Stockholm School of Economics
Masters Thesis in Finance

The Microeconomics of Fixed Costs and the Impact of Operating Leverage on US Lodging Stock Return

Antoine Barbara[†]
Daniel Carrasco-Terrazas[††]

November 27, 2006

In this paper, we developed on the topic of operating leverage and used it to analyze the hotel industry. Microeconomics provided the general framework to understand firm behavior, especially with respect to its cost-structure and how it evolves over time. We found a significant relationship between the estimated proxy and the conventional fixed and variable approach to estimate the degree of operating leverage (DOL) for hotels. We developed our analysis into assessing the impact of the DOL on stock returns; covering a sample of 10 US listed lodging firms. From a corrected dynamic Least Square Dummy Variable model, the statistical significance of our estimates and the robustness of the model allowed us to conclude that the relationship between the stock returns and operating leverage exists in the selected sample of US firms in the hotel industry. Using three approaches to address a bias that leads to inconsistent estimators, we obtained estimates that greatly improved on previous studies and led to gains in estimate consistency.

Supervisor: Prof. Dr. Andrei Simonov
Discussants: Jonas Samlin
Maja Walla Enander

[†] 80307@student.hhs.se, Masters in Finance
[††] 80298@student.hhs.se, Masters in Economics

Table of Contents

Figures

INTRODUCTION AND MOTIVATION

By minimizing the cost of producing their output, firms seek to maximize their profits, subject to the constraints imposed by the market environment in which they operate. In this paper, we will investigate the impact of a change in the cost structure on US listed hotel chains. We examine the theory and empirical evidence available from previous research and will offer an alternative robust empirical analysis.

In the following section we briefly review the microeconomics behind firm behavior. It provides the analytical framework to understand how the evolution of the cost-structure over time affects value. Furthermore, the case of firms with constant output and variable pricing is considered, as observed in the hotel industry. After describing and deriving the degree of operating leverage, we highlight the impact of this measure on a firm's performance.

In Section III, we review the existing literature dealing with fixed and variable cost. We express the different methods of estimating the degree of operating leverage and highlight their specificities. Those models are analyzed and a rationale for model selection is presented. The section ends with a description of the limitations related to the selected methodology.

Section IV we bridge the gap between theory and practice and assess the relationship between the degree of operating leverage and stock market returns. We address the least-square dummy variable corrected unbalanced panel data and illustrate its shortcoming.

In Section V, we present the case of the hotel industry. We briefly underline the industry dynamics with regards to cost factors. After describing the data sources and sample selection criteria, we perform the empirical estimates and develop the analysis in the subsequent sections. Results are offered and alternative tests are conducted, leading to a summary and interpretation of our findings.

I. MICROECONOMIC CONSIDERATIONS

Output, Revenue, Cost, and Planning Horizon

Consider a firm's production function represented as[1]

$$f\left(x_{1t}, x_{2t}, x_{3t}, \ldots, x_{nt}\right) = Q_t$$

where f requires some inputs to produce some level of output Q_t. The production function observes constant returns to scale and decreasing marginal output with respect to its input factors. In the case of the output being constant[2], the function concave shape of marginal output is translated in a straight line.

Total sales revenue depends on how much of the output is absorbed by the market at price p_t on any given day[3]. The revenue function is given by

$$R_t = p_t Q_t$$

Total cost depends on how many inputs a firm utilizes to produce output and how much resources it pays for their use. Let $I_t = \left\{x_{1t}, \ldots, x_{it}, \ldots x_{nt}\right\}$ be the set of all actual inputs of production at time t and let total cost function, C_t, be represented as

$$C_t = \sum_{i \in I_t^V} \omega_{it} x_{it} + \sum_{i \in I_t^F} \omega_{it} x_{it} \tag{2.1}$$

where

- ω_{it} represents the marginal cost of the i-th factor input at t
- $x_{it} \in I_t^V$ represents the i-th variable production factor of which its level varies to produce output at t
- $x_{it} \in I_t^F$ represents the i-th fixed production factor of which its level does not vary to produce output at t
- $I_t^V \subseteq I_t$ represents the set of all variable inputs factors at t
- $I_t^F = I_t \setminus I_t^V$ represents the set of all fixed input factors at t.

---

[1] For a formal proof, please refer to Jehle and Reny, (2003).
[2] The notion of constant output is introduce as the industry we analyze in this paper behave as such.
[3] It is important to mention that the market structure where the firms operate is perfectly competitive. Additionally, we will assume that all the production is absorbed by the market at any time such that we are able to use revenue as a proxy for production.

In theory, whether an input is variable or fixed, i.e. an element of either I_t^V or I_t^F [4, 5], will depend on which planning horizon is considered. In long-run, to generate output a firm is able to freely adjust the level of all its factors of production, implying that $I_{LR}^V = I_{LR}$ and $I_{LR}^F = \{\varnothing\}$. In the short-run, a firm is able to vary the level of at least one input in its production function, thus holding the level of all $x_{it} \in I_t^F$ fixed[6].

It is important to note that since in the long run all inputs are variable, the cost structure changes over time. The difference between variable and fixed costs thus depends on the length of time to which the level of a particular factor input is committed to. Because the level of all production factors varies with time, the time difference between variations will determine whether it is a fixed or variable factor: as the time between variations shortens, the less it varies, the more its level becomes fixed to produce output. The implication for our analysis is that the cost structure parameters vary over time, further supporting the fact that these parameters do not remain fixed over time.

Behavior Motivation: Profit and Value

Profit for the firm at time t is defined as the difference between the revenue and cost functions,

(2.2) $$\pi_t = p_t Q_t - C_t \,.$$

The short-run objective of the firm is to maximize (2.2). The problem can be represented as,

$$\max_{(\mathbf{x}_t, y) \geq 0} \pi_t \text{, such that } Q_t \geq y_t \,.$$

where y_t represents the demand at t.[7]

---

[4] $I_t^V \cap I_t^F = \{\varnothing\} \; \forall t$

[5] For a clear definition of what constitutes variable, fixed, and sunk costs please refer to Wang and Yang (2001).

[6] In actuality, a firm is always operating in the short-run, thus, all the accounting data observations are generated by the firm's behavior in the short-run.

[7] It's important to note that a firm's management might not consider maximizing value as their long-run objective. Instead, their behavior might be driven by other decisions that might not necessarily maximize share-holders value considering an objective

In the case where output is fixed, maximizing profit is a function of the demand, where demand meets all output at t.

