and destinations (airports) as independent observations and use the cross-sectional variation in demand volatility at this level as exogenous variation to identify its effect on the capacity utilization rates of different segments of hotels or airlines. Additionally, with *monthly* observations, I am able to focus on differences in demand volatility within the year, which are likely to be dominated by differences in seasonality patterns, lending more support for my identification strategy.

Figures 1 and 2 provide preliminary evidence of the main results. The figures display capacity utilization and annual demand volatility for both hotels (Figure 1) and airlines (Figure 2). For hotels, I observe 2,063 separate metro area–segment (that is, luxury, upscale, economy)-year combinations. For airlines, I observe 2,420 separate destination-airline-year combinations. (I go into more detail on the sources of the data and the construction of both capacity utilization and demand volatility below.)[1] Given the discussion above, demand volatility should have a negative association with capacity utilization (occupancy rates) for hotels, an industry with high adjustment costs, and no association with capacity utilization (load factor) for airlines, an industry with low adjustment costs. Figures 1 and 2 display exactly these relationships.

In the analysis to follow, I find that moving from no demand volatility to the maximum observed in the sample of hotels is associated with a 15 percent decrease in occupancy rates. Based off of raw correlations alone, differences in annual demand volatility explain 13 percent of the variation in occupancy rates of hotels. Additionally, as much as 25 percent of the variation of a traditional measure of productivity for hotels could in fact be attributed purely to within-year demand variation. In contrast, differences in annual demand volatility have no effect on the load factors of airlines. Similar levels of variation in demand volatility have no effect on the capacity utilization of airlines, because airlines adjust their capacity at a destination to match these fluctuations in demand.

Finding that demand volatility and adjustment costs have such strong implications on capacity utilization rates has broad implications for other investigations of the factors driving productivity differences. First, it suggests value in considering how sensitive results involving measures of productivity are to the effect of demand volatility. To the extent that other factors (internal or external to the firm) are

[1] For comparison purposes only, this figure omits five observations that have a demand volatility over one. However, the linear projection displayed in this figure is based off of all 2,420 observations.

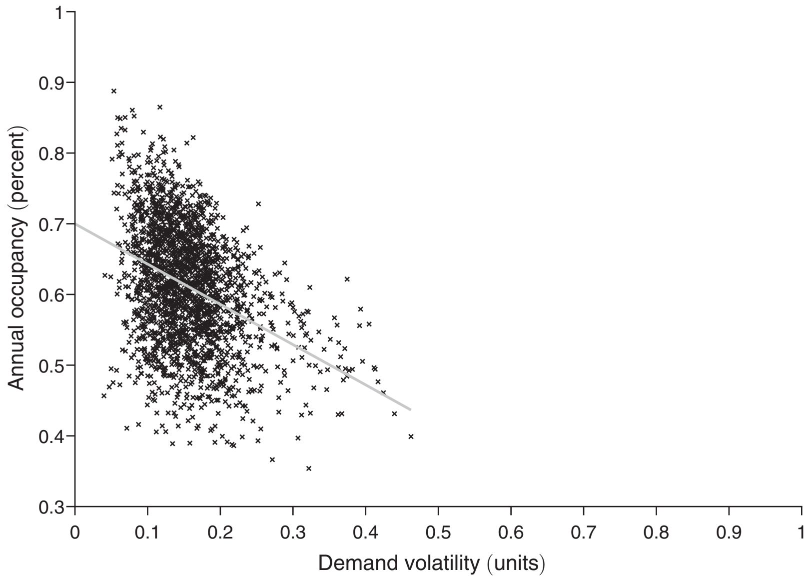

Figure 1. Capacity Utilization (Occupancy Rates) and Demand Volatility for Hotels

Notes: I display the relationship between capacity utilization and demand volatility among the 2,063 metro area–segment-years in my hotel sample. Along the vertical axis is capacity utilization as given by annual occupancy, while along the horizontal axis is a measure of demand volatility. For an explicit summary of the construction of each variable, see Section II, and for a discussion of the sources of the data, see Section III.

Sources: Smith Travel Research (STR) and author's calculations

correlated with the demand volatility firms face, inferences based on analysis void of demand volatility considerations are misleading. In fact, the sort of variation in demand volatility highlighted in this study is at a frequency (within the year) that is virtually undetectable in many of the productivity studies using annual survey data. Second, the effect outlined in this paper could serve as the underlying mechanism for how other factors influence productivity—in particular the factors internal to the firm. For example, some of the utilization of ITs or entry into export markets' impacts on productivity could be driven by producers being better equipped to accommodate demand volatility when facing adjustment costs. This paper also suggests that caution should be exercised on welfare calculations and aggregate productivity decompositions that are based on variation in the measured productivity across firms that have not accommodated variations in the demand environments.

The results of this paper underscore how differences in demand volatility, together with adjustment costs, lead to variation in capacity utilization levels and ultimately in inferences of productivity. The role of quasi-fixed factors on capacity utilization and its relation to measuring productivity has been the focus of aggregate productivity growth studies (Jorgenson and Griliches 1967, Berndt and Morrison 1981, Berndt and Fuss 1986, Morrison 1986, Hulten 1986). One could view this paper as providing empirical evidence of how demand volatility can make these considerations particularly salient at a micro or establishment level. Likewise, the

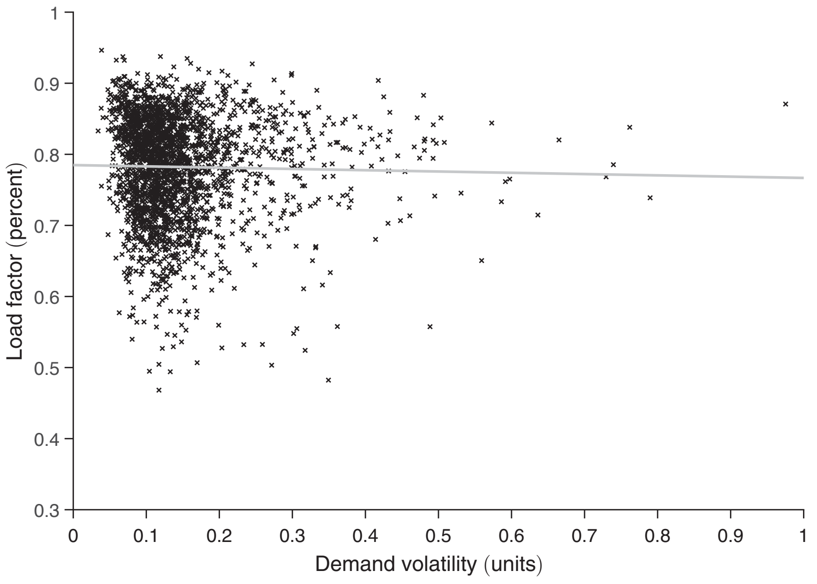

Figure 2. Capacity Utilization (Load Factor) and Demand Volatility for Airlines

Notes: I display the relationship between capacity utilization and demand volatility among 2,415 destination-airline-years in my airline sample. Along the vertical axis is capacity utilization as given by load factor, while along the horizontal axis is a measure of demand volatility. For an explicit summary of the construction of each variable, see Section II, and for a discussion of the sources of the data, see Section III.

Sources: Bureau of Transportation Statistics and author's calculations

impact of demand volatility on investment incentives both on the intensive (Pindyck 1988; Abel and Eberly 1996; Collard-Wexler, Asker, and Loecker 2011) and extensive margin (Dixit 1989, Bloom 2009, Collard-Wexler 2013), as well as on costs (Friedman and Pauly 1981, Gaynor and Anderson 1995, Baker et al. 2004), have been investigated and found to have economically meaningful impacts.[2] In these settings, however, the volatility is linked to the level of *uncertainty* in the demand environment. Here, I show how differences in *predictable* demand volatility across firms can influence inferences of productivity. Another insightful aspect of the results is the illustration of how temporal aggregation can affect inferences, a theme that has been found in other contexts (Taylor 2001, Bloom 2009, Butters 2019).

This paper proceeds as follows. Section I develops a theoretical model of production with demand volatility and adjustment costs. Section II outlines my empirical strategy through a comparison of the hotel and airline industries. Section III briefly summarizes the data, and Section IV presents the empirical results. Section V provides context for the empirical results relative to the existing productivity

[2] Morikawa (2012) finds evidence of short-term demand fluctuations affecting productivity in several service industries in Japan. With a limited measure of capacity, however, Morikawa's (2012) results suggest the effect outlined in this paper is likely to influence measures of labor productivity in service sectors as well.

literature, while Section VI and an online Appendix provide a series of robustness checks. Section VII concludes the paper.

I. Simple Model of Production

In this section, I present a simple two-period model of production with demand volatility and adjustment costs. The goal of this section is threefold. First, the model formalizes the intuition for how increases in demand volatility, together with adjustment costs, lead to decreases in measured productivity. Second, the model illustrates that as the elasticity of substitution between inputs decreases, the effect of demand volatility on productivity measures is concentrated to the utilization rate of the factor facing adjustment costs. Third, the model provides a testable prediction for the level of the elasticity of substitution between inputs.

There are two firms (A and B), both with identical constant elasticity of substitution production functions defined by $Y = \Omega\left(\alpha^k K^\sigma + \alpha^l L^\sigma\right)^{1/\sigma}$, where Y is the output resulting from using K units of capital and L units of labor, Ω is the Hicksian neutral total factor productivity of each firm, and σ is a parameter governing the elasticity of substitution between the two inputs of production.

Firms A and B face the same set of prices for both capital, r, and labor, w, with each input supplied by a competitive market. Each firm produces for two periods, and storage is impossible. Even though the setting is dynamic, the firms do not discount their costs in period 2. Because of adjustment costs in capital, each firm's level of capital remains fixed over the two periods. In contrast, labor is perfectly flexible.

Up to this point, firms A and B are identical by construction. The two firms differ, however, in the volatility of their demand. Specifically, firm A faces constant demand each period and produces the same profit-maximizing output of $\overline{Q}$ units in both periods 1 and 2: $Q_1^A = Q_2^A = \overline{Q}$. Firm B, on the other hand, faces lower demand in period 1 than in period 2, and its profit-maximizing response is to produce $\overline{Q} - D$ units in period 1 and $\overline{Q} + D$ units in period 2: $Q_1^B = \overline{Q} - D$, $Q_2^B = \overline{Q} + D$.

Figure 3 displays the cost-minimizing production plans for firms A and B. The left panels display firm A's cost-minimizing production plan, while the right panels display firm B's cost-minimizing production plan. The top panels display the production plans for firms A and B when the elasticity of substitution between inputs is one, while the bottom panels display the production plans when the elasticity of substitution is zero. I keep all the other parameters of the model constant, including the technical productivity of both firms.[3] In each panel, the production isoquants of each firm are displayed for both periods. Each panel labels the optimal production points on each isoquant and displays the price vector of capital and labor at the production points. In the case with some elasticity of substitution, I also display the

[3] The parameter values include the parameter governing the elasticity of substitution in the production function, σ. In the top two panels, $\sigma \to 0$, while in the bottom two panels, $\sigma \to -\infty$. The other parameter values are the same across all the panels in the figure and include the share parameter of capital, the share parameter of labor ($\alpha^l = \alpha^k$), the price of capital $r = 1$, the price of labor $w = 1$, and the technical productivity of each firm $\Omega = 1$, as well as the demand parameters $\overline{Q} = 20$ and $D = 5$. To avoid a normalization across the two types of elasticity of substitution, $\alpha^l = \alpha^k = 0.5$ in the top panel, and $\alpha^l = \alpha^k = 1$ in the bottom panel.

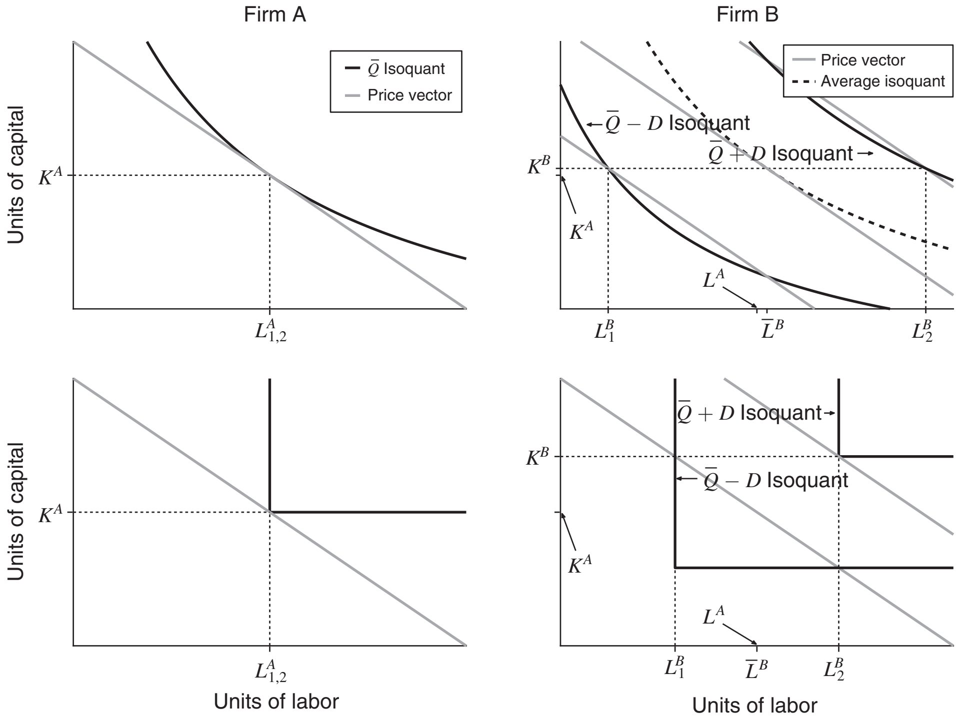

Figure 3. Optimal Production Plans of Firm A and Firm B

Notes: This figure displays the optimal production plans of firm *A* in the left panels and firm *B* in the right panels. In the top panels, the elasticity of substitution between capital and labor is one, while in the bottom panels, the elasticity of substitution between capital and labor is zero. On the horizontal axis of all panels are units of labor, and on the vertical axis of all panels are units of capital. In each figure, the isoquants of each firm for both periods are displayed in black, while the price vector(s) for capital and labor at a point of production is displayed in gray. For each firm, the optimal production plan is denoted by the black dashed lines.

average of the two isoquants to better illustrate the cost minimization behavior of firm *B* (top-right panel).[4]

Firm *A*, with constant demand, faces a straightforward cost minimization problem. The most cost-effective level of capital and labor is the same in both periods. Using the same amount of capital in both periods is cost effective even with no adjustment costs. In other words, firm *A* in both periods produces at a point where the short-run cost curve coincides with the long-run cost curve.

The cost minimization problem for firm *B* is quite different, because the constraint on adjusting capital is binding. Because of the demand volatility, firm *B* weighs the benefits of more capital in period 2 with the costs of having excess capital in period 1. Firm *B* chooses a level of capital that balances this trade-off. Ultimately, firm *B* uses more capital than firm *A*, as well as more total labor, over

[4] The average of firm *B*'s two isoquants is different than the $\bar{Q}$ isoquant because of Jensen's inequality and the convexity of the isoquants.

the two periods. Thus, firm *B* uses more inputs than firm *A* over the two periods to produce the same amount of output: $2\overline{Q}$.

Most measures of productivity will equate the use of more inputs over a period of time to produce the same level of output as being less productive.[5] The two-period model of production provides the intuition for how demand volatility and adjustment costs together affect measured productivity. Over the two periods, the measured productivity of firms *A* and *B* is different. The difference in measured productivity comes despite both firms having identical technical productivity. More specifically, the firm experiencing more demand volatility is inferred to be less productive.

Furthermore, any temporal aggregation will conceal the differences in the volatility of quantity demanded across firms. If adjustment costs are important, this concealing of the demand environment is problematic for inferences of productivity. Alternatively, if adjustment costs are small, the impact of demand volatility on measured productivity is minimal.

When the elasticity of substitution is zero (bottom panels), firm *B*'s use of more inputs is concentrated to the input with adjustment costs (capital); see bottom-right panel. Firm *B*'s total use of the flexible input (labor) is the same as firm *A*'s. As the elasticity of substitution decreases, the influence of demand volatility on measured productivity becomes more concentrated to the input facing adjustment costs. In the event of quasi-fixed capital, as the elasticity of substitution approaches zero, the influence of demand volatility on measured productivity will be summarized by its impact on capacity utilization rates.

Furthermore, with no technical substitution, relative input prices do not affect the cost-minimizing mix of inputs. The bottom panels of Figure 3 illustrate this insight by noting that the optimal production plan for both firms is invariant to rotations of the price vector. Essentially, how input ratios vary with (exogenous) variation in relative input prices identifies the elasticity of substitution.

For the rest of the paper, I use the insights of this section to investigate empirically the effect of demand volatility with adjustment costs on measured productivity by examining capacity utilization rates. For both hotels and airlines, this approach is appropriate given the limited amount of technical substitution between their primary forms of capital (rooms for hotels and seats for airlines) and other inputs.

II. Empirical Strategy

Two characteristics of the hotel and airline industries provide the basis for my empirical strategy. The first key is the availability of monthly observations of output. Observing monthly observations of output allows me to measure the volatility of demand within a year, the key variable of interest. Second, the broad similarity of

[5] Specifically, any measure of productivity that uses the same input elasticities across firms will equate higher input use conditional on the same level of output as a less productive firm. Traditionally, both the index approach to calculating productivity (Caves, Christensen, and Diewert 1982) and the structural approaches (Olley and Pakes 1996; Levinsohn and Petrin 2003; Ackerberg, Caves, and Frazer 2015) employ constant input elasticities across firms. Mairesse and Griliches (1988) and Klette (1999) estimate a random coefficient model when estimating productivity, but the identification of these coefficients depends critically on distributional assumptions, and in neither case are they informed by variation in any measure of demand volatility. For a more thorough description of the methods to estimate productivity, see Ackerberg et al. (2007) and Van Biesebroeck (2007, 2008).

the hotel and airline industries, with the exception of the size of adjustment costs in capital at any one location, serves as the point of comparison. Finding that increases in demand volatility lead to decreases in capacity utilization for hotels and not for airlines supports the predictions of the theoretical model.

The foundation of the empirical analysis involves four distinct components. First, I require a measure of capacity utilization. Second, I need a measure of demand volatility. Third, I need an estimating equation that identifies the effect of interest. Fourth, I require a source of exogenous variation in demand volatility. I will cover each of these components in turn before proceeding to the empirical results.

A. *Capacity Utilization: Concept and Measure*

The keys to my measure of capacity utilization are two assumptions involving the production technology of hotels and airlines. I assume that there is no technical substitution between capital (rooms in hotels and available seats in airplanes) and other inputs, as well as constant returns to scale in the long run (i.e., when capital is flexible). While labor, materials, and energy are all necessary to produce output in both the hotel and airline industry, there is no technical substitution between capital and these other inputs.[6] Furthermore, for both hotels and airlines, assuming long-run constant returns to scale is warranted.[7]

Under these conditions, the production function for both hotels and airlines can be described as $Y = \min\{K, g(X)\}$, where Y denotes output, K denotes capital, and the potentially multidimensional X includes all the other inputs—including labor, materials, and energy. The lack of any technical substitution between capital and the other inputs leads to the Leontief functional form. The long-run constant returns to scale assumption further requires that $g(\cdot)$ must be homogenous of degree one. In the short run, if all the other inputs are fully flexible, this production function would imply that marginal costs are constant up to the capacity constraint (K), at which point marginal costs also include the shadow value of an additional unit of capital. Given these assumptions, I construct a measure of capacity utilization given observations of Y_{imt} and K_{imt}, where Y_{imt} is the level of output, K_{imt} is the level of capital for metro area (destination) i, segment (airline) m, in year t.[8]

[6] As a robustness check, in Section VIA I estimate the elasticity of substitution between capital and labor in hotels using regional variation in relative input prices. I find no evidence of technical substitution between capital and labor. Recent evidence suggests that even for manufacturing industries, the elasticity of substitution between capital and labor is less than one (Oberfield and Raval 2012, Raval 2019).

[7] The assumption of constant returns to scale can be empirically tested. In Section D of the online Appendix, I provide estimates of the returns to scale for hotels across several different estimation specifications. For all specifications, the estimate of the returns to scale is within 0.05 of 1, and the results presented here are not sensitive to using any of the values suggested by this exercise.

[8] Empirically, the capacity of airlines at the destination level is not fixed, at least at the monthly frequency that I observe. The purpose of including airlines in the study is for exactly this fact. Despite the capacity of airlines not being fixed, I still concentrate on capacity utilization because it is likely to be more fixed at the destination level than labor, fuel, and other energy inputs, and it does not have any technical substitution between these other inputs. Busse (2002) suggests that airport slot restrictions and the need to coordinate with other airlines using the same airport make an airline's flight schedule fixed to some extent.

Specifically, following Berndt and Morrison (1981) and Berndt and Fuss (1986), I define the capacity utilization for hotels and airlines to be

$$\begin{aligned}\text{Capacity Utilization}_{imt} &= \frac{K^*_{imt}(Y_{imt})}{K_{imt}} = \frac{Y_{imt}}{K_{imt}} \\ &= \frac{\text{Room Nights Sold}_{imt}}{\text{Room Nights Available}_{imt}} \equiv \text{Occupancy Rate}_{imt} \\ &= \frac{\text{Passenger Miles}_{imt}}{\text{Available Seat Miles}_{imt}} \equiv \text{Load Factor}_{imt},\end{aligned}$$

where $K^*_{imt}(Y_{imt})$ is the optimal long-run amount of capacity conditional on supplying Y_{imt}. I measure capacity utilization at the level of a metro area–segment-year or destination-airline-year.[9] Given the insights from the theoretical section involving the role of the elasticity of substitution on productivity outcomes, capacity utilization provides a sufficient summary measure of the role of demand volatility and adjustment costs on the productivity differences across firms despite abstracting from the use of labor, materials, and energy.[10] For the rest of the paper, I interchange occupancy rate and load factor with capacity utilization.[11]

B. *Demand Volatility: Concept and Measure*

The next major component of the empirical analysis involves constructing a measure of demand volatility for both the hotel and airline industries. The basis for my measure of demand volatility is that fundamentally, the variation in demand conditions that affect the capacity utilization of hotels and airlines are those that ultimately move quantity demanded.[12] This has two important consequences. First, while variation in demand conditions alone, in principle, can leave the quantity

[9] At this level of observation, some amount of aggregation is taking place across hotel establishments and individual aircrafts serving different origins. Given the assumption of constant returns to scale, the measure of capacity utilization given above constitutes the output-weighted average capacity utilization of the individual hotels and aircrafts serving different origins. For a discussion on the role cross-sectional aggregation might have on the results, see Section E in the online Appendix.

[10] To the extent that firms minimize costs and these other inputs are flexible, achieve constant returns to scale, and have no technical substitution with capital, the difference between the capacity utilization measure given above and a more traditional measure of productivity that includes all inputs would only be a constant. Given that the goal of this paper is to explain productivity differences, this constant shift would have no impact on the results presented here. Alternatively, one could interpret the measure of capacity utilization given above as the "traditional measure of productivity" accounting for all the other inputs plus a measurement error. Under this interpretation, the results presented here serve as a *lower-bound* estimate of the role of demand volatility and adjustment costs, provided that the covariance between demand volatility and the idiosyncratic use of other inputs conditional on total output produced is positive.

[11] Mazzeo (2002a) and Conlin and Kadiyali (2006) use the number of rooms as a measure of capacity in their study of the lodging industry. Baltagi, Griffin, and Vadali (1998) investigates several different measures of capacity for the airline industry, one of which is available seat miles. Unlike some productivity studies, I observe the quantities of the capital input as opposed to expenditures on inputs. Because I observe these capacities directly, I avoid having to deflate expenditures potentially with an industry deflator and confounding differences in factor prices with differences in factor utilization.

[12] I also require that the quantity demanded given prices is equal to the equilibrium quantity I observe in the data, or in other words that neither airlines nor hotels have instances of supply shortages. At the monthly frequency of observation, I do not observe any hotel segment or airline that achieves full capacity utilization, and thus there is a limit to the possibility that not picking up censored demand would influence the results.

demanded unchanged, these sorts of demand fluctuations are immaterial in explaining the variation in productivity driven by demand volatility and adjustment costs. For instance, if, absent supply-side considerations, the level and price elasticity of demand fluctuated in a way that resulted in constant levels of quantity demanded, there would be no scope for these sorts of fluctuations to impact productivity through capacity utilization rates.[13] Second, while variations in demand conditions alone (i.e., absent variations in supply conditions) are inherently a multidimensional object, in order to address the influence of these fluctuations (jointly) on productivity through capacity utilization, it is sufficient to measure the volatility of quantity demanded. For example, demand variations that represent either "shifts" or "tilts" that ultimately result in the variation of quantity demanded are dimensions of demand volatility that I hope to capture in my measure. In this way, variation in demand that leads to movements in quantity demanded both directly (holding prices constant) and indirectly (through the price responses of firms) will be captured by this measure of demand volatility.

To measure the volatility in quantity demanded, I utilize the coefficient of variation and the log-normal transformation to accommodate the skewness in my sample. The coefficient of variation, a normalized measure (with the mean serving as the scale), measures the dispersion of a distribution by taking the ratio of the standard deviation and the mean: σ/μ. Using a normalized measure allows demand volatilities across demands with varying mean levels to be comparable. Formally, for a given metro area (destination) i, segment (airline) m, year t, I use the monthly observations (denoted by s) of quantity demanded and calculate the coefficient of variation given by the following equation:

$$\text{(1)} \qquad \text{Demand Volatility}_{imt} = \sqrt{e^{\text{std}\left(\ln\left(Q_{imts}\right)\right)^2} - 1},$$

where $\text{std}\left(\ln\left(Q_{imts}\right)\right)$ is the standard deviation of the logarithm of monthly room nights sold (passengers flown) within the year.[14]

This measure of demand volatility captures the volatility within a year.[15] Differences in volatility occurring at this frequency are concealed when data are

[13] For example, in the case of linear demand $\left(Q_t(p) = a_t - b_t p\right)$ and monopoly pricing under constant marginal costs of zero, variation in b_t does not result in changes in the quantity demanded. One concern about this view of demand volatility is that for some firms, potentially, variation in prices is the only evidence of the demand volatility they face. In Section VIC, I provide results under an alternative formulation of demand volatility that incorporates price fluctuations into the measures as well. The main results presented are robust to this alternative measure of demand volatility.

[14] Four alternative specifications of demand volatility include (i) using the measure above but applying a small sample correction $\left(1 + \left(1/4n\right)\right) \approx 1.021$; (ii) using sales as opposed to quantities; (iii) using the nonparametric quartile coefficient of dispersion, i.e., the interquartile range divided by the median; and (iv) using the sum of quantity sold and some scale of the average price. Using the sum of quantity sold and a scale of price has the interpretation of being the demand shifter of a constant elasticity demand function, with the scale used representing the price elasticity of demand. The results presented are robust to each of these alternative measures of demand volatility. Results involving either (i) the small sample correction, (ii) sales, or (iii) the quartile coefficient of dispersion are available from the author upon request. Results using the quantity and a scale of price are presented in the robustness checks Section VIC.

[15] The most pressing issue involving this measure of demand volatility involves the case where the capacity constraint is binding and the covariance of the expansions in demand and the shifts in the price elasticity of demand is positive. In this instance, it could be the case that both the quantity demanded (given the capacity constraint) and the price (because of the competing forces of shifts in demand with the price elasticity of demand) display very

observed at the annual level. Consequently, one could view the empirical results to follow as exposing the effect of demand volatility on measures of productivity that would go unaccounted for in a study of annual data alone.

Another key feature of demand volatility at the monthly frequency within a year is that it is predictable, likely well ahead of time. The reasons why many more tourists come to some locations in one month relative to another month are understood by hotel and airline industry participants, and they are persistent from year to year.[16] Consequently, the volatility of demand from month to month within a year is much easier to predict than movements from week to week or year to year.

The predictability of demand at this frequency plays an important role in the comparison between the hotel and airline industries. The difference between the adjustment costs of capacity between the two industries hinges on the scheduling efforts of airlines. For the costs of adjusting capacity to a particular destination to be low, some lead time is required in being able to arrange the change in crew schedules, gate assignments, and operations surrounding booking tickets. To the extent that the demand fluctuations at the monthly frequency represent fluctuations in demand that can be factored into monthly or even annual operation schedules, the adjustment costs of capacity for airlines relative to hotels will be small.