(2.3) $\max_{(\mathbf{x}_t, y)\geq 0} \pi_t$, such that $Q_t \leq y_t$.

The value of the firm at t is the value of all present and future profits discounted at some rate r_t given by the market. Since future profits are unknown, the continuous definition of the market given value for a firm is expressed as

(2.4) $$\mathrm{v}(\pi) = \int_0^\infty \pi_t e^{-r_t t} dt .$$

which can be thought of being the market capitalization of the firm at any point in time.

Measuring the Cost Structure: Degree of Operating Leverage

To measure the cost-structure of firms, i.e. degree of operating leverage (or DOL for short), we compute the revenue elasticity of profit. Consider the following equations:

$w_t = \frac{1}{Q_t} \sum_{i \in I_V} \omega_{it} x_{it}$ and $\bar{w}_t = \frac{1}{Q_t} \sum_{i \in I_F} \omega_{it} x_{it}$, such that

(2.5) $$w_t + \bar{w}_t = \frac{C_t}{Q_t} \Rightarrow C_t = (w_t + \bar{w}_t) Q_t .$$

Inserting (2.5) into (2.1) we get

$$\pi_t = p_t Q_t - (w_t + \bar{w}_t) Q_t$$

(2.6) $$\pi_t = p_t Q_t - w_t Q_t - \bar{w}_t Q_t$$

function that can be represented by $\max U[v(\pi)]$, where U represents the utility function of management. This problem relates to the conflict of interest that owners and management face when taking decisions regarding the direction of a firm.

where p_t represents the average price charged for a firm's output at t, w_t represents the variable share cost and $\bar{w}_t$ the fixed share of C_t. Taking the derivative of the logged profit with respect to logged revenue in (2.6), we obtain the textbook definition of the degree of operating leverage:

$$(2.7) \qquad DOL_t = \frac{\partial \ln \pi_t}{\partial \ln Q_t} = \frac{p_t - w_t}{p_t - w_t - \bar{w}_t} \text{ assuming } p_t, w_t, \bar{w}_{t,} > 0 \ \forall \ t.$$

Cost structure Dynamics and Firm Behavior

As mentioned earlier, the cost structure parameters of the firm vary over time.[8] This notion can be represented by expressing the degree of operating leverage as a function of time, namely

$$(2.8) \qquad D\dot{O}L_t = \frac{(p_t - w_t)\dot{\bar{w}}_t - \bar{w}_t(\dot{p}_t - \dot{w}_t)}{(p_t - w_t - \bar{w}_t)^2} \text{ such that } p_t \geq w_t > 0 \text{ and } \dot{\bar{w}}_t > 0 \ \forall \ t,$$

where the dot represents the time derivative of the variable in question. In the case of a perfectly competitive market structure (where the maximum level of profits will be reached when marginal revenue completely offsets marginal costs, i.e. $p_t = w_t$), the level of operating leverage of a firm will be reduced to zero and $D\dot{O}L = (\dot{w}_t - \dot{p}_t)/\bar{w}_t$. In the case of constant output $p_t \geq w_t$, and $D\dot{O}L \geq (\dot{w}_t - \dot{p}_t)/\bar{w}_t$. Thus, the rate of change of the DOL will depend solely on the differential of between factor-cost and price inflation, $\dot{w}_t - \dot{p}_t$, which are exogenous to the firm and are the only factors that can cause the actual operating leverage of the firm deviate from its optimal level. From (2.8), the first term in the numerator will be positive and will have a positive effect on $D\dot{O}L_t$. Thus, it is apparent that the fixed-share of total costs will increase when there are declining sales revenue for the firm. Fixed-costs can also increase when the

---

[8] We are assuming that at all times the firm has maximized achieved its objective to maximize its profit function with respect to its endogenous variables, $\pi_t^* \equiv \max \pi_t$. Invoking the Envelope Theorem, we can focus our analysis of the cost structure dynamics solely with respect to its changing operating environment parameters: $\pi_t^{**} \equiv \max_{p_t, w_t, \bar{w}_t} \pi_t^*$. While this notion is only theoretical, it provides the adequate support to understand our analysis. Since it is implausible that this assumption holds in reality at all times, its violation can provide a possible explanation to potential biases in the estimates.

burden from an increase in the number of elements in I_t^F, such as investing to expand capacity, is not offset by an accompanying increase in revenue generated from those investments.[9] Ceteris paribus, if the price increase is greater than variable factor-cost increase, a firm will decrease its degree of operating leverage over time and generate profits that are not driven by productivity gains.

This analysis is supported by the empirical findings of Gourio (2005) developed a full dynamic stochastic general equilibrium model and found that firms that are relatively more productive than others are less sensitive to shocks in the business cycle, macroeconomic risk, and observe a DOL that is close to unity. He refers to this disproportionate benefit enjoyed by less productive firms as an *operating leverage effect*. It follows that low productivity firms are more procyclical and earn higher average returns. Because a high book-to-market ratio indicates higher capital intensity, firms with a higher capital share of output will have operating costs that are less correlated with the business cycle. Gourio summarizes the relationship of the DOL to the business cycle by noting that since the proportional change in operating costs is less than the proportional change in revenue, profits have higher volatility than GDP.[10]

This discussion is consistent with economic theory. Evaluating the profit function (2.2), it is easy to see that the only stochastic variable is sales revenue (demand for output) where as the rest of the other variables are deterministic[11]. The source of the other variables deterministic nature can be attributed to the market structure that a particular firm faces. Market conditions constrain the firm to an operating environment where these variables observe higher degree of rigidity towards change. For example, in a perfectly competitive environment, firms are price takers such that the change in the price is synonymous

[9] The derivation of (2.8) is shown in Appendix I below.

[10] It's important to note that Gourio (2005) measures operating leverage in a slightly different way. From his definition of profit, he measures the operation leverage of a firm by the changes in the total factor productivity, *A*, to profit:

$$\varepsilon_{\pi,A} = d\ln\pi / d\ln A = 1/s_\kappa$$

where s_κ is the capital share of output.