Measuring the volatility in quantity demanded at the monthly frequency does aggregate fluctuations at other higher frequencies—some of which are likely to be just as predictable. For example, demand for hotel rooms and airplane seats at certain locations also exhibits periodic fluctuations at a daily frequency that are predictable to firms and managers. For most locations, the relative size of these fluctuations is dominated by the fluctuations at the monthly frequencies. Auxiliary analysis involving daily information on room nights sold at a metro area and the number of scheduled flights by airlines into a destination suggests that at an aggregate level, demand for hotel rooms/flights peaks on Tuesdays and Wednesdays, most likely from business travelers, but these fluctuations are dominated by the seasonal fluctuations that occur from month to month (see Section C in the online Appendix). Therefore, I abstract from the variation at metro areas or airports in demand volatility at the daily frequency and note that variations at higher frequencies are likely to only reinforce the results I report here.

In both these industries, fluctuations in demand at other frequencies are likely to be less predicable. For example, demand movements from week to week are driven by unforseen factors such as unpredictable weather patterns and the irregular scheduling of events, while the movements of the factors that drive year-to-year fluctuations in demand such as personal income and the business cycle are often difficult to predict. To this point, both the hotel and airline industries did experience

little in the way of volatility, but along any dimension, the demand volatility is high. While this issue is one that I will not be able to address adequately, it should be noted that for this to be a substantial problem, the comovement of the expansions in demand and the shifts in the price elasticity of demand needs to be of a very particular type in order for their movement to not result in changes in the quantity demanded or price and, as a consequence, not get picked up by the alternative measure of demand volatility used in a set of robustness checks in Section VIC. Furthermore, at the monthly frequency for hotels, no metro area–segment-years experience full capacity utilization throughout the year, and so it would seem unlikely that this last type of issue could have much scope for altering the empirical findings.

[16] The correlation of the demand volatility in adjacent years for hotels is 0.86 in my sample.

a decline in room nights sold and passenger miles flown during the Great Recession, a business cycle that was notoriously difficult to identify even coincidentally. Even though these business-cycle-induced shifts in demand are also likely to impact the capacity utilization for at least hotels, which are still unlikely to be able to cheaply adjust capacity in that time horizon, the goal of the empirical approach is to focus on the portion of demand variation that is likely to be predictable to the firms and persistent, the two aspects of the variation in demand underpinning the theoretical model. Consequently, the within-year fluctuations in quantities measured at the monthly frequency are an appealing measure of demand volatility for the rest of the analysis.

C. *Main Estimating Equation*

The main objective of the empirical section is to identify how variation in within-year demand volatility affects capacity utilization and how this effect compares across the hotel and airline industries. The regression equation I use in the main results to estimate that effect takes the following form:

$$\log\left(\text{Capacity Utilization}\right)_{imt} = \rho\,\text{Demand Volatility}_{imt} + X_{it}\beta + \lambda_t + \psi_m + \varepsilon_{imt}, \tag{2}$$

where λ_t is a year fixed effect, ψ_m is a segment (airline) fixed effect, and ε_{imt} is an error term. Additionally, X_{it} includes a set of variables summarizing input prices, the overall market size, and the price elasticity of demand, as well as other demographic or metro area (destination)–year controls.[17] The theoretical section predicts that ρ will be negative for industries with large adjustment costs (hotels) and zero for industries with small adjustment costs (airlines). In this specification, I control for any systematic differences across hotel segments or airlines through the segment/airline fixed effect. The variation used to identify the coefficient on demand volatility occurs within segments/airlines, not across them. Variation of demand volatility across metro areas (destinations) within segments (airlines) is less likely to confound how aspects of pricing, vertical differentiation, and switching costs impact the distribution of demand volatility across segments (airlines) within a metro area (destination).[18] A noteworthy omission from the regression equation is any measure of market structure. Consequently, the results are sensitive to misspecification due to the strategic interaction between firms.[19]

[17] None of the metro area (destination)–year controls included in X_{it} vary across the segments (airlines) within a metro area (destination)–year. Accordingly, the estimates of the coefficients on X_{it} are primarily identified off of differences in these variables across metro areas (destinations). In principle, the coefficient on X_{it} could vary by segment (airline)—that is, I could estimate $X_{it}\beta_m$. I choose this more limited setup for the main empirical specification for exposition and precision considerations. The resulting coefficient estimates of ρ for the more flexible specification, with β_m, are qualitatively similar to the ones presented here.

[18] I looked into estimating the model with segment-year fixed effects, ϕ_{mt}, as well. These did not change the estimated coefficient of ρ significantly.

[19] Mazzeo (2002b) documents the presence of such strategic interaction in a study of endogenous product quality and entry in the lodging industry. Conlin and Kadiyali (2006) finds evidence of excess capacity in more concentrated markets in a sample of Texas hotels. Campbell (2011) provides a nonparametric hypothesis test in which the null hypothesis is *atomistic* competition. Campbell (2011) derives the test by building a general model of competition that generates the testable prediction that if firms' choices are related to market size, then strategic

D. *Source of Exogenous Variation in Demand Volatility*

The goal of my identification strategy is to isolate the component of the volatility in quantity demanded that I observe for each hotel segment (or airline) at a metro area (destination) that is exogenous to the possible idiosyncratic variation of productivity and/or capacity conditions of those hotels making up the segment (or airlines' flights to a destination).

Ideally, like the theoretical model, I would have a measure of how much of the variation in quantity demanded at the metro area (destination), segment (airline), year level is driven by demand shocks alone. In the event that within-year variations in quantity demanded (and prices) are driven solely by demand shocks, then the most appropriate measure of demand volatility for the empirical analysis would be exactly the volatility in quantities faced by each segment (airline) in each metro area (destination). To the extent that supply conditions like factor prices and market structure are stable within the year, such an approach could be appropriate. Alternatively, the volatility of quantity demanded could confound fluctuations driven by idiosyncratic supply-side considerations. The most problematic of supply-side factors would be if the underlying productivity or actual available capacity of a hotel segment/airline known by the firm(s), but not the econometrician, influences the volatility of quantities observed within the year. The reason why these serve as the most potentially concerning factors is because they represent exactly the outcomes that I am suggesting could be affected by differences in demand volatility, leading to a simultaneous causality issue.

As an example, imagine that a hotel in an otherwise highly seasonal demand area, through difficulties in scheduling labor, knows that it will not be able to service a floor of rooms during the high season, and it subsequently prices its rooms accordingly to result in a lower level of quantity demanded during that time, given these actual available capacity considerations. Then, the likely muted movements in quantities observed over the seasons would be a consequence of the idiosyncratic capacity conditions of that hotel and not exclusively the variability (or lack thereof) of the underlying demand conditions faced by the firm. Alternatively, if a hotel chooses to conduct traditional maintenance on a set of rooms during the off-season in an otherwise highly seasonal area, then it could be the case that the variation in quantity demanded observed for that firm is in fact inflated relative to the fluctuations in demand for the hotel(s) in that area.

considerations exist between firms. This test is not appropriate, however, in a setting of fluctuating demand, a characteristic of both hotel and airline demand. I explored whether market structure could affect my results for hotels in two ways. First, I ran the same main empirical specification in equation (2), but I included two measures of market structure: (i) the concentration of capacity in the particular metro area–segment-year as measured by the Herfindahl index and (ii) the number of hotels in the metro area–segment-year. Including these two measures of market structure does not have meaningful impacts on the coefficient estimates on demand volatility. Next, I ran the empirical specification in equation (2), but instead of using the logarithm of the occupancy rate as the dependent variable, I use the logarithm of the revenue per available room nights (REVPAR) in the metro area–segment-year. In this specification, I find after controlling for segment-level fixed effects, demand volatility has *no effect* on the revenue per available room, an implication that would result from a model of monopolistic competition. The regression results, including the two measures of market structure, are available from the author upon request. The regression results with revenue per available room are reported in Table 13 in the online Appendix.

For airlines, given the observed fluctuations in aircraft capacity at destinations, this simultaneity issue becomes even more salient. For example, imagine that an airline for fleet management considerations alters the type of the aircraft flying into a destination over the seasons that has otherwise stable demand and subsequently prices flights into that destination reflective of this change in supply and the available capacity considerations. Then, the likely accentuated movements in quantities observed over the seasons for that airline would be mostly a consequence of movements *along* the demand curve, as opposed to changes in it. These sorts of issues are likely to lead to a simultaneity issue and possibly biased estimates of the influence of demand volatility on capacity utilization.

To provide a level of robustness to these considerations, I tailor an identification strategy that has been employed in studies examining firm-level productivity outcomes (Klette and Griliches 1996, De Loecker 2011) and in particular the study of Fabrizio, Rose, and Wolfram (2007). In summary, the approach assumes that while the volatility of quantity demanded in the market as a whole will be correlated with the volatility of demand facing the individual firms, it should be uncorrelated to the idiosyncratic changes in supply conditions facing those firms. For example, while the volatility of room nights sold within the year at the Myrtle Beach, South Carolina, market as a whole is correlated with the volatility in demand faced by an economy hotel in that market, it seems unlikely that temporary shifts in the actual available number of rooms at any one economy hotel, due to maintenance or scheduling issues, could impact the volatility of room nights sold at the aggregate market level.

In Fabrizio, Rose, and Wolfram's (2007) study of the productivity of electricity plants, they argue that the statewide *level* of annual quantity demanded can serve as an instrument to the individual plant *level* of annual quantity produced by plants within that state. Similarly, I argue that a similar degree of cross-sectional aggregation can serve as the basis for constructing an instrument for the *volatility* of quantity demanded (within the year) at the segment/airline level.

To operationalize the identification strategy, I construct an instrument that isolates the level of demand volatility for any particular segment or airline that can be explained by the demand volatility occurring at the metro area or destination at large as well as the share that that segment or airline maintains in other markets in the country.[20] The construction of this instrument has similarities to others used in the labor (Bartik 1991; Blanchard and Katz 1992; Charles, Hurst, and Notowidigdo 2013) and demand estimation (Hausman 1997, Nevo 2001) literatures. Specifically, to create this instrument for any metro area (destination) i, segment (airline) m, at year t, I interact the demand volatility at the aggregate metro area (destination) level i in that year t with the average share of that segment (airline) m over all other metro areas (destinations) and years. Formally, the instrument for my application is given by

$$\text{Instrument}_{imt} = \overline{S}_{im} \times \text{Demand Volatility}_{it}, \tag{3}$$

$$\overline{S}_{im} = \frac{1}{\#Markets(m) - \#Markets(m)_i} \sum_t \sum_{j \neq i} \frac{Q_{jmt}}{\sum_l Q_{jlt}}. \tag{4}$$

[20] For a more analytical treatment of the acceptability of this instrumental variable approach, see Section B in the online Appendix.

As discussed above, two conditions support the credibility of this instrument. First, this instrument must relate to the demand volatility faced by any individual segment (airline) in a metro area (destination). This condition is empirically testable and is likely to hold given that an individual segment (airline) in a metro area (destination) inherits the demand conditions of the metro area (destination) as a whole and that market shares of segments (airlines) should be similar across metro areas (destinations).[21] Second, this instrument must not be affected by any supply conditions of that segment (airline) in the metro area (destination). I argue that the second condition is reasonable given the size of the metro areas (destinations) in my sample. Any idiosyncratic changes in available capacity or the productivity of a particular metro area–segment (destination-airline) are unlikely to affect the aggregate demand volatility of the metro area (destination) or the market share of that segment (airline) in the other markets of the country. With this empirical strategy in mind, I now summarize the key variables that I use to implement this empirical strategy and their sources.

III. Summary of the Data

The primary source of information for the hotel application comes from the consulting firm Smith Travel Research (STR).[22] The STR report includes monthly hotel performance data for 92 large metro areas from 2006–2009. In general, these metro areas resemble the Census Bureau's Metropolitan Statistical Areas (MSA) but in some cases align more closely to Metropolitan Statistical Divisions.[23] STR gathers individual hotel occupancy, room count, and daily rate information from participating hotels in each metro area and summarizes the observations for industry participants.[24] The overall coverage of the hotels in the STR sample represents close to 40 percent of the total number of hotels in the country and 60 percent of national sales. To prevent revealing performance information of any individual hotel, STR provides summary measures at the geographic level. In addition to the geographic location, STR separates hotels in each metro area into seven different scales or segments. These scales range from economy to a luxury segment and include an independent segment as well.[25] With at most 7 different segments across 92 metro areas, I have close to 620 units of observation in the cross section each year. For any given metro area–segment-year, I have monthly observations of occupancy rates, room nights sold, number of rooms available, revenue, and average daily rates.

[21] For the scatter plot of the measure of demand volatility and the instrument for the hotel and airline samples, see Figures 4 and 5 in the online Appendix.

[22] More information on STR's research initiative can be found at https://www.str.com/products/share-center.

[23] For an exhaustive list of the matches between STR's definition of a geographic market and the MSA or Metro Statistical Division that I use, see Tables 4–5 in the online Appendix. For the geographic definitions of the Census Bureau's MSA and Metro Statistical Divisions, see https://www.census.gov/programs-surveys/metro-micro.html.

[24] STR does impute values for hotels in their census of hotels that do not participate in the individual surveys. STR imputes these values using hotels of similar scale and type that do report in order to impute the missing values. This source of measurement error is unlikely to drive any of the main results. Of the 2,063 individual metro area–segment-years, over 80 percent of the markets have 80 percent coverage as measured by number of rooms. Furthermore, the results are qualitatively similar if I drop the observations from metro area–segment-years where less than 80 percent of rooms in the market are covered by the STR respondent sample.

[25] A full list of the hotel chains that constitute each segment is available from the author upon request.

The primary source of information for the airline application comes from the US Department of Transportation (DOT) Bureau of Transportation Statistics (BTS).[26] Sample construction for the airline application was done to best parallel the geographic makeup of the hotel sample. To accomplish this goal, I focus only on airports in the 92 metro areas in the STR sample. All the available information, including passenger counts and load factors, was gathered for any of the five major airlines (American Airlines, Delta, Southwest, US Airways, and United) that maintained operations at an airport in any of the 92 metro areas over the entire duration of the years 2003–2013.

For each airline-destination-year, I gather monthly passenger counts, passenger-miles, available seat-miles, load factors, and number of flights.[27] With five different airlines each serving an average of 45 destinations in the sample, I have 225 units of observation in the cross section. To control for other factors that might influence capacity utilization, I gather information on input prices, the aggregate level of demand, and the price elasticity of demand, as well as other key market characteristics. For an exhaustive list of these variables and their sources, see the online Appendix Section A.

Table 1 provides summary statistics of the key variables used in the empirical analysis for both hotels and airlines.[28] Several facts pertinent to the empirical strategy are evident immediately from the summary statistics. First, there is significant variation in occupancy rates and load factors. Next, the metro areas and destinations in both samples are large. On average, there are 43 hotels in a metro area–segment and over 5,000 rooms. The average number of annual flights by an airline to a destination is over 12,000. Furthermore, the segment shares suggest that the average individual hotel sells less than 1 percent of the annual total of room nights sold in its metro area (across all segments). Similarly, even though airlines are large in terms of their scope nationally, the average airline's share of passengers at any one destination is less than one-fifth of the total. There is also immediate evidence of the difference in adjustment costs between the industries. Despite the average demand volatility in hotels (0.16) and airlines (0.15) being similar, the volatility (measured by the coefficient of variation) of capacity of hotels (0.03) is one-fourth of the volatility in capacity of airlines (0.12).

IV. Results

A. *The Effect of Demand Volatility on Capacity Utilization*

Table 2 provides the regression results for several alternative specifications of the regression specified by equation (2) for the hotel industry. Specification (a) summarizes the explanatory power of demand volatility and adjustment costs on capacity

[26] For more information on the information gathered by the Bureau of Transportation Statistics, see their website: https://www.bts.gov/topics/airlines-and-airports-0.

[27] For a list of the destinations and the associated airport that I use for each airline in that destination, see Tables 6–7 in the online Appendix.

[28] For a full summary of the data used in the hotel application, see Table 9 in the online Appendix. For a full summary of the data used in the airline application, see Table 10 in the online Appendix.

Table 1—Descriptive Statistics for Hotels and Airlines

	Mean	SD	Min	Max
Hotel sample $N = 2{,}063$				
log(occupancy) (log(%))	−0.50	0.14	−1.04	−0.12
Demand volatility (units)	0.16	0.06	0.04	0.46
Number of hotels	43	48	4	577
Number of rooms	5,292	7,346	521	141,036
Number of rooms volatility (units)	0.03	0.03	0.00	0.21
Market share (room nights sold)	16.55	8.21	1.17	85.19
Airline sample $N = 2{,}420$				
log(load factor) (log(%))	−0.25	0.10	−0.76	−0.06
Demand volatility (units)	0.15	0.10	0.03	2.39
Number of flights	12,196	21,842	298	210,750
Available seat miles (thous.)	1,640,346	3,019,793	14,373	27,279,706
Number of flights volatility (units)	0.11	0.11	0.02	1.81
Available seat miles volatility (units)	0.12	0.13	0.02	2.34
Market share (passengers)	15.54	16.75	0.12	97.25

Sources: STR and author's calculations for the occupancy, demand volatility, number of hotels, number of rooms, and market share for each of the 2,063 metro area–segment-years observed in the hotel sample. BTS and author's calculations for the load factor, demand volatility, number of flights, number of available seat miles, and market share for each of the 2,420 destination-airline-years observed in the airline sample.

utilization in the hotel industry. The results from (a) indicate that demand volatility has a strong negative and statistically significant association with capacity utilization, explaining 13 percent of the variation in capacity utilization for hotels.

In specification (b), the full array of controls, including those designed to control for longer-run movements in demand and the business cycle, are used, as are segment and year fixed effects. Controlling for these additional factors results in an estimated coefficient on demand volatility of −0.42. The interpretation of the coefficient is a semi-elasticity. Based on the coefficient from specification (b), moving from no demand volatility to the maximum amount observed in the sample (0.46) is associated with about a 20 percent decrease in capacity utilization.

Both of the previous estimates of the effect of demand volatility on capacity utilization could be biased if the demand volatility observed for any particular segment is affected by that segment's movements in available capacity causing a simultaneity causality bias. For example, if the pricing response of many hotels in the economy hotel segment of a metro area to the scheduled maintenance of some rooms during the off-season induced even greater volatility in quantity demanded, then the estimates provided in (a) and (b) would be confounding this effect. To alleviate these concerns, in specification (c), I use the instrument described in the empirical strategy section (Section IID), which largely reflects the demand volatility experienced at the metro area at large, and estimate the regression using two-stage least squares. In this specification, the coefficient decreases slightly in absolute magnitude to −0.32. Using this estimate of the direct effect of demand volatility suggests a one standard deviation increase in demand volatility leads to a 2 percent, or about a seventh standard deviation, decrease in capacity utilization. The fact that the coefficient decreases in magnitude suggests that some of the volatility in quantity demanded that I observe at the segment level could be explained by movements *along* the demand curve induced by individual segments' response to changing supply conditions. For

Table 2—Main Regression Results for Hotels

	(a)	(b)	(c)	(d)	(e)	(f)
Demand volatility	−0.95	−0.42	−0.32	−0.38	−0.29	−0.45
	(0.13)	(0.08)	(0.10)	(0.10)	(0.09)	(0.14)
Dependent variable mean	−0.50	−0.50	−0.50	−0.50	−0.50	−0.50
Year/segment fixed effects		Yes	Yes	Yes	Yes	Yes
Controls		Yes	Yes	Yes	Yes	Yes
Drop independents				Yes		
Drop 2008					Yes	
Instrument			Yes	Yes	Yes	Yes
Use employment						Yes
Hausman test			0.02	0.13	0.01	0.84
Adjusted R^2 (first stage)			0.70	0.69	0.69	0.49
Adjusted R^2	0.13	0.72	0.72	0.72	0.73	0.72
Observations	2,063	2,063	2,063	1,792	1,549	2,063

Notes: Regression results for several alternative versions of the regression specified in equation (2) for hotels. The estimated coefficient of demand volatility is reported for all specifications in the first row, with the standard errors clustered at the metro area level reported in the second row within parentheses. Additional statistics for each specification are given, including the mean of the dependent variable over the estimation sample, the p-value of the Hausman endogeneity test (if applicable), the adjusted R^2 statistic of the first-stage regression (if applicable), the adjusted R^2 statistic, and the number of observations. Specification (a) reports the coefficient, absent any fixed effects or metro area–year controls. Specification (b) adds a set of controls at the metro area–year level, including logarithm of the average salary in the leisure and hospitality sector, logarithm of the US Department of Housing and Urban Development's fair market rent for a three-bedroom, logarithm of the average price of electricity for commercial customers, logarithm of personal income per capita, logarithm of personal income, logarithm of employment in the leisure and hospitality sector, the unemployment rate, the logarithm of the share of total nonfarm employment in the leisure and hospitality sector, logarithm of employees in the leisure and hospitality sector per square mile, five-year log change in personal income per capita, five-year log change in personal income, and five-year log change in employment in the leisure and hospitality sector, as well as year and segment fixed effects. In specifications (c)–(f), an instrument is used for demand volatility (see Section IID). Specification (d) reports the coefficient when one drops the segment-year observations that involve independently affiliated hotels. Specification (e) reports the coefficient when one drops the segment-year observations that were in 2008. Specification (f) reports the coefficient when one uses the annual coefficient of variation in employment in leisure and hospitality at the metro area–year level as the instrument for demand volatility.

this reason, I interpret the coefficient reported by specification (c) as a conservative and appropriate estimate of the effect of demand volatility on capacity utilization rates of hotels.

Specifications (d) and (e) provide estimates for alternative subsamples. Specification (d) reports the regression results dropping all metro area–segment-year observations involving independents. In the STR report, hotels included in the independent segment could be an economy or a luxury hotel but are not affiliated with a national chain. Because of this reporting practice, the ability for the segment fixed effects in the main specification to control for the role of vertical differentiation could be limited. Additionally, I provide regression results dropping all metro area–segment-year observations that occurred in 2008, the lone year in the STR sample experiencing a recession as defined by the National Bureau of Economic Research (NBER) over the entire 12 months of the year.[29] In both specifications (d) and (e), the estimate of the demand volatility coefficient remains close to the baseline specification (c). These results suggest that the underlying variation in the sample that

[29] The Great Recession began in December of 2007 and lasted until June of 2009. For business cycle dates from the NBER of past recessions, see https://www.nber.org/cycles.html.

generated the results in the baseline specification is not confined to either the independent hotels or driven by the height of the Great Recession. Across all relevant specifications ((c)–(f)), the adjusted R^2 statistics from the first-stage regressions suggest that the possibility of suffering from a weak instrument bias is minimal. Furthermore, the results of the Hausman test across specifications suggest that there is mixed evidence that the demand volatility experienced at the metro area–segment level is exogenous.

Lastly, I provide the regression results substituting the coefficient of variation of employment in the leisure and hospitality sector at the metro area–year level for the instrument of demand volatility (specification (f)). Employment in the leisure and hospitality sector should track with movements in demand for hotels. Employment in the leisure and hospitality sector does not suffer from any censoring that measuring demand with room nights sold might suffer from.[30] With the employment series substitution, the estimate of the demand volatility coefficient suggests a strong negative effect that falls within the ranges of all the previous specifications in magnitude.

To provide further context for the results, I present a summary of the coefficient estimates for the controls included in the main regression results. Table 3 reports these coefficient estimates across the specifications (b)–(f).[31] Very few of the other indicators have as strong of an effect on measured productivity as demand volatility.[32] For example, the size of the effect of demand volatility on capacity utilization is twice as large as the effect of demand density (as measured by the logarithm of employees in the leisure and hospitality sector per square mile) in hotels. Syverson (2004a) found that increases in demand density raised the average productivity levels and reduced the spread of productivity in ready-mix concrete. Here, I find that increasing demand density does lead to a modest increase in the average performance of hotels across all but one specification, but this effect is small in comparison to the effect of annual demand volatility.

A couple of patterns across the alternative specifications are worth highlighting. First, the role of the price of capacity, which I capture using the US Department of Housing and Urban Development's fair market rent for a three-bedroom unit, has a positive and statistically significant effect on the capacity utilization of hotels. As one would expect, as the cost of a room (occupied or otherwise) increases, the

[30] For an additional robustness check regarding the censoring (from above) that might exist in the demand volatility measure, see Section VIC.

[31] Table 14 in the online Appendix provides a summary of the expected sign and the sign of the estimated coefficient (if it is the same for all specifications (b)–(f)), as well as whether the coefficient estimate is statistically significant from zero for all of the specifications (b)–(f) at a 5 percent significance level for a subset of the control variables included in the main hotel regressions.

[32] The overall size of the effect of demand volatility with adjustment costs on capacity utilization of hotels is not the only reason why the effect is important. Omitting the role of demand volatility and adjustment costs on performance leads to misleading inferences of other contributing factors to hotel occupancy rates. For example, using the same sample of hotel data, I find that omitting demand volatility controls would alter the inference of the role of right-to-work state legislation on hotel occupancy rates, as well as the share of chain-affiliated hotels versus independents. In separate regressions, omitting controls for demand volatility lead to negative and statistically significant coefficients on both a "right-to-work dummy" variable and a share-of-chain-affiliated-units variable. These results are not robust to the role of demand volatility and adjustment costs. As soon as demand volatility controls are included in each regression, the coefficients on the "right-to-work" and share-of-chain-affiliation variables are not statistically distinguishable from zero.

Table 3—Estimated Coefficients for Control Variables in Hotel Regressions

	(b)	(c)	(d)	(e)	(f)
log(average salary)	0.132	0.143	0.145	0.151	0.129
	(0.041)	(0.041)	(0.039)	(0.042)	(0.044)
log(fair market rent three-bedroom)	0.090	0.094	0.082	0.102	0.089
	(0.034)	(0.034)	(0.033)	(0.034)	(0.033)
log(average electricity price)	0.005	0.005	0.010	0.005	0.005
	(0.027)	(0.026)	(0.026)	(0.026)	(0.027)
log(personal income/capita)	−0.054	−0.066	−0.065	−0.065	−0.052
	(0.062)	(0.064)	(0.064)	(0.062)	(0.064)
log(personal income)	−0.035	−0.031	−0.031	−0.031	−0.036
	(0.043)	(0.044)	(0.043)	(0.044)	(0.043)
log(employment in leisure and hospitality)	0.044	0.041	0.039	0.038	0.045
	(0.043)	(0.044)	(0.043)	(0.044)	(0.043)
Unemployment rate	−0.016	−0.016	−0.016	−0.014	−0.016
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
log(share of total employment in leisure and hospitality)	−0.044	−0.046	−0.052	−0.047	−0.043
	(0.045)	(0.046)	(0.046)	(0.043)	(0.045)
log(employment in leisure and hospitality/square mile)	0.002	0.000	0.001	−0.000	0.003
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Five-year log difference in personal income/capita	0.580	0.591	0.556	0.536	0.577
	(0.182)	(0.177)	(0.178)	(0.184)	(0.180)
Five-year log difference in personal income	−0.204	−0.207	−0.184	−0.164	−0.203
	(0.167)	(0.165)	(0.166)	(0.161)	(0.165)
Five-year log difference in employment in leisure and hospitality	0.438	0.450	0.430	0.440	0.435
	(0.113)	(0.111)	(0.112)	(0.108)	(0.113)

incentive to expand capacity decreases. The consequence of this incentive, all else equal, is higher levels of capacity utilization.

Second, the price of labor, as measured by the average salary in the leisure and hospitality sector in the metro area, and the price of energy, as measured by the average statewide price of electricity for commercial customers, also both have positive associations with capacity utilization, although these are not statistically significant across all specifications. Again, this is consistent with the incentive to decrease capacity as the marginal cost of a rented room increases.

Last, the overall level of demand is positively associated with capacity utilization. Here, I use the employment in the leisure and hospitality sector in the metro area and the metro area's unemployment rate to measure both the activity of the leisure and tourism sector and the overall state of business activity. These two measures provide a summary measure of both the aggregate level of demand from the transient (tourism) segment of travelers and the business segment. In both cases, increases in demand are positively associated and statistically significant across all specifications with capacity utilization. This positive association is consistent with the effect that level shifts in demand will have on capacity utilization when demand fluctuates.

Other broad trends that can be found from the additional controls include the role of longer-run movements in the personal income and tourism activity of a metro area. Both the five-year log change in personal income per capita and the five-year log change in employment in the leisure and hospitality sector are positively associated with capacity utilization. These results provide even further support for the large adjustment costs in capacity for hotels. Even five-year movements in factors driving demand have significant impacts on capacity utilization rates of hotels.