[11] This was duly pointed by Mandelker and Rhee (1984).

with demand and influenced by market conditions, not by the behavior of the firm itself. To the extent that this is true, firms that operate in a market where menu costs are relatively high are less able to efficiently adjust their cost structure in the short-run in the face of stochastic demand as opposed to firms that face more flexible market conditions. From a perspective independent of productivity, looking at equation (2.8) we can see that since the firm has limited control (or no control at all) over the level of its output and factor prices, thus a sudden increase – a positive shock – in the price and factor-cost price differential will have a negative effect on the development operating leverage of the firm over time, causing the firm to generate above average profits.

II. LITERATURE REVIEW AND EMPIRICAL ESTIMATION MODELS OF DOL

Accounting Data Surrogates

Since Canning (1929) the economic relevance of accounting information to observed behavior has been studied. The issue naturally arises if one analyzes great deal of evolution in legislation and practices that have affected accounting methodologies over time. Ball and Brown (1966) investigated whether accounting variables contained the substantive meaning necessary for empirical analysis and concluded that the income number was a good measure of behavior, capturing at least half of what the market expected.[12] While this can be a source of poor fit of estimates, they still posses the necessary qualities we require for our empirical analysis.

To define our profit function in terms of accounting variables, let $w_t Q_t = v_t R_t$ and $\bar{w}_t Q_t = F_t$ and substitute these into (2.6) to get $\pi_t = R_t - v_t R_t - F_t$ where v_t is the share of variable cost and F_t the level of fixed costs. Just as above, we take the logs and differentiate to obtain the measure of operating leverage, $DOL_t = (1 - v_t) R_t / (R_t - v_t R_t - F_t)$.

[12] Ball and Brown measured the relevance and sustainability of accounting data based on the expectations of the market

Breaking down the accounting data into fixed and variable-cost is a challenging exercise as they are not readily available from the financial statements. Lev (1974) estimated the fixed cost component in the cost function by regressing the aggregate of total costs on real output. The interpretation of the regression parameters was that the estimated coefficient on output constituted the marginal cost of output and the intercept constituted the fixed-cost component.

Measuring Operating Leverage Empirically

In the literature, we encountered that most research refer back to the models developed by Mandelker and Rhee (1984) and O'Brien and Vanderheiden (1987) to measure operating leverage. Mandelker and Rhee (M&R) use a simple log-linear approach to estimate the *DOL* coefficient the specified as a the time-series regression model shown below,

(3.1) $\ln \pi_{jt} = \alpha_j + \beta_j^{\text{M\&R}} \ln R_{jt} + u_{jt}$, for j -th company at t,

where $\beta_j^{\text{M\&R}}$ is the *DOL*; π_{jt} is earnings before interests and taxes (EBIT); R_{jt} is the sales revenue; and u_{jt} is the error term.

M&R focused their analysis on the logarithms of EBIT and Sales for two reasons. First, the logarithmic transformation has more constant variance than the original variables and this enables the regression analysis to proceed under the assumption of homoskedastic residual errors[13]. Second, the slope parameter of (3.1) , $\beta_j^{\text{M\&R}}$, has a direct interpretation as an elasticity measure.

In their subsequent paper, O'Brien and Vanderheiden (O&V) addressed some technical issues regarding the M&R estimation method. Specifically, they argued that M&R fails to account for the growth in sales and operating earnings and thus not eliminating the trend factor in the times series data. The consequence on estimation, they argue, is that M&R measures the trend of operating earnings to the trend

[13] "Estimation of the Elasticities of the Residual Supply of Gas", UK Commission of Competition Reports, 2003

of sales since trend is dominant in the residual variation. To address this problem, O'Brien and Vanderheiden include a trend growth component that attempts to separate growth from single period variation[14]. The O&V approach to estimate the DOL is performed in two steps. The first step involves performing two trend regressions:

(3.2) $$\ln \pi_{jt} = \alpha_0^{\pi} + g_j^{\pi} t + \mu_{jt}^{\pi}$$

(3.3) $$\ln R_{jt} = \alpha_0^{R} + g_j^{R} t + \mu_{jt}^{R}$$

where a_{j0}^{π} and a_{j0}^{R} represent approximations of $\ln \pi_{j0}$ and $\ln R_{j0}$; g_j^{π} and g_j^{R} represent the approximate period growth rates of EBIT and sales revenue; and μ_{jt}^{π} and μ_{jt}^{R} represent the trend regression residuals, respectively. The residuals from both regressions are saved and are used to perform the following regression

(3.4) $$\hat{\mu}_{jt}^{\pi} = \beta_{jt}^{\text{O\&V}} \hat{\mu}_{jt}^{R} + \varepsilon_{jt},$$

where $\beta_{jt}^{\text{O\&V}}$ represents the DOL and ε_{jt} represents the error term. From (3.4), it is easy to see that the coefficient is consistent with the definition of the degree of operating leverage, since it approximates relative percentage changes when changes in the variables are small:

$$\beta^{O\&V} \approx \frac{\%\Delta\pi}{\%\Delta R} \approx \frac{\partial \ln \pi}{\partial \ln R}.$$

In comparison to M&R, O'Brien and Vanderheiden contend that their estimation yields more intuitive results. They cite that the DOL estimates from (3.1) tend to be biased downward and "cluster around the value of one". More importantly, they mention that their method measures the ratio of relative changes in the deviations from trend between EBIT and sales revenue.

---

[14] O'Brien and Vanderheiden measure operating leverage as $DOL = [\pi_t / E(\pi_t) - 1] / [R_t / E(R_t) - 1]$ where $E(\cdot)$ is the expectations operator. As opposed to M&R, this definition measures the ratio of relative changes within the same period between the realized and expected observations.

Model Limitations

In a paper directly comparing both methods, Dugan and Shriver (1992) supported the claim that O&V is a better approach to estimate DOL. In a time-series analysis of 245 companies across seven industries, the estimated DOL using both methodologies resulted in significantly different outcomes. It is important to note, however, that while their comparison suggests that the O&V method is consistent with the ex-ante model of DOL as expressed by (2.8), both methodologies generally estimate DOL coefficients that are less than unity, thus posing an interpretation challenge. A degree of operating leverage of less than one suggests that fixed costs are negative, an interpretation that is not plausible. They found that the proportions of estimated DOLs above unity were around 19% using M&R and around 57% using O&V. However, testing the significance of the proportions for related samples using McNemar's test of significance, the former was significant at the 1% level while the latter was significant at the above 10% level.