The influential role of demand volatility on capacity utilization, however, does not translate to the airline industry. Table 4 provides the regression results for several alternative specifications of the regression specified by equation (2) for the airline industry. In specification (a), the regression is run absent any demographic or destination-year controls, while in specification (b), the full set of controls for input prices, level of demand, other market controls, and airline and year fixed effects are included. In both specifications (a) and (b), the estimate of the demand volatility coefficient is negative but very small, both economically and statistically. Annual demand volatility has no explanatory power on variation in load factors. Controlling for additional factors has a limited effect on the estimate of the demand volatility coefficient, which remains close to zero.

Like in the hotel application, if airlines differentially respond via prices or promotions over the demand cycle, it is possible that my estimate for the effect of demand volatility on load factors is biased. In specification (c), I report the coefficient on demand volatility using the instrument described in Section IID, which leverages the demand volatility experienced at the destination level at large (i.e., experienced by all the airlines at this destination). In this specification, the coefficient increases slightly to 0.06. The coefficient has the interpretation of a semielasticity. So, the baseline specification (c) suggests that a unit increase in the within-year demand volatility increases average load factors at a destination by 6 percent. I cannot reject the hypothesis, however, that the size of this effect is zero.

Based on the results thus far, demand volatility has little effect on capacity utilization for airlines at the destination level. Specification (d) provides a robustness check by dropping observations involving US Airways. US Airways experienced a significant merger with America West during the sample. In specification (d), the estimate of the demand volatility coefficient remains close to the baseline specification (c) and is not statistically distinguishable from zero. This result suggests that the underlying variation in the sample that generated the results in the previous specifications is not confined to US Airways.

B. *The Adjustment of Capacity*

The strong differences in results between the hotel and airline applications are consistent with the differences in the flexibility of capacity of both industries. Hotels face large adjustment costs in available rooms, while airlines are more flexible in adjusting the available seats to any destination in their network. As mentioned before, this intuition appears in the summary statistics of both these industries. The average volatility of the number of available rooms within the year for hotels in the sample is 0.03, with a maximum of 0.21. Alternatively, the average volatility of the number of available seat miles within a year for all five airlines used in the airline sample was 0.12, with a maximum of 2.34.

Figures 4 and 5 provide a visualization of the adjustment of capacity in the two industries. In each figure, I display the within-year peak to trough levels of capacity

Table 4—Main Regression Results for Airlines

	(a)	(b)	(c)	(d)
Demand volatility	−0.02	−0.03	0.06	0.05
	(0.03)	(0.03)	(0.06)	(0.06)
Depend variable mean	−0.25	−0.25	−0.25	−0.25
Airline/year fixed effects		Yes	Yes	Yes
Controls		Yes	Yes	Yes
Instrument			Yes	Yes
Drop US Airways				Yes
Hausman test			0.09	0.17
Adjusted R^2 (first stage)			0.37	0.44
Adjusted R^2	0.00	0.44	0.43	0.45
Observations	2,420	2,420	2,420	2,079

Notes: Regression results for several alternative versions of the regression specified in equation (2) for airlines. The estimated coefficient of demand volatility is reported for all specifications in the first row, with the standard errors clustered at the destination level reported in the second row within parentheses. Additional statistics for each specification are given, including the mean of the dependent variable over the estimation sample, the *p*-value of the Hausman endogeneity test (if applicable), the adjusted R^2 statistic of the first-stage regression (if applicable), the adjusted R^2 statistic, and the number of observations. Specification (a) reports the coefficient, absent any fixed effects. Specification (b) adds a set of controls at the destination-year level including passenger facility charge tax rate, logarithm of the US Department of Housing and Urban Development's fair market rent for a three-bedroom, logarithm of personal income, logarithm of personal income per capita, logarithm of employment in nonfarm employment, the unemployment rate, five-year log change in personal income, five-year log change in personal income per capita, and five-year log change in total nonfarm employment, as well as airline and year fixed effects. In specifications (c) and (d), an instrument is used for demand volatility. Specification (d) reports the coefficient when one drops the observations involving US Airways.

and quantity demanded for hotels (Figure 4) and airlines (Figure 5). Along the vertical axis, the percentage of the peak value is displayed, while along the horizontal axis, the month's rank of that year for quantity demanded (descending) is reported. For both the hotels and airlines, the ninetieth and tenth percentiles are provided for capacity, with light gray shading, and quantity demanded, with dark gray shading. For airlines, I also provide the average across all five airlines in my sample of the peak-to-trough fall of the total number of flights across all US destinations over the year.

The strong difference in the movement of capacity relative to demand across the two industries is clear from Figures 4 and 5. Hotels, while exhibiting similar median peak-to-trough falls in quantity demanded, have as little as a third of the movement in capacity along the peak-to-trough, with seemingly no association of entry and exit rates coinciding with the within-year demand cycle. Furthermore, the large spread in the troughs of quantity demanded for hotels between the ninetieth and tenth percentiles illustrates the key variation used in this section. Airlines' ability to fluctuate capacity to meet demand seems to only be partially explained by movements on the number of flights. This fact suggests that some amount of substitution of capacity occurs within an airline's destination network within a year.

To provide further documentation of the difference in the scope of capacity adjustment between hotels and airlines, I also provide regression evidence. In particular, for both hotels and airlines, I regress a measure of the available monthly capacity on the monthly measure of quantity demanded already described above as well as a set of metro area (destination)–segment (airline)-year fixed effects. From

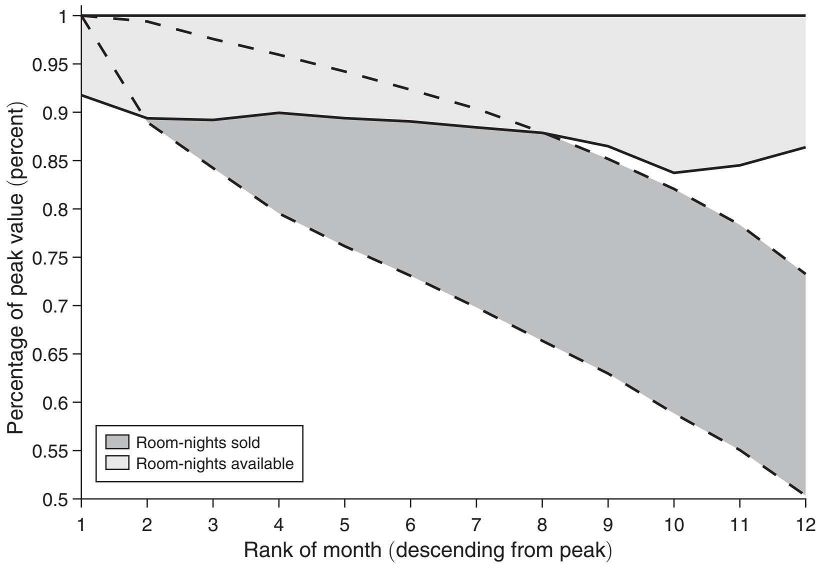

Figure 4. Annual Peak-to-Trough Demand and Capacity for Hotels

Notes: I display the ninetieth and tenth percentiles of annual peak-to-trough patterns for both quantity demanded (dark gray) and capacity (light gray) among hotels. Along the vertical axis for both panels is the percentage of the peak value, while along the horizontal axis is the month's rank of quantity demanded for the year. For an explicit discussion of the sources of the data, see Section III.

Sources: Smith Travel Research (STR) and author's calculations

these regressions, the estimated coefficient on the measure of quantity demanded reflects the extent to which movements in capacity are tied to the movements in quantity demanded within the year for a particular metro area (destination)–segment (airline). It is important to emphasize that while these regressions are informative of the underlying association between quantity and capacity movements at the monthly frequency for both hotels and airlines, they are not meant to be interpreted as causal—merely descriptive.

Table 5 reports four regression coefficients. Both specifications (a) and (b) report the coefficient on the logarithm of room nights sold for hotels. In specification (a), the logarithm of room nights available is used as the dependent variable, while in specification (b), the logarithm of active hotels is used as the dependent variable. Specifications (c) and (d) report the coefficient on the logarithm of number of passengers for airlines. In specification (c), the logarithm of the number of flights is used as the dependent variable, while in specification (d), the logarithm of the quantity-weighted average number of daily flights per aircraft is used as the dependent variable. For all specifications, given the log-log functional form, the coefficient estimates are interpretable as elasticities.

By comparing the coefficients across specifications, in particular between both specifications for hotels ((a) and (b)) and the number of flight specification for airlines (c), a strong difference in the association of capacity and demand within the year between the two industries is evident. For airlines, within-year fluctuations in the number of flights to a destination scales almost one for one with the fluctuations

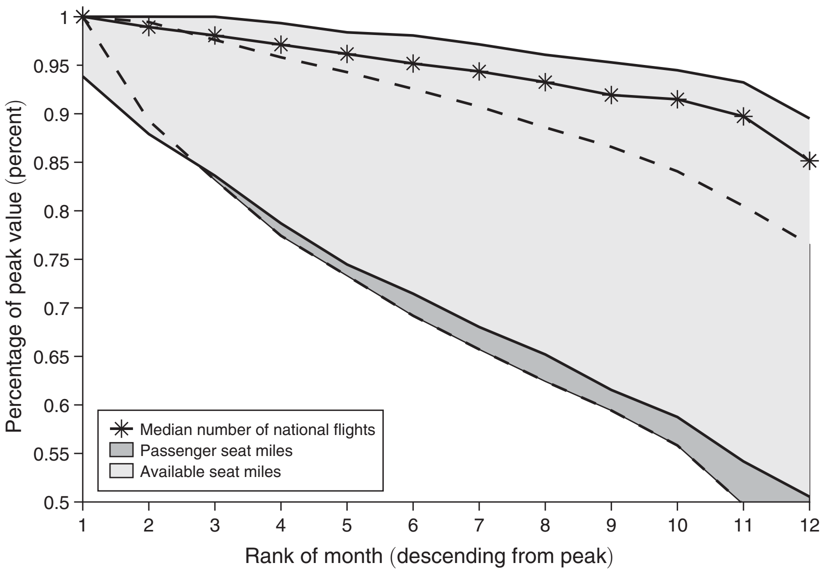

Figure 5. Annual Peak-to-Trough Demand and Capacity for Airlines

Notes: I display the ninetieth and tenth percentiles of annual peak-to-trough patterns for both quantity demanded (dark gray) and capacity (light gray) among airlines. I also display the average annual peak-to-trough pattern of the total number of flights (crosses) across all US destinations for each of the five airlines in my sample. Along the vertical axis for both panels is the percentage of the peak value, while along the horizontal axis is the month's rank of quantity demanded for the year. For an explicit discussion of the sources of the data, see Section III.

Sources: Bureau of Transportation Statistics and author's calculations

Table 5—Additional Capacity Regression Results for Hotels and Airlines

	(a)	(b)	(c)	(d)
log(monthly demanded)	0.069	0.031	0.734	0.011
	(0.005)	(0.003)	(0.024)	(0.006)
Dependent variable mean	11.62	3.35	6.14	0.07
Metro-segment-year fixed effects	Yes	Yes		
Destination-airline-year fixed effects			Yes	Yes
Adjusted R^2	0.05	0.02	0.75	0.00
Within R^2	0.05	0.02	0.75	0.00
Observations	24,756	24,756	29,040	24,948

Notes: Regression results reporting the association between measures of monthly capacity and quantity demanded for hotels and airlines. The estimated coefficient on the logarithm of monthly quantity demanded is reported for all specifications in the first row. Standard errors clustered at the metro area level for the hotel specifications ((a)–(b)), and the destination level for the airline specifications ((c)–(d)) is reported in the second row within parentheses. Additional statistics for each specification are given, including the mean of the dependent variable over the estimation sample, the adjusted R^2 statistic, the within R^2 statistics, and the number of observations. The measure of quantity demanded for hotels is the number of room nights sold, while for airlines it is the number of passengers. Specification (a) reports the coefficient using the logarithm of room nights available at the metro area–segment-month level as the dependent variable. Specification (b) reports the coefficient using the logarithm of the number of active hotels at the metro area–segment-month level as the dependent variable. Specification (c) reports the coefficient using the logarithm of the number of monthly flights at the destination-airline-month level as the dependent variable. Specification (d) reports the coefficient using the logarithm of the quantity-weighted average number of daily flights per aircraft at the destination-airline-month level as the dependent variable, dropping the US Airways observations. For the hotel specifications, metro area–segment-year fixed effects are included, while for the airline specification, destination-airline-year fixed effects are included.

in passengers flying to that destination. Specifically, a 1 percent increase in the passengers flying to a destination is associated with a 0.73 percent increase in the number of flights to that destination. Purely descriptively, the within-destination-airline-year variation in passengers explains as much as 75 percent of the variation in the number of flights.

The results from specification (c) indicate that a large degree of the adjustment of capacity to a particular destination airline's practice comes from airlines scheduling additional flights into a destination. Airlines could increase the number of flights to a destination by (i) routing more aircraft to a destination, keeping the daily flights per aircraft the same, and/or (ii) increasing the number of (daily) flights per aircraft to a destination, holding the number of aircraft routed to the destination the same. Specification (d) provides insights into the form of adjustment for airlines.[33] Here, the coefficient on the logarithm of the monthly passengers has an economically small coefficient and is statistically insignificant. Thus, it appears that almost all of the within-year adjustment in number of flights for airlines to destinations comes through their management of the fleet across a network of destinations, as opposed to "local" adjustments for aircraft on a particular route. However, it is also likely that some amount of the overall capacity adjustment to a destination is also being managed by adjusting the size of the aircrafts flying into the destination.

For hotels, a very different picture emerges for how capacity adjusts within the year. The within-metro-area-segment-year variation in room nights sold explains only 5 percent of that within-variation of room nights available (specification (a)). While already very small, this descriptive summary of the variation in room nights available explained by room nights sold is partially picking up the small changes in the number of days across different months. Similarly, variation in the number of room nights sold within the metro area–segment-year explains as little as 2 percent of the variation in the number of active hotels (specification (b)). The entry and exit of hotels makes up the primary adjustment in capacity at a metro area. The results of specification (b) indicate that the specific within-year timing of entry/exit patterns of hotels do not appear to be strongly linked to the within-year fluctuations of demand of that area. Both specifications for hotels portray a similar disconnect between within-year movements in capacity and demand. These comparative results complement the evidence provided in Figures 4 and 5 in providing context for the main results presented above and the reason for the stark contrast between the hotel and airline industries. The differential impact of demand volatility on capacity utilization between hotels and airlines can be attributed to the differences in the adjustment of capacity within the year across the two industries.