The illogical measures that both models tend to estimate, has spurred concerns by researchers on the viability of the regression outputs and present challenges to interpretation. In relation to the basic concept of operating leverage, there are several authors that cite a lack of definitional consistency in the financial literature of operating leverage, which is plagued with invalid implications and contradictions (McDaniel (1984) and Lord (1999))[15]. One shortcoming suggested from our analysis is implied by the fact that accounting proxies capture only part of the actual firm behavior, thus becoming a source for low coefficients of determination or biases in the estimates.

A more fundamental explanation to illogical results can be derived from the actual formulation of empirical models. Lord (1999) attempts to document the sources of biases prevalent in the DOL estimation methodologies. He claims that they are due to the fact that the dynamic characteristics of the

[15] Throughout this paper, we will use the DOL definition given by equation (2.7).

operating parameters of the firm, namely p_t, w_t, and $\overline{w}_t$, are assumed constant in the M&R model and only partly considered in the O&V model. He further adds that these biases are exacerbated when the firm faces low demand volatility and relatively high operating parameter volatility. Lord says that the O&V estimates are victim to high variances and large standard errors, a big shortcoming when using logs when changes in the variables are large. In spite of its empirical estimation shortcomings, using operating leverage to analyze stock performance is very appealing and M&R remains the dominant method for researchers to measure operating leverage. (Gahlon and Gentry (1986), Huffman (1989), Chung (1989), Dugan et al. (1994), Griffin and Dugan (2003)).

Operating leverage and Risk

The discussion on cost-structure dynamics above briefly mentioned the relationship of operating leverage to risk. While the main objective of our thesis is not to provide a thorough interpretation of this relationship, we feel it should be mentioned for a complete overview of its implications in analysis. In the literature, firm specific risk has been decomposed into both sources of leverage – operating and financial – and intrinsic market risk.[16] As given in Mandelker and Rhee (1984), the systematic risk beta is decomposed as

(3.5) $\beta_j = \left(DOL_j\right)\left(DFL_j\right)\beta_j^0$ at time t for the j-th levered firm,

where $\beta_j^0 = \text{cov}\left[\left(\Pi_{jt}/R_{jt-1}\right)\left(R_{jt}/E_{jt-1}\right), R_{mt}\right] \big/ \text{var}\left(R_{mt}\right)$ and

- β_j represents the common stock beta
- DOL_j represents the degree of operating leverage
- DFL_j represents the degree of financial leverage
- Π_{jt} represents the earnings net of interest payments, taxes, and depreciation
- R_{jt} represents the sales revenue at time

[16] For further reading on the accounting beta and its decomposition, please refer to Beaver et al. (1970), Hamada (1972), Rubinstein (1973), Lev (1974), Hill and Stone (1980), Chance (1982), and Gahlon and Gentry (1982).

- E_{jt} represents the market value of equity

Here is clearly shown that the systematic risk beta of a firm depends on both degrees of leverage, operating and financial, and the intrinsic risk of the market.

III. COST-STRUCTURE DYNAMICS AND STOCK RETURNS

So far we have provided the theoretical relationship between market value and cost-structure dynamics, and how to measure operating leverage empirically. We now bridge the gap between theory and practice and assess the relationship between of the DOL to stock market returns. De Medeiros et al. (2006) recently used DOL analysis to study the behavior of stock returns on the Brazilian stock market. Based on the efficient market hypothesis, their approach was to understand whether *non-expected* changes in the degree of operating leverage (NEDOL) were the source of *non-expected* stock market returns (NER). Based on the efficient market hypothesis, they implicitly expected stocks to observe some degree of operating leverage in the future and reflect it on the current share price traded on the exchange. They hypothesized that the positive association between risk and operating leverage should lead to a positive relationship between the DOL and stock returns[17]. Using panel-data analysis, they estimated coefficients consistent with their expectations on this relationship and obtained results with below the 1% significance level. From their results, they were able to infer that indeed there is a positive relationship between the non-expected degree of operating leverage of firms and the return of their shares on the stock market and substantiate our theoretical analysis about this relationship that we've developed so far in our discussion. Their analysis led to the conclusion that operating leverage is one of the factors that determines the risk of stocks with a positive and statistically significant relationship to stock returns, as suspected from (3.5).

[17] For a thorough discussion on the relationship between systematic risk and *DOL* please refer to Lev (1979), Hamada (1972), and Mandelker and Rhee (1984) among others.

Panel Analysis

De Medeiros et al. (2006) used panel data across 4 industries to assess the impact of DOLs on stocks traded in the São Paulo Stock Exchange in Brazil. The study was very conclusive and offered a step forward over previous methodologies. Their panel data analysis used as multiple cases up to 44- of multiple NEDOL-NER pairs of longitudinal data. A panel data technique allows to consider the cross-sectional data reflected in the differences between the non-expected returns and the non-expected degrees of operating leverage, and the time-series data reflected in the changes within the two factors over time[18].

Like de Medeiros et al. we will use a dynamic panel data approach in our main empirical analysis, but we will modify it to correct for biases in the estimated coefficient on NEDOL. Before, we address the bias, we present our baseline panel data model:

(4.1) $$\mathrm{NER}_{jt} = \theta_{jt} + \delta \mathrm{NEDOL}_{jt} + u_{jt},$$

where

- NER_{jt} represents the non-expected return on the stock of the j-th firm at time t
- NEDOL_{jt} represents the non-expected degree of operating leverage of the j-th firm at time t
- θ_{jt} represents the unknown entity and time intercept

Likewise, we assume that markets are efficient when pricing a particular stock. Thus, any deviation from what the market expects should be regarded as non-expected values. Form regression (4.1), we anticipate a positive estimate of the unknown parameter δ and statistically significantly different from zero.

The non-expected sock returns were calculated using the following formula:

(4.2) $$\mathrm{NER}_{jt} = \mathrm{R}_{jt} - E_{t-1}\left(R_{jt}\right).$$

18 Data and Statistical Service, Princeton University, online edition, 2006

We estimated the expected returns on a stock by regressing the realized return on the stock j on the return on the market, R_{mt}, at t and computed the values from the following regression:

(4.3) $$E_{t-1}\left(R_{jt}\right) = \hat{\gamma}_0 + \hat{\gamma}_{1j} R_{mt} .$$

We estimated the expected DOL by performing the following linear regression:

(4.4) $$\text{EBIT}_{jt} = \phi_0 + \phi_{1j}\text{INCOME}_{jt} + u_{jt}$$

where EBIT_{jt} represents the operating earnings and INCOME_{jt} represents the sales revenue of firm j at t respectively. To obtain the *observed* the degree of operating leverage, we multiplied the estimate of the coefficient in (4.4), $\hat{\phi}_{1j}$, by the ratio of EBIT to INCOME per firm per period. Using the method developed my Mandelker and Rhee we estimated the *expected* DOL for the whole sample. This procedure is represented as:

(4.5) $$\text{NEDOL}_{jt} = \text{D\hat{O}L}_{jt}^{\text{linear}} - \text{D\hat{O}L}_{j}^{\text{M\&R}} .$$

The baseline analysis is done using the Least Squares Dummy Variable (LSDV) estimator to take into account each of the ten hotel companies' specific effects. The methodology is based upon the market model in such a way that it allows us to analyze potential changes in the operating leverage over time and, therefore, changes in stock returns. To carry out this task, LSDV panel data models are employed to measure the impact that the DOL has on stock return. This empirical application is the main novelty the way this effect is measured.

Data Limitations

Before we continue, it is important to comment on data limitations. A major source of bias in DOL estimation is a negative EBIT. Researchers have clearly stated the drawbacks negative EBIT observations have on estimates, since they lead to negative coefficients, that is $D\hat{O}L < 0$. Since the sales revenue variable is stochastic and given the limited maneuvering space managers face to accommodate a changing economic environment in the short-run, it is not uncommon to see negative EBIT observations in the data. To control for this problem, we cleaned the data in the following way: if the incidence of negative EBITs is low and irregular for a certain entity, the data are simply treated as outliers and removed from the sample; On the other hand, if the incidence is high or a series of negative EBITs are observed, the entity is removed from the sample.

Unbalanced Panel Problem

Cleaning the sample data-set, however, will inevitably lead to an unbalanced panel. In our case, our initial sample consisted of 50 hotel companies and was reduced to one fifth of that. Further cleaning of the data caused a firm-specific data to experience 20% reduction of the observations on average. Researchers, have different approaches to work with unbalanced panels. For example, Gourio (2005) grouped firms by book-to-market bins, such that each group had always a positive EBIT. More generally, if the sample data-set is drawn from a well diversified and heterogeneous sample of companies in different industries, the unbalanced panel problem will be abased.

Nickell's Bias

Another limitation with our data is that dynamic LSDV estimates suffer from a downward bias. Nickell (1981) showed that time-series LSDV models yield estimates that are not consistent and are only corrected as $T \to +\infty$. Since our data consists of 40 quarterly observations, this bias poses a high risk of rendering our results with inconsistent estimates.

To address Nickell's bias, Anderson and Hsiao (1982) suggest using the lagged dependent variable as an instrument variable to eliminate the heterogeneity unobserved in the panel data entities. Arellano and Bond (1991) claim, however, that a gain in estimation efficiency is obtained over the simple instrument variable approach of Anderson and Hsiao by using a Generalized Method of Moments (GMM) and including additional internal variables as instruments. However, Blundell and Bond (1998) argue that that highly autocorrelated data may fall victim to sample bias since lagged levels of the series are weak instruments variables in first differences, thus providing with poor precision. To address this problem, they suggest using the GMM approach with first-differenced instruments for the equation in levels and instrument in levels for the first-differenced equation. The effectiveness of these approaches to correct this bias was tested using Monte Carlo simulations by Arellano and Bond (1991), Kiviet (1995), Judson and Owen (1999), and Bun and Kiviet (2003), with very conclusive results.

LSDV Corrected Model for Unbalanced Panels

While this correction is very convincing, none of these procedures are feasible when the panel is unbalanced. Bruno (2004) accommodates these procedures to unbalanced panels and tested the correction robustness using Monte Carlo simulations in the manner of previous researchers. Given that Bruno's procedure fits our purposes, we present below the procedure he developed to accommodate unbalanced panels and the general form of the bias-corrected LSDV approach as in (4.1).

Let ρ_{it} be the selection indicator such that $\rho_{it} = 1$ if the pair $\left(\mathrm{NER}_{it}, \mathrm{NEDOL}_{it}\right)$ is observed and $\rho_{it} = 0$ otherwise. Using the selection indicator, the dynamic selection rule $s\left(\rho_{it}, \rho_{it-1}\right)$ selects the observations by implementing the following criterion

$$s_{it} = \begin{cases} 1 & \text{if } \left(\rho_{it}, \rho_{it-1}\right) = 1 \\ 0 & \text{if otherwise} \end{cases} \quad \forall\, j \in \{1, \ldots, 10\} \;\wedge\; t \in \{1, \ldots, 40\}.$$

The LSDV corrected regression model is given by the following equation,

$$(4.6) \qquad s_{it}\mathrm{NER}_{jt} = s_{it}\left(\theta_{jt} + \gamma \mathrm{NER}_{jt-1} + \delta_{\mathrm{LSDVC}}\mathrm{NEDOL}_{jt} + \eta_j + e_{jt}\right) \;\forall\, j \in \{1, \ldots, 10\} \;\wedge\; t \in \{1, \ldots, 40\},$$

- where η_j are the unobserved entity effects, for which no distributional assumption is made apart from being fixed over time

- e_{it} are iid over the whole sample with variance σ_e^2
- It is also assumed that η_i and e_{it} are independent for each i over all t.[19]

Bruno (2005) coded this unbalanced panel data regression in a Stata routine, `XTLSDVC`, and programmed the procedure to address Nickell's dynamic LSDV bias using all of the above mentioned approaches, i.e. Anderson and Hsiao, Arellano and Bond, and Blundell and Bond. The LSDV corrected estimator is given by

$$\delta_{\text{LSDVC}} = \left(\sum_{j=1}^{10} \sum_{t=1}^{40} s_{it} \left(\text{NEDOL}_{jt} - \overline{\text{NEDOL}}_{j} \right)^2 \right) \Big/ \left(\sum_{j=1}^{10} \sum_{t=1}^{40} s_{it} \left(\text{NEDOL}_{jt} - \overline{\text{NEDOL}}_{j} \right) \left(\text{NER}_{jt} - \overline{\text{NER}}_{j} \right) \right).$$