[33] The data on unique aircraft (identified by tail numbers) used for the daily flights into a destination come from the On-Time Performance data table from the Bureau of Transportation Statistics. For this specification, the observations for US Airways were dropped because of the large merger that occurred within the sample period (see Section IVA). For more discussion surrounding the daily flight information, see Section C in the online Appendix.

V. Implications for Measures of Productivity

A. *A Calibrated Model for Hotels*

Given the results above, the presence of demand volatility and adjustment costs is likely to distort traditional measures of productivity in hotels (and not in airlines). In this section, I provide an explicit measure—through a variance decomposition—of how large this effect could be. Ultimately, it can be shown that an appropriate decomposition for determining how the role of demand volatility differences across firms can distort our measures of productivity is given by

$$\text{Measured Productivity} \;=\; \Omega \times CU\big(\text{Demand Volatility Effect}\big),$$

where Ω denotes the *true* productivity of the firm and $CU\big(\text{Demand Volatility Effect}\big)$ denotes the capacity utilization rate driven by the demand volatility they face. The possibility of confounding differences in output-to-input ratios to productivity as opposed to utilization rates has been a well-known complication with measuring productivity (e.g., Griliches and Mairesse 1999). The main results indicate that this complication will be problematic in settings where differences in demand volatility across firms and adjustment costs are present.

As an example of this decomposition, I revisit the model of Section I and its implications on measuring the productivity of the firm with varying demand (firm B). Figure 6 replicates the isoquants for the firm facing demand volatility over two periods that must make a capacity decision that will remain fixed over those two periods and labels this optimal capacity decision $K^B = \big(\overline{Q} + D\big)/\Omega$. Alternatively, a firm that produced the same $2\overline{Q}$ over the two periods but faced constant demand over both periods (i.e., producing $\overline{Q}$ each period) would choose a capacity level of $\overline{Q}/\Omega$. Consequently, the firm facing more volatility in demand but with the same technical productivity requires more capacity (optimally) to meet its fluctuating demand than a firm facing smooth demand, using $2D/\Omega$ more capital over the two periods to produce the same amount of output, $2\overline{Q}$. Temporarily abstracting from labor use (which would be equivalent between firms A and B), the output-to-capital ratio for the firm facing demand volatility is

$$\begin{aligned}\frac{Q_1 + Q_2}{K_1 + K_2} &= \frac{2\overline{Q}}{2\big(\overline{Q} + D\big)/\Omega} \\ &= \Omega\left[\frac{\overline{Q}}{\overline{Q} + D}\right] \\ &= \Omega \times CU\big(\text{Demand Volatility Effect}\big).\end{aligned}$$

Any measure of productivity that is not able to adequately control for the differences in capacity utilization driven by demand fluctuations will have its measure of productivity contaminated by this effect. In the setting where capital is effectively fixed over of a period of time and there is no technical substitution between

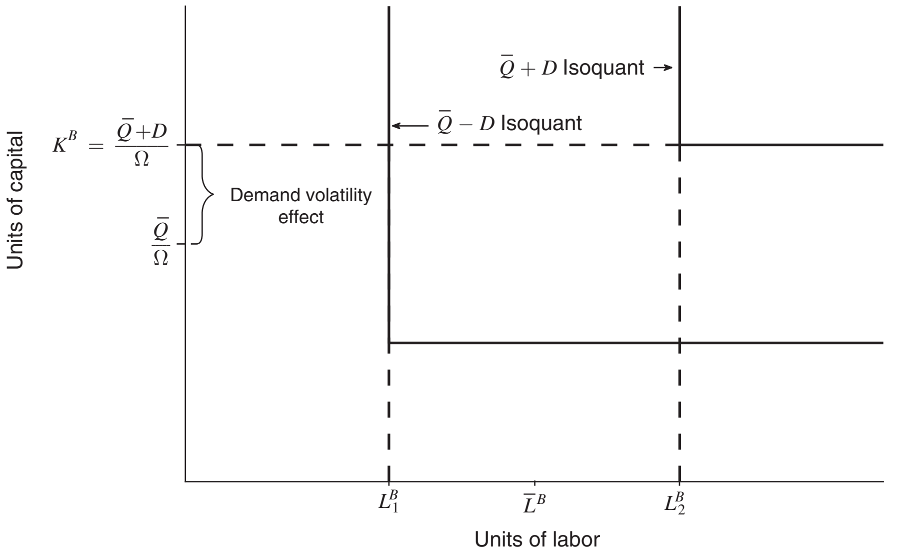

Figure 6. Demand Volatility with No Technical Substitution

Notes: The figure displays the optimal production plan of a firm when the elasticity of substitution is zero. On the horizontal axis are units of labor, and on the vertical axis are units of capital. The isoquants of the firm are displayed in solid lines, and the optimal production plan is denoted by the dashed lines.

capital and the other (flexible) inputs, the effect of demand volatility on measured productivity can be summarized by exactly the gap between the amount of capacity required during the peak period of demand $(\overline{Q} + D)$ and the capacity required to meet the total amount of quantity served but under constant demand conditions $(\overline{Q})$. Moreover, the simple model illustrates that an appropriate measure of productivity would be the maximum output-to-capital ratio achieved, $Q_2/K^B = \Omega$.

I use the insights from Figure 6 to provide an assessment of how much of an impact the variation in demand volatility could have on traditional measures of productivity for hotels. To construct this estimate, I make four assumptions. These assumptions are made largely to allow me to estimate the influence of demand volatility and adjustment costs on traditional productivity measures without observing other input use (beyond capital).

First, I assume that hotels' capacity (available rooms) is fixed over the year. In my sample, the capacity of hotels is not exactly fixed over the year, but almost all of the movements in capacity are driven either (i) by small differences in the number of days in a month or (ii) through the entry/exit of hotels. The first of these factors is innocuous. Because entry/exits do not seem to be correlated with the peak/troughs of within-year demand variation (see Figure 4 and Table 5), the assumption of fixed capacity over the year is unlikely to influence the decomposition to follow.

Next, I assume that hotels' production function takes the Leontief functional form:

$$Y_{imts} = \Omega_{imt} \min\left\{CU_{imts} K_{imts}, g\left(X_{imts}\right)\right\},$$

where, as before, X_{imts} and the function $g(\cdot)$ summarize how other inputs factor into production and are assumed to exhibit constant returns to scale up to the capacity constraint. Additionally, CU_{imts} is the capacity utilization rate—which could differ from full utilization because of demand volatility and adjustment costs. Here, the underlying productivity of the hotels, Ω_{imt}, is Hicks neutral and constant over the year but can vary arbitrarily over metro areas, segments, or years.[34]

Third, I assume that the distribution of room nights sold by hotels over the year is in fact optimal, if only at the yearly horizon, and that the distribution represents movements in demand. In other words, given their factor costs, hotels are appropriately pricing their rooms, in so much as the variation in quantity demanded can be interpreted as the result of both the direct (e.g., holding prices constant) and indirect (e.g., responses to changes in price) impacts of within-year variation in demand.

Finally, I must choose a measure of productivity. For the purposes of this analysis, I use the cost-share-based total factor productivity (TFP) index approach as my conventional measure of productivity. In particular, for any metro area–segment-year, this approach will take the amount of capital, labor, materials, and energy used in production and measure productivity as

$$\text{Measured Productivity} = \frac{Y_{imt}}{K_{imt}^{\alpha_K} L_{imt}^{\alpha_L} M_{imt}^{\alpha_M} E_{imt}^{\alpha_E}},$$

where α_K, α_L, α_M, and α_E are the output elasticities of capital, labor, materials, and energy, and under the assumption of constant returns to scale, $\alpha_K + \alpha_L + \alpha_M + \alpha_E = 1$.[35] The cost-share-based TFP index approach to measuring productivity uses each inputs' expenditure share of costs as estimates of each inputs' output elasticity. While the Cobb-Douglas form of the input index in this measure of productivity is restrictive, this approach can be interpreted as a first-order approximation to any production function (e.g., Syverson 2011).[36] Under the assumptions made to this point, as well as cost minimization, it can be shown through the use of conditional factor demands of the other inputs besides capital that the index approach to measuring productivity will take the following form:[37]

$$\begin{aligned}\text{Measured Productivity}_{imt} &= \Omega_{imt}^{1-\alpha_c}\left(\frac{Y_{imt}}{K_{imt}}\right)^{\alpha_c}\text{Constant}\\ &= \Omega_{imt}^{1-\alpha_c}\left(\Omega_{imt} CU_{imt}\right)^{\alpha_c}\text{Constant}\\ &= \Omega_{imt} CU_{imt}^{\alpha_c}\ \text{Constant},\end{aligned}$$

[34] This form of productivity does abstract from potential factor-biased differences in productivity (e.g., Raval 2019, Doraszelski and Jaumandreu 2018).

[35] For hotels, assuming constant returns to scale is warranted and largely supported by the data (see Section D of the online Appendix).

[36] An alternative approach to estimating productivity would be to estimate the elasticities through a control-function-type approach (e.g., Olley and Pakes 1996; Levinsohn and Petrin 2003; Ackerberg, Caves, and Frazer 2015). A critical requirement of these approaches, however, is that productivity is the only unobservable impacting input decisions, a condition not likely to hold in this setting given the differences in demand volatility across markets (see Section D of the online Appendix for more discussion).

[37] Assuming constant returns to scale, no adjustment costs for the other inputs, and no elasticity of substitution between capital and the other inputs, each inputs' conditional factor demand takes the following form: $X_{imt} = (1/\Omega_{imt}) Y_{imt} h(\mathbf{R}_{imt})$, where $h(\cdot)$ is only a function of the vector of other prices ($\mathbf{R}_{imt}$).

where α_c is the appropriate output elasticity (to be discussed more below), and the constant in the expression will only be a function of factor prices and the specific elasticity of substitution among the other inputs beyond capital.

Accordingly, conditional on an approach that decomposes the variation in Y_{imt}/K_{imt} into variation in capacity utilization rates generated by demand volatility (CU_{imt}) and residual variation in output to capital (Ω_{imt}), a rescaling of these two components generates an estimate of how the cost-share-based TFP index approach would have measured productivity and how much of it would have been driven by differences in demand volatility and adjustment costs alone $(CU_{imt}^{\alpha_c})$. Conveniently, both the simple model just outlined and the regression results reported in Section IV provide estimates of exactly such a decomposition. This is particularly appealing in my setting because even though I observe quantity (as opposed to revenue/expenditure) information on both output and capital, I do not observe information on other input use for the individual hotel segments.

I use two different approaches toward decomposing the variation in Y_{imt}/K_{imt}. The first approach, henceforth "Demand Volatility #1," uses the key insight from the simple model described above, namely that a more appropriate estimate of productivity in the face of demand volatility and adjustment costs would be the maximum output-to-capital ratio experienced over the period of time that capital is fixed.

In principle, the regression evidence from the previous section for hotels is an estimate of the impact of within-year demand volatility on capacity utilization rates of hotels. Thus, in the second approach—henceforth "Demand Volatility #2"—I use the estimates of ρ reported in Table 2. More formally, the two approaches decompose variation in occupancy rates of hotels into a capacity utilization through demand effect $(\widehat{CU}_{imt})$ and a productivity effect $(\hat{\Omega}_{imt})$ given by the following relationships:

$$\text{Demand Volatility \#1} = \begin{cases} \hat{\Omega}_{imt} = \max_s\{Y_{imts}/K_{imts}\} \\ \widehat{CU}_{imt} = (Y_{imt}/K_{imt})/\hat{\Omega}_{imt}, \end{cases}$$

$$\text{Demand Volatility \#2} = \begin{cases} \widehat{CU}_{imt} = \exp\{\overline{cu} + \rho DV_{imt}\} \\ \hat{\Omega}_{imt} = (Y_{imt}/K_{imt})/\widehat{CU}_{imt}, \end{cases},$$

where $\overline{cu}$ is the sample average of log occupancy rates and DV_{imt} is the within-year measure of demand volatility (given by equation (1)) and the estimate of ρ used is the midpoint (-0.62) of the range $(-0.95, -0.28)$ of estimates from the main results (Table 2).

The final step requires determining the appropriate value for α_c. If capital is the only input that faces adjustment costs, then the appropriate output elasticity to use above for α_c is the capital output elasticity (α_K). It is likely, however, that using the capital output elasticity might understate the variation in productivity had observations of other inputs like labor, materials, and energy been used. A primary reason why is that those inputs, especially labor, do face adjustment costs. Additionally, some of those other inputs (like energy) are likely to be used through the course of maintaining available rooms regardless of their occupancy. In each of these cases, the capacity utilization rates driven by demand volatility scaled to the capital output elasticity would understate the induced variation in traditional measures of productivity. One way to better capture those considerations without observing the use of other inputs directly is to incorporate those inputs' output elasticities into α_c. This approach is the most appropriate when the elasticity of substitution among the inputs facing adjustment costs is low.[38]

To provide transparency about how this part of the calibration influences the results, I report results for three values of α_c. The first value sets α_c to the average cost share of capital expenditures for the accommodation sector over the 2006–2009 period alone ($\alpha_K = 0.20$). Given the discussion above, this serves as a lower bound for the scope that demand volatility and adjustment costs could influence traditional productivity measures. The second value sets $\alpha_c = 0.55$, which represents the average cost share of capital and labor expenditures (i.e., $\alpha_L = 0.35$). The notion that some amount of labor might also face significant adjustment costs within the year has been used in other settings (e.g., Allcott, Collard-Wexler, and O'Connell 2016) and is likely to be the most appropriate for hotel management staff. If hotels do face adjustment costs in the other inputs (e.g., materials and energy), or if those other inputs are required to maintain rooms even during nights when they are not booked, then even this measure is likely to understate the variation in traditional productivity measures. The final value sets $\alpha_c = 1$ and serves as an assessment of how much differences in within-year demand volatility could impact traditional productivity measures if their influence was pervasive across most of the inputs used in production.

Table 6 presents the results of these decompositions for each of the two measures of the demand volatility effect and the three different parameterizations of α_c. For each demand volatility measure (#1 and #2), the productivity ratio of the top decile to bottom decile of all metro area–segment-years is reported for each of the three calibrations of α_c. Additionally, in the next column for each demand volatility measure, the implied ratio of the top decile to the bottom decile associated with the demand volatility effect alone is reported. In the third column for each demand volatility measure, I report the share of the (log) measured productivity variance explained by the demand volatility effect.[39]

Not surprisingly, given the results from the previous section, the impact of demand volatility on productivity measures is economically important. Focusing on the calibration that uses both the capital and labor cost shares for α_c (second row) and the first demand volatility measure, the estimated ratio of the top to bottom decile for productivity measure is 1.40. However, the implied ratio from demand volatility alone is 1.11, accounting for just under 10 percent of the variation in productivity of hotels. For each of the values for α_c, using the demand volatility effects implied by the regression results (i.e., #2) mutes the overall estimate of the impact of demand volatility and adjustment costs on traditional measures of productivity. This effect partly reflects that those estimates only use the independent variation in

[38] In the case of hotels, the elasticity of substitution among the primary inputs is likely very low; see Section VIA.

[39] If $Y = X_1 + X_2$, then $\text{var}(Y) = \text{var}(X_1) + \text{var}(X_2) + 2\text{cov}(X_1, X_2)$. Thus, for the decomposition, I allocate $\text{cov}(X_1, X_2)$ to each of the X_1 (Demand Volatility) and X_2 (True Productivity) terms after taking logs.

Table 6—Calibrated Estimates of Demand Volatility's Influence on Productivity Measures

	Demand Volatility #1			Demand Volatility #2		
α_c	Productivity 90th–10th ratio	Demand effect 90th–10th ratio	Variance share	Productivity 90th–10th ratio	Demand effect 90th–10th ratio	Variance share
α_K	1.39	1.04	0.01	1.42	1.02	0.01
$\alpha_K + \alpha_L$	1.40	1.11	0.08	1.43	1.04	0.04
1	1.45	1.21	0.26	1.45	1.08	0.09

Notes: This table reports the decomposition results described in Section V. For three alternative cost share parameterizations (along the rows), the measured productivity ratio of the top decile to bottom decile of hotels at the metro area–segment-year level are reported (first column) in conjunction with the implied top-decile-to-bottom-decile ratio coming from within-year demand volatility influences alone from a calibrated model (second column), in addition to the implied ratios using the demand volatility effect implied by the midpoint of the range of estimates from Table 2. Finally, the share of the variance of (log) measured productivity that can be accounted for by each demand volatility measure is reported for each calibration. Parameters α_K and α_L are set to the average cost shares of capital (0.20) and labor (0.35) experienced for the accommodation sector over the 2006–2009 period, respectively.

demand volatility after conditioning on other factors like secular trends in the size of the hospitality sector across metro areas.

Examining the results across the alternative values of α_c illustrates how the influence of demand volatility on measures of productivity scales with the range of inputs that face adjustment costs. For instance, to the extent that most of the inputs used by hotels are in effect to maintain rooms regardless of their occupancy, the variation in demand volatility within the year across hotels could account for nearly a quarter of the variation in traditional measures of productivity.

B. *What about Other Industries?*

At this point, it is useful to comment on how the impacts of demand volatility on productivity measures could generalize to other industries and empirical settings. Settings in which the firms/establishments within an industry are subject to differences in the predictable fluctuations of demand and some form of adjustment costs to inputs are likely to have traditional measures of productivity confound the effects documented here with actual technical productivity. To the extent that these differences in demand fluctuations are masked by temporal aggregation (e.g., because of the use of annual surveys), then it is even more likely that this effect is likely to have gone unnoticed.

Perhaps the most transparent way to identify industries with differences in the demand volatility across firms is to identify industries with geographically segmented markets like hotels and airlines. In these industries, the differences in the volatility of demand across locations can serve as a suitable measure of the differences in demand volatility facing firms/establishments that are otherwise producing the same product. Examples of other industries with geographically segmented markets include ready-mix concrete, Portland cement, block and processed ice, electricity, gasoline, and bread manufacturing.[40]

[40] One way to determine the degree of market segmentation geographically is to use information on the share of production that is shipped large distances from the point of production. Foster, Haltiwanger, and Syverson (2008,

For electricity and gasoline, casual inspection indicates a modest degree of heterogeneity in the amplitude of the seasonal component of final consumption across states, mostly driven by differences in the seasonal weather patterns within the year.[41] Given the size of adjustment costs in capacity for both electricity and gasoline, it seems likely that differences in demand volatility are likely to have meaningful impacts on traditional (annual) measures of productivity for these two industries.

For ready-mix concrete and Portland cement, a common measure of (final) demand is the employment/output in the construction sector.[42] Following Shea (1993), the traditional justification for this approach has been that the individual manufacturing industries (e.g., ready-mix concrete) make up a small portion of the overall input costs of the construction sector, and the construction sector makes up a sizeable portion of the final consumption of these sectors. For example, in Syverson's (2004a) study of the ready-mix concrete industry, employment in the construction sector is used as a measure of demand for ready-mix concrete, given that according to the 1987 Benchmark Input-Output tables, only 2.0 percent of the construction sector's costs come from the ready-mix concrete industry, and yet the construction sector buys 97.2 percent of the ready-mix concrete industry's output (Syverson 2004a, 1202).[43]

Geremew and Gourio (2018) examines the seasonal fluctuations of employment within several different industries, including construction and the leisure and hospitality sector. For many industries—especially construction and the leisure and hospitality sector—they find a large degree of seasonality in employment, and in many instances the amplitude of the seasonal fluctuations are comparable to the fluctuations at business cycle frequencies. Specifically, they report the standard deviation of the seasonal component (measured at the monthly frequency) of aggregate employment for the construction industry to be 6.59 percent, while the standard deviation of the seasonal component for the aggregate leisure and hospitality sector is near 2.0 percent (Geremew and Gourio 2018).

Furthermore, they find that for both the construction and the leisure and hospitality industries, there is a large degree of heterogeneity in the amplitude of the seasonal cycle across locations (e.g., states). Specifically, the standard deviation across states of the seasonal component of employment for construction is 3.67 percent, while for the leisure and hospitality sector, it is 2.81 percent. Given these patterns, the role of capacity for production in each industry and the difficulty in storing ready-mix concrete and cement for long periods of time, it seems likely that the effects documented here are likely to impact the (annual) productivity measures of ready-mix concrete and cement firms. It is also likely that the heterogeneity in the

footnote 22) reports that over 99 percent of ice products and 95 percent of ready-mix concrete production are shipped less than 100 miles, while 63, 62, and 53 percent of box, bread, and gasoline, respectively, is shipped less than 100 miles.

[41] In the case of electricity, this is particularly the case for final consumption of electricity net the supply coming from renewable resources (e.g., hydroelectricity, solar, and wind), or "net load," as the supply of electricity from these resources themselves have different seasonal components across locations in the United States.

[42] The cement industry sells most of its product to the ready-mix concrete industry.

[43] Other examples in which the employment in the construction sector has been used as a measure of demand for the ready-mix concrete industry include Collard-Wexler (2011, 2013, 2014), and Backus (2019).

amplitude of the seasonal component for the leisure and hospitality sector leads to some differences in demand volatilities across ice manufacturing firms.

Just these few descriptive statistics indicate that purely on geographical grounds, some of the variation in measured productivity within manufacturing industries could be coming from differences in the demand volatility across firms. This is unlikely to be the only source of segmentation along final consumers, however, that contributes to different demand volatilities across firms within the same industry. Heterogeneity in the uses of products on the demand side—for instance, like energy demands of residential and industrial customers—are also likely to generate differences in demand volatilities across firms that serve different types of customers even within the same geographical market. While the influence of demand volatility and adjustment costs on traditional measures of productivity is not a universal explanation for the variation in productivity observed to date, for some industries —especially those that supply local construction activity—its influence is likely to be of a similar magnitude to those found for the hotel industry.

VI. Robustness of Results

To document the role of demand volatility and adjustment costs on capacity utilization, I made several assumptions and modeling choices. In this section, I provide justifications or alternative specifications for several of the key assumptions and modeling choices to provide evidence of the robustness of the results. Because the primary results of the paper pertain to the effect of demand volatility with adjustment costs on the capacity utilization of hotels, I limit the discussion in this section to the hotel application.

A. *Technical Substitution of Capital and Labor*

In the hotel industry, capital in the form of available rooms serves a fundamental role in producing output (room nights sold). While other inputs are necessary to generate a room night sold, there is almost no technical substitution between available rooms and these other inputs. In the previous sections, I use the lack of technical substitution between capital and other inputs to justify my measure of capacity utilization when uncovering the role of demand volatility. In particular, because I assumed that the elasticity of substitution between capital and labor (and other inputs) was zero, I did not have to account for differences in the optimal mix of inputs driven by variation in factor prices when measuring capacity utilization.

I justify this choice empirically in two different ways. First, I use the insight from the theoretical section and estimate the elasticity of substitution using variation in regional relative input prices.[44] Next, I construct an alternative measure of capacity utilization where I assume that the elasticity of substitution between capital and labor is one. In the former case, I find little evidence of any elasticity of substitution

[44] A similar strategy is used by Morrison (1988) and Raval (2019) to estimate the elasticity of substitution between inputs of a production function.

between capital and labor. In the latter case, I find that imposing a degree of elasticity of substitution between capital and labor does not affect the main results.

To estimate the elasticity of substitution, I assume a constant elasticity of substitution production function for capital and labor in metro area i in year t.[45] Formally, the production function is given by the following equation:

$$Y_{it} = \left(\alpha K_{it}^{\sigma} + (1-\alpha) L_{it}^{\sigma}\right)^{1/\sigma}, \tag{5}$$

where $1/(1-\sigma)$ is the elasticity of substitution between capital and labor. Assuming cost minimization, I solve for the conditional factor demand functions of both capital and labor. Using the factor demand functions, I characterize the capital-labor ratio given by the following equation:

$$\frac{K_{it}}{L_{it}} = \left[\frac{R_{it}}{W_{it}}\right]^{\frac{1}{\sigma-1}} \left[\frac{1-\alpha}{\alpha}\right]^{\frac{1}{\sigma-1}}, \tag{6}$$

where R_{it} is the price of capital and W_{it} is the wage.

Equation (6) formalizes the intuition of the theoretical section. Variation in the capital-labor ratio resulting from exogenous variation in relative input prices (R_{it}/W_{it}) identifies the elasticity of substitution. To operationalize this strategy, I use the same measures of capital from the STR reports, as well as measures of the number of employees in the leisure and hospitality sector from the Quarterly Census of Employment and Wages at the metro area–year level, together with the measures of price of capital and labor used in the main results, to estimate the following regression:

$$\log\left(K_{it}/L_{it}\right) = \text{Constant} + \frac{1}{\sigma-1}\left[r_{it} - w_{it}\right] + \epsilon_{it}. \tag{7}$$

The estimated coefficient on relative input prices corresponds to the negative of the elasticity of substitution. For hotels, I find the point estimate of the elasticity of substitution to be a small negative number that is not statistically significantly different from zero.[46] This result supports the assumption of a small elasticity of substitution between capital and labor.

Fixing the elasticity of substitution between labor and capital to be higher (e.g., one as in Cobb-Douglas) does not change the inferences of the previous section either. To demonstrate this robustness to the substitution pattern between capital and labor, I provide an alternative form of the production technology given by

$$Y_{imt} = \min\left\{V_{imt}, g\left(M_{imt}, E_{imt}\right)\right\}, \tag{8}$$

$$V_{imt} = K_{imt}^{\alpha^k} L_{imt}^{\alpha^l}, \tag{9}$$

[45] The use of labor that I observe comes from the Quarterly Census of Employment and Wages data, which are aggregated to the metro area level. Consequently, I am unable to conduct this empirical analysis at the individual hotel segment level.

[46] Regression results are available from the author upon request. Figure 8 in the online Appendix displays the scatter plot between the log of the capital-labor ratio and the log of relative input prices.

where M_{imt} is material use and E_{imt} is energy use, while $g(\cdot)$ is some function that aggregates the two inputs and V_{imt} constitutes the value-added portion of the production function.[47] Furthermore, the value-added elasticity of capital is α^k, and labor is α^l. I assume constant returns to scale in value added, that is, $\alpha^k \equiv \alpha$ and $\alpha^l \equiv 1 - \alpha$. In the formulation given by equations (8) and (9), the production function of gross output Y_{imt} is Leontief in value-added V_{imt} and some aggregate of materials and energy, while the production function of value added is Cobb-Douglas in labor and capital.[48] In other words, I force the elasticity of substitution between capital and labor to be one.

To derive a measure of capacity utilization under this alternative assumption of the elasticity of substitution between labor and capital, I solve for the cost-minimizing capital demand as a function of quantity, the price of capital, and the wage where both inputs are supplied by competitive markets. Using the conditional capital demand then allows me to characterize the capacity utilization as I did before using the convention of Berndt and Morrison (1981) and Berndt and Fuss (1986) as follows:

$$(10) \qquad \log(\text{Capacity Utilization})_{imt} = \log\left(K^*_{imt}(Y_{imt})\right) - \log\left(K_{imt}\right)$$
$$= y_{imt} - k_{imt} - (1-\alpha)\left[r_{it} - w_{it}\right],$$

where K^*_{imt} is defined as the optimal long-run level of capital conditional on Y_{imt}, r_{it} is the log price of capital, and w_{it} is the log wage. It is insightful to note how this adjustment might affect inference. If hotels in particularly high-labor-cost areas were both able and actively substituting capital for labor in the production process, and as a consequence experiencing lower output-to-capital ratios, this alternative measure will make the appropriate adjustment.

With auxiliary information on α, I am able to construct an alternative measure of capacity utilization.[49] Table 7 provides the regression estimates of the main estimating equation (equation (2)) using the alternative measure of capacity utilization given by equation (10) and a value of $\alpha = 0.4$.[50] The results in Table 7 are almost the same as the results presented earlier. Overall, the pattern along alternative specifications compared to the baseline results is also very similar, suggesting that

[47] Bernanke and Parkinson (1991) utilizes the technical substitution assumption to estimate a value-added production function when they observed gross output without observing material use. Gandhi, Navarro, and Rivers (2011) discusses the collinearity issues of estimating the production function and how this relates to the distinction between the gross output production function and the value-added production function.

[48] The formulation used here is similar to the formulation of the production function of Burnside, Eichenbaum, and Rebelo (1995) and Basu and Kimball (1997).