IV. THE CASE OF THE HOTEL INDUSTRY

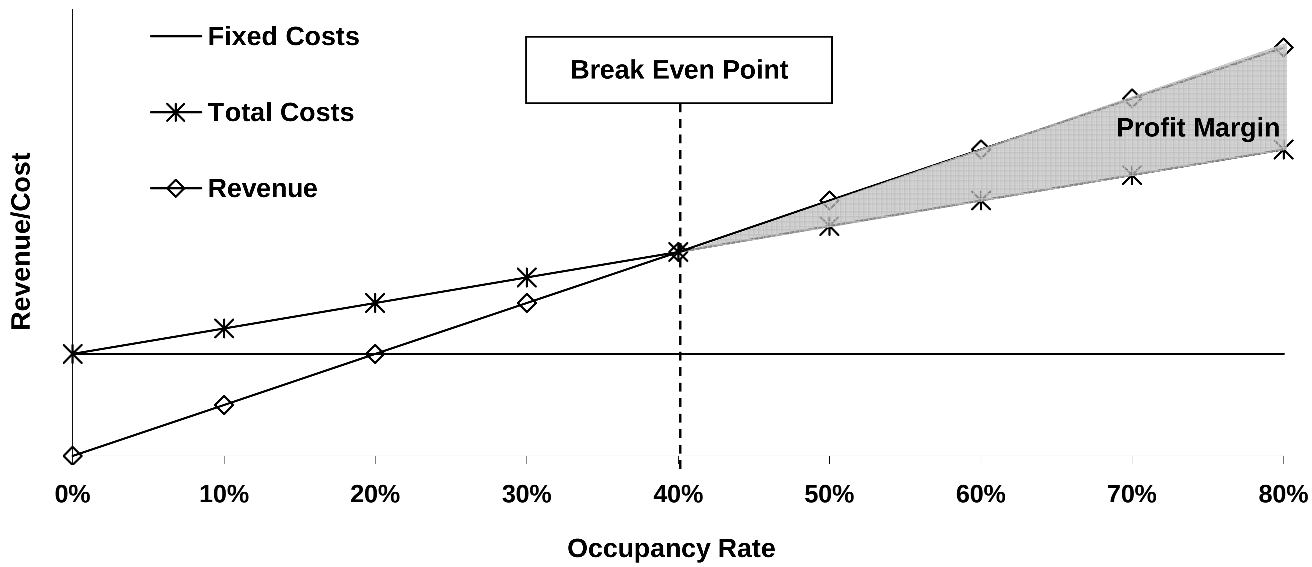
Armed with the theory and the review of existing empirical models, we proceed to test our discussion on the hotel industry. As we will elaborate, the industry possesses very appealing characteristics that make it a particularly interesting candidate to analyze stock-performance using operating leverage.

The hotel business belongs to the real estate industry in general, dealing with the buying, selling, and renting of space. Surprisingly, all previous research on the operating leverage never addressed the lodging industry. We suspect the main reason being that the COMPUSTAT PST tape, widely used in previous publications, included relevant data on several industries but not the lodging industry. Furthermore, there is little literature dealing with costing in the hotel industry, and most of it goes back to the 1980s.

Hotels operate in a highly procyclical industry. According to Hanson (2004), between the years 1991 and 2000, the number of rooms sold in the US experienced demand elasticity and a correlation to real GDP of 0.8 and 0.93 respectively. Hence hotels are largely affected by changes in the economy, mainly Real GDP and interest rates. Ahmed et al. (2004) showed that the average rate charged per room is correlated with GDP, given that it is a fixed-capital intensive and investment driven industry.

[19] From equations (4.1) and (4.6), we can see that $u_{it} = \eta_j + e_{jt}$.

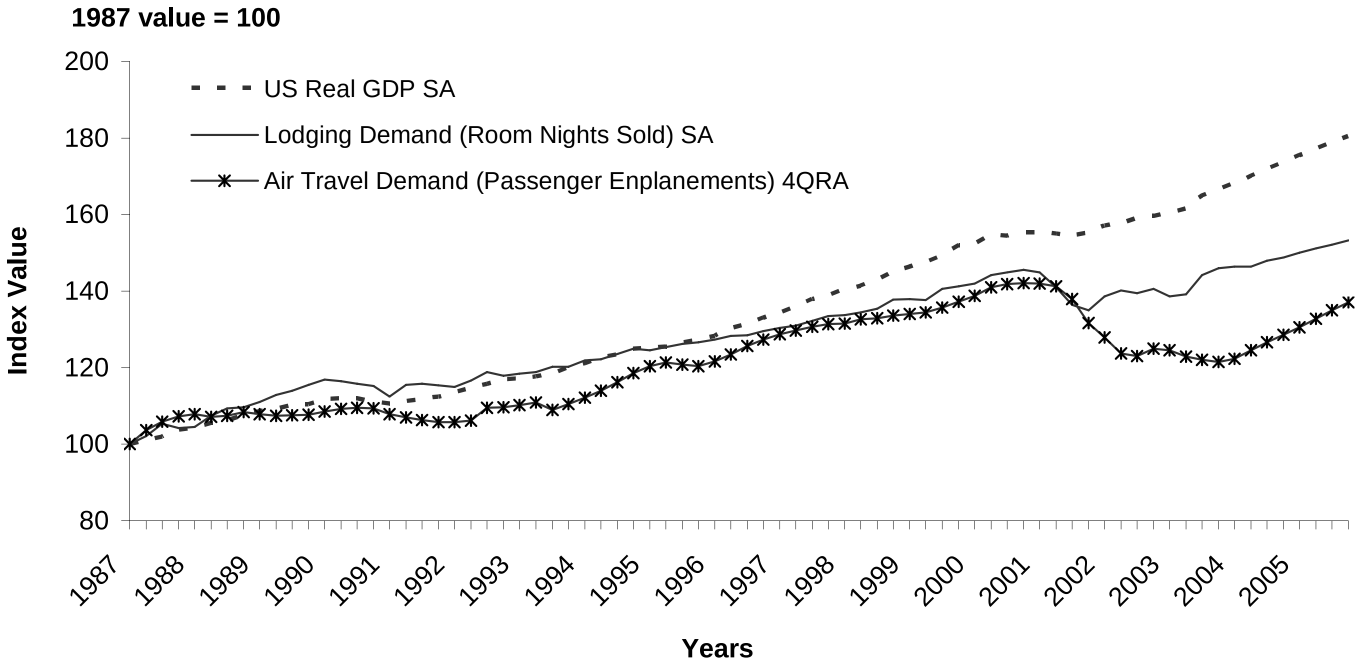
Figure 1: Hotels Profit Margin



With regards to the cost structure of hotels, Elgonemy (1999) confirms that a large portion of their expenses are fixed and adds that they do not vary significantly with occupancy, therefore profits increase with occupancy as soon as the income from a hotel reaches the breakeven point. The author duly notes,

"A hotel's significant operating leverage heightens its sensitivity to economic cycles and necessitates underwriting to a higher debt service coverage ratio than for other property types. Because of the higher operating leverage inherent to the lodging sector, investors can naturally expect higher return potential compared to other types of real estate investments. However, the downside risk in the hotel industry is greater if economic or company-specific issues produce insufficient cash flow to cover the high fixed-cost structure of this asset class".

Figure 2: Evolution of rooms demand with respects to GDP.



Sources: PricewaterhouseCoopers LLP based on Smith Travel Research data

This statement by Elgomeny underlines the relevance of the DOL to the lodging industry, and presents observations inline with the theoretical framework stated above. From the Figure 2, obtained form a study conducted on the industry by the consulting arm of PricewaterhouseCoopers, we can see that the lodging demand is highly correlated with the US real output, observing a correlation coefficient above 0.8, providing support to the finding's of Hanson (2004). Likewise, Rushmore (1997) analyzed the increase in profitability with the increase in occupancy above the operating leverage breakeven point and the correlation to business cycle. Hotels operate by yearly budgeting and reduce the accommodation quality, service quality, or both to meet their earnings objectives in downturns. What is applied is a corollary to Parkinson's Law: The work has contracted to fit the budget available. (Coombs (2003))

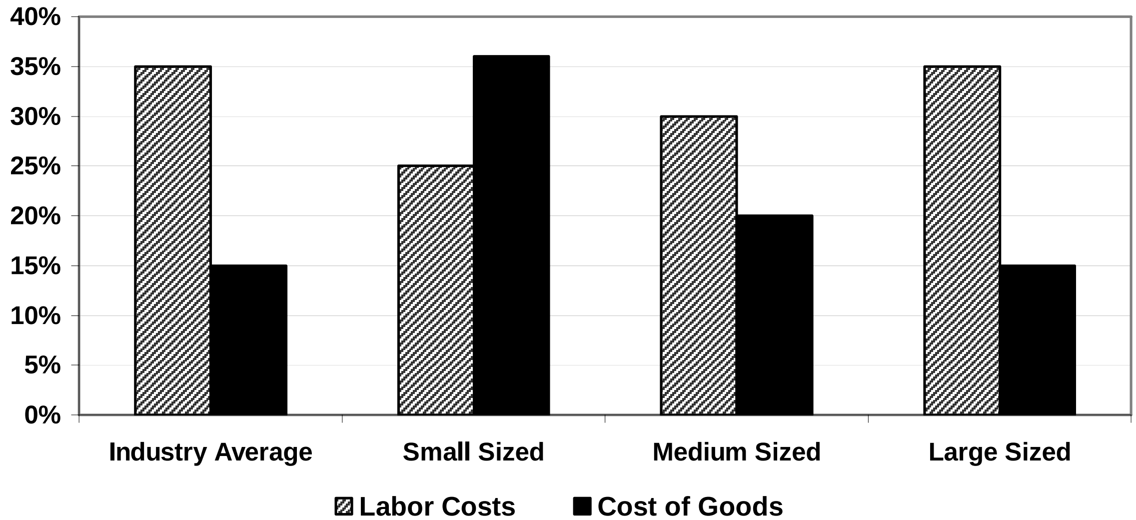
Costs in the lodging industry are a major competitive element. The initial capital expenditure in property, lodging facilities, and equipment is necessary to gain market share. By renting rooms, hotels sell a perishable service. Just like for airlines, hotels are required to sell their whole rooms' inventory on a daily basis. And just like airlines, hotels adopted flexible pricing model to accommodate demand fluctuation. Besides initial capital expenditure, regular capital expenditure is carried out to repair and maintain the hotel property and fixed asset. Last, strategic capital expenditure is employed for acquisition and organic growth through new property development. Fending off competition is done by a substantial investment in the existent portfolio of properties (constant investments in maintenance, fixture and work force) driving the operating expenses well above many other industries.

The Average Daily Rate (ADR) is the trade name for average price hotel firms charge per room and is equally subject to fluctuation in demand. The relationship between occupancy rate and average daily rate is described by Corgel (2004) “During periods of abnormally high (low) occupancy, ADR increases (decreases) causing occupancy to fall (rise).”

Graham and Harris (1999) discovered that high fixed costs in the lodging industry lead to profit instability during periods of fluctuating demand as hotels become more revenue-dependent. Furthermore, Nicolau (2005) suggests that hotels with high fixed costs are ‘‘market-oriented’’ and are required to maintain high revenue levels to survive and generate adequate profit returns.

In 1997 a panel of 970 Canadian hotels offering an aggregate of 129,500 accommodation guest units was surveyed. The hotels where grouped in three categories dependently of their size: Small (Expense/Revenue Ratio = 91%); Medium (87%) and Large (84%). (Lévesque G. and Little D., (2000))