[49] I also looked into constructing an alternative measure of capacity utilization, using the labor measure used in estimating the elasticity of substitution. Using labor at the metro area–year level and the same assumptions regarding the output elasticities used here does not change the qualitative results. Demand volatility still has a strong negative association with capacity utilization.

[50] According to the economic census, labor's cost share of revenue for all hotels (NAICS: 721110) in 2007 was 0.26. According to the Bureau of Labor Statistics, the average cost share of labor among expenditures on labor and capital alone was 0.62 for the entire Accommodation sector (NAICS: 721) for the four years in the STR sample (2006–2009). The results presented are not sensitive to the choice of α. Regression results with alternative choices of α are available from the author upon request.

Table 7—Regression Results for Cobb-Douglas Technical Substitution

	(a)	(b)	(c)	(d)	(e)	(f)
Demand volatility	−1.01	−0.42	−0.32	−0.38	−0.28	−0.45
	(0.22)	(0.08)	(0.10)	(0.10)	(0.09)	(0.14)
Dependent variable mean	1.19	1.19	1.19	1.19	1.19	1.19
Year/segment fixed effects		Yes	Yes	Yes	Yes	Yes
Controls		Yes	Yes	Yes	Yes	Yes
Drop independents				Yes		
Drop 2008					Yes	
Instrument			Yes	Yes	Yes	Yes
Use employment						Yes
Hausman test			0.01	0.14	0.01	0.84
Adjusted R^2 (first stage)			0.70	0.69	0.69	0.49
Adjusted R^2	0.09	0.83	0.83	0.83	0.84	0.83
Observations	2,063	2,063	2,063	1,792	1,549	2,063

Notes: Regression results for several alternative versions of the regression specified in equation (2), with alternative of measure of capacity utilization given by equation (10) and $\alpha = 0.4$. The estimated coefficient of demand volatility is reported for all specifications in the first row, with the standard errors clustered at the metro area level reported in the second row within parentheses. Additional statistics for each specification are given, including the mean of the dependent variable over the estimation sample, the p-value of the Hausman endogeneity test (if applicable), the adjusted R^2 statistic of the first-stage regression (if applicable), the adjusted R^2 statistic, and the number of observations. Specification (a) reports the coefficient, absent any fixed effects or metro area–year controls. Specification (b) adds a set of controls at the metro area–year level, including logarithm of the average salary in the leisure and hospitality sector, logarithm of the US Department of Housing and Urban Development's fair market rent for a three-bedroom, logarithm of the average price of electricity for commercial customers, logarithm of personal income per capita, logarithm of personal income, logarithm of employment in the leisure and hospitality sector, the unemployment rate, the logarithm of the share of total nonfarm employment in the leisure and hospitality sector, logarithm of employees in the leisure and hospitality sector per square mile, five-year log change in personal income per capita, five-year log change in personal income, and five-year log change in employment in the leisure and hospitality sector, as well as year and segment fixed effects. In specifications (c)–(f), an instrument is used for demand volatility (see Section IID). Specification (d) reports the coefficient when one drops the segment-year observations that involve independently affiliated hotels. Specification (e) reports the coefficient when one drops the segment-year observations that were in 2008. Specification (f) reports the coefficient when one uses the annual coefficient of variation in employment in leisure and hospitality at the metro area–year level as the instrument for demand volatility.

allowing for the elasticity of substitution between labor and capital to be greater than zero does not affect the results significantly.[51]

B. *Alternative Instrumental Variable*

In the main results, the instrument for demand volatility primarily leverages the volatility in quantity demanded at the aggregate metro area level. While this instrument was argued to be exogenous to segment-level supply conditions and made the comparison between hotels and airlines more consistent, it might suffer from a potential problem involving the role of aggregate market-level shifts in supply (see Section B of the online Appendix). In particular, if the overall price level for hotels in a metro area rises due to (unobservable) shifts in supply like the effective capacity of the aggregate metro area—due to, say, a temporary labor shortages of hotel staff—and this in turn induces movements in quantity demanded at the aggregate

[51] The results here are likely to generalize to other inputs, including materials and energy, provided these inputs also achieve constant returns to scale.

level, then the main results will inappropriately attribute these movements to shifts in demand as opposed to movements along a demand curve.

I test whether the main empirical results are sensitive to this issue by leveraging the aggregate sales information I have available for hotels at the monthly frequency. Looking at the volatility of aggregate sales of any particular metro area, *i*, over the year *t* could better isolate the aggregate market-level movements that reflect demand shocks as opposed to supply shocks.[52] Thus, to build this alternative instrument, I simply replace the measure of aggregate demand volatility, using quantities in equations (3)–(4), with aggregate sales.

Table 8 presents the regression results from the main estimating regression given by equation (2) using the alternative instrument (specifications are labeled (c)–(e) for consistency with the main results). The results presented in Table 8 are very similar to the estimates presented in the main results. In fact, if anything, the estimated coefficient on demand volatility becomes larger in absolute magnitude across comparable specifications. As was found in the main results (for hotels), the estimated coefficient on demand volatility is negative and statistically significant from zero across all the regression specifications. These additional results indicate that my approach to using the volatility of quantity demanded at the aggregate metro area level is unlikely to be inappropriately attributing this variation to variation driven by (exogenous) movements in demand, as opposed to even aggregate movements in supply conditions.

C. *Measure of Demand Volatility*

In the main results the measure of demand volatility is a dispersion measure of the quantity of room nights sold within the year. While this measure was easy to compute from the available data, it suffers from two potential problems. First, the number of room nights demanded is censored (from above) by the aggregate capacity of the hotels in any metro area–segment.[53] It should be noted, however, that at the aggregate metro area level at a monthly frequency, I do not observe any such censoring. Second, using quantity demanded as a measure of demand might confound movements *along* the demand curve with *shifts* in the demand curve.

I test whether the main empirical results are sensitive to either of these potential problems by incorporating the price information I have for the hotel application. I assume that the aggregate demand for hotels of any particular metro area–segment, *im*, in year *t* and month *s* is given by the constant elasticity functional form $Q_{imts} = D_{imts} P_{imts}^{-\eta}$, where P_{imts} is the average daily price and η is the (constant) price elasticity of demand with $\eta > 1$. Taking logs and rearranging this function

[52] In particular, if one assumes the utility function of the representative agent takes the following form: $U(x,y) = x + y$, where y is the "outside" numeraire good, and the subutility function for x (the "inside" goods, e.g., hotel rooms) takes the constant elasticity of substitution (CES) structure $x = \left(\sum_i q_i^{\rho}\right)^{1/\rho}$, then the volatility in sales at the aggregate level will better reflect the exogenous portion of demand volatility faced by any hotel segment.

[53] Censored dependent variables are commonplace. Handling independent variables that are censored is somewhat less common. For interval censored regressors, see Manski and Tamer (2002). For endogenous censored regressors, see Rigobon and Stoker (2009).

Table 8—Regression Results with Alternative Instrumental Variable (Sales)

	(c)	(d)	(e)
Demand volatility	−0.35	−0.43	−0.31
	(0.11)	(0.12)	(0.11)
Dependent variable mean	−0.50	−0.50	−0.50
Year/segment fixed effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Drop independents		Yes	
Drop 2008			Yes
Instrument	Yes	Yes	Yes
Hausman test	0.27	0.76	0.15
Adjusted R^2 (first stage)	0.60	0.58	0.59
Adjusted R^2	0.72	0.72	0.73
Observations	2,063	1,792	1,549

Notes: Regression results for several versions of the regression specified in equation (2), with an alternative instrumental variable for specifications (c)–(e). The estimated coefficient of demand volatility is reported for all specifications in the first row, with the standard errors clustered at the metro area level reported in the second row within parentheses. Additional statistics for each specification are given, including the mean of the dependent variable over the estimation sample, the p-value of the Hausman endogeneity test (if applicable), the adjusted R^2 statistic of the first-stage regression (if applicable), the adjusted R^2 statistic, and the number of observations. All specifications include a set of controls at the metro area–year level, including logarithm of the average salary in the leisure and hospitality sector, logarithm of the US Department of Housing and Urban Development's fair market rent for a three-bedroom, logarithm of the average price of electricity for commercial customers, logarithm of personal income per capita, logarithm of personal income, logarithm of employment in the leisure and hospitality sector, the unemployment rate, the logarithm of the share of total nonfarm employment in the leisure and hospitality sector, logarithm of employees in the leisure and hospitality sector per square mile, five-year log change in personal income per capita, five-year log change in personal income, and five-year log change in employment in the leisure and hospitality sector, as well as year and segment fixed effects. In specifications (c)–(e), an alternative instrument is used for demand volatility that leverages aggregate sales instead of aggregate room nights sold. Specification (d) reports the coefficient when one drops the segment-year observations that involve independently affiliated hotels. Specification (e) reports the coefficient when one drops the segment-year observations that were in 2008.

allows me to construct an alternative measure of the demand for any particular metro area–segment-year-month:

$$\log(D_{imts}) = \log(Q_{imts}) + \eta \log(P_{imts}). \tag{11}$$

Assuming a value of η, I can substitute D_{imts} in for the quantity in both the measures of demand volatility and the construction of the instrument given by equations (1) and (3)–(4). This measure of demand has a few advantages to the measure of demand volatility used in the main results. First, movements in D_{imts} coincide with shifts in the demand curve by controlling for any movements in price. The other advantage of this measure is that it does not suffer from any censoring from above. In the event that any metro area–segment faces a capacity constraint, shifts in the demand curve are reflected in movements in price given the binding capacity constraint.

Table 9 presents the regression results from the main estimating regression given by equation (2) using a price elasticity of demand parameter of 1.85. I use the

Table 9—Regression Results for Alternative Measure of Demand Volatility

	(a)	(b)	(c)	(d)	(e)	(f)
Demand volatility	−0.16	−0.11	−0.09	−0.11	−0.08	−0.14
	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)
Dependent variable mean	−0.50	−0.50	−0.50	−0.50	−0.50	−0.50
Year/segment fixed effects		Yes	Yes	Yes	Yes	Yes
Controls		Yes	Yes	Yes	Yes	Yes
Drop independents				Yes		
Drop 2008					Yes	
Instrument			Yes	Yes	Yes	Yes
Use employment						Yes
Hausman test			0.06	0.40	0.05	0.39
Adjusted R^2 (first stage)			0.80	0.79	0.80	0.52
Adjusted R^2	0.03	0.71	0.71	0.71	0.72	0.71
Observations	2,063	2,063	2,063	1,792	1,549	2,063

Notes: Regression results for several alternative versions of the regression specified in equation (2), with alternative demand volatility measure and price elasticity of demand of 1.85. The estimated coefficient of demand volatility is reported for all specifications in the first row, with the standard errors clustered at the metro area level reported in the second row within parentheses. Additional statistics for each specification are given, including the mean of the dependent variable over the estimation sample, the *p*-value of the Hausman endogeneity test (if applicable), the adjusted R^2 statistic of the first-stage regression (if applicable), the adjusted R^2 statistic, and the number of observations. Specification (a) reports the coefficient, absent any fixed effects or metro area–year controls. Specification (b) adds a set of controls at the metro area–year level, including logarithm of the average salary in the leisure and hospitality sector, logarithm of the US Department of Housing and Urban Development's fair market rent for a three-bedroom, logarithm of the average price of electricity for commercial customers, logarithm of personal income per capita, logarithm of personal income, logarithm of employment in the leisure and hospitality sector, the unemployment rate, the logarithm of the share of total nonfarm employment in the leisure and hospitality sector, logarithm of employees in the leisure and hospitality sector per square mile, five-year log change in personal income per capita, five-year log change in personal income, and five-year log change in employment in the leisure and hospitality sector, as well as year and segment fixed effects. In specifications (c)–(f), an instrument is used for demand volatility (see Section IID). Specification (d) reports the coefficient when one drops the segment-year observations that involve independently affiliated hotels. Specification (e) reports the coefficient when one drops the segment-year observations that were in 2008. Specification (f) reports the coefficient when one uses the annual coefficient of variation in employment in leisure and hospitality at the metro area–year level as the instrument for demand volatility.

price elasticity of demand of 1.85 because it is the average of the price elasticity of demands that rationalize the average of the Lerner indices implied by the average marginal costs reported by Kalnins (2006) for economy and luxury hotels.[54] To benchmark these results to the main empirical specification, it is important to note that the standard deviation of the demand volatility measure for this specification is almost twice as large as the demand volatility measure used for the main results. Taking the difference of variation in demand volatility into account, the results presented in Table 9 are very similar to the estimates presented in the main results. The estimated coefficient on demand volatility is negative and statistically significant from zero across all the regression specifications. To the extent that the price elasticity of demand is constant within the year, any issues with not incorporating price or censoring from above do not seem to be driving the main empirical results.

[54] Kalnins (2006) reports that the marginal cost difference for a rented room and an unoccupied room is \$20 for an economy hotel and \$75 for a luxury hotel. At a similar period, the average daily rate for an economy hotel was \$52, while for a luxury hotel it was \$144. For regression results using a price elasticity of demand parameter of four, a price elasticity of demand used in Bloom (2009) to model the aggregate economy, see Table 12 in the online Appendix.

VII. Conclusion

In this paper, I demonstrate that demand volatility and adjustment costs together affect capacity utilization and ultimately our inferences on productivity. I document this effect empirically by comparing the hotel and airline industries. In the hotel application, I find demand volatility with adjustment costs has a meaningful impact on the variation in capacity utilization at the metro area–segment-year level. The strong effect of demand volatility on capacity utilization in hotels is robust to assumptions involving scale and substitution elasticities. In contrast, demand volatility has no effect on the capacity utilization of airlines at the destination-airline-year level. The difference in the results highlights the role of adjustment costs on the influence of demand volatility on measures of productivity. Furthermore, given the relatively high-frequency nature of the effect, it seems possible that such an effect could account for some of the productivity differences documented in other industries using lower-frequency surveys.

These results lay the groundwork for several paths for further research. One path involves reevaluating the relationship of some factors—including the propensity to export and produce multiple products—with productivity, with the goal of understanding how these factors might relate to smoothing fluctuations in demand. Next, efforts to gather or match higher-frequency information to the annual observations on producers in many production survey would allow one to disentangle how much of what is observed as measured productivity differences is coming from differences in demand volatility and adjustment costs. Finally, exploring how demand volatility interacts with industry structure and how the interaction affects performance outcomes would create a much deeper understanding of what drives the widely different outcomes across producers.

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