Figure 3: Expenses Breakdown per Hotel size

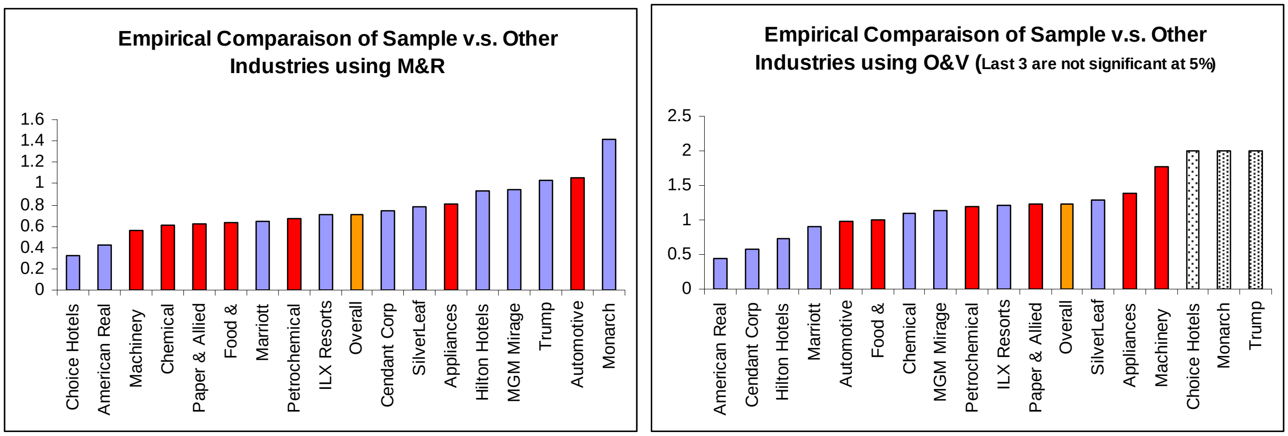


Large hotels have the higher proportion of labor costs (35%) and the lowest of cost of goods (10%) but are the most profitable of all three categories. This could be explained by the management of larger hotels ability to adjust to the business cycle. It is therefore noticeable that an expense analysis model of a given category cannot be adapted to another. The effect of market segments on ADR and occupancy rate is highlighted in the plots of Appendix II. Our aim in this study is not to test for the size effect on DOL. We counter the size divergence by choosing a sample of large listed hotel chains serving all market segments, from budget to upper luxury.

In the following plots, we present a comparison of DOL estimates using both the M&R and O&V approaches for several industries and firms. The regressions were run on quarterly data over 10 years for 10 large hotel chains[20]. The results are compared to industry estimation provided in Dugan and Shriver (1992).

[20] Further information about the firm selection is found on page 24 in "Sample Construction and Data Sources"

Figure 4: Hotel's Sample DOL estimation using M&R (*right*) and O&V DOL (*left*)



In general and in line with theory, DOL estimates using the M&R tend to be lower in comparison to those estimated using O&V. The column colored with orange represents the overall sample average of our lodging firms. The last three columns in the right figure above are not significant to an acceptable level, which reflect the tendency of M&R to yield more statistically significant results when compared to O&V estimates. Mainly for that reason, and because M&R has been more widely used in research overall, we decide to use it to study the relationship of the DOL to stock returns later in this paper.

Nevertheless, to test the strength of this proxy, we compare it to the accounting DOL estimated in (2.7) from the proportion of fixed and variable costs. For that purpose, Switzerland-based privately-owned Hyatt international provided us with data on three hotel properties in Azerbaijan, France, and Dubai[21]. The three properties have been selected for their revenue disparities and operate in the similar market segments. In particular, the Azerbaijani property is distinguished by a high volatility in its occupancy rate; the French property has experienced revenue-decline over the past 10 years; and the property in Dubai has experienced significant growth. Monthly data was provided from 1995 to 2004 with the deliberate exclusion of the July and August data for confidentiality purposes.

[21] Data provided by Hyatt under strict confidentiality agreement for academic purposes only.

Table 1: Characteristics of Hotel Properties

	Available Rooms	Occupancy Rate	Guests per Room	Rooms Revenue	Rooms Expenses	House Profit
Azerbaijan	4,236	57.63%	1	66.01%	11.26%	33.00%
France	10,698	60.46%	1.1	59.57%	30.97%	25.80%
United Arab Emirates	11,029	66.12%	1.19	41.46%	19.60%	41.09%

The data file provided us with the five main cost centers affecting the room's department revenue. We ran a simple regression of each cost center over the room's revenue. The regression's beta coefficient is the variable-cost element of the respective cost center, i.e. the proportion that directly varies with revenue. The estimated coefficients from the regression are summarized in the table below where most of variable-cost estimates are statistically significantly different form zero at the 5% confidence level. In table 2 below, "The Total VC" column reflects the sum of the five variable-input components of each hotel of the properties cost structure. The regression intercept represents the fixed-cost level of each property and are summed up in the column labeled "Total FC".

Table 2: Regression Output

	Rooms Payroll	Rooms Provision for O.E.	Rooms Other Expenses	Energy costs	Repair & Maintenance	**Total VC**	**Total FC**[22]
Azerbaijan	3.03%	0.93%	4.19%	2.57%	1.23%	**11.95%**	**33222.9**
France	5.16%	0.13%*	5.71%	-1.55%	2.57%	**12.01%**	**288770.9**
United Arab Emirates	1.51%*	0.04%*	4.62%	-1.41%	-0.22%*	**4.53%**	**1084094.4**

After computing the monthly operating leverage for each hotel, we averaged the values and presented them in the first column of the next table. We subsequently perform the M&R regression in equation (3.1) and compare them with the averaged monthly operating leverages. The coefficients, all being significant, are presented in the second column.

[22] The fixed-cost values differ largely due to a denomination in different currency.

Table 3: Average OL estimation vs. M&R DOL

		M&R DOL				
	Avg. OL	**Coef.**	Std. Err.	t	P>|t|	R^2
Azerbaijan	**1.093**	**1.110**	0.013	84.15	0.000	0.988
France	**1.684**	**1.640**	0.041	40.02	0.000	0.946
United Arab Emirates	**1.459**	**1.443**	0.023	61.62	0.000	0.976

We conclude that the average error margin of 0.026 or 1.846% among the three properties is very small[23]. Hence we can proceed, with confidence, in using the M&R as a proxy to estimate the OLs.

Sample Construction and Data Sources

The sample was constructed filtering the Bureau Van Dyck ORBIS database for publicly listed US hotel lodging chains belonging to SIC code 7100. Our first criteria were that the firms needed to have been public for at least 10 years and have accurately proceeded with quarterly fillings on EDGAR. Therefore, we target 40 data points, twice more than previous researchers on the same topic. The 50 firms offered by Bureau van Dyck ORBIS were carefully examined.

- Firms will less than 10 years of data were not included.
- Firms with more than 20% of negative EBITs were excluded.
- Firms with high variability in earnings or high volatility in share price were excluded.

The final sample included the following 10 companies: Mariott, American Rea Estate Group, Cendant, Choice Hotels, ILX, Monarch, Trump, Hilton, MGM Mirage and Silverleaf. The data ranged from 1995 to 2005, quarterly. Balance sheets were extracted from Thomson financial DATASTREAM. Share price were extracted from Reuters 3000 XTRA. The market proxy index is the CRSP value weighted engineered at the University of Chicago.

[23] Tests of robustness and stationarity are not presented as this exercise is for illustration purposes only and not part of the core empirics.

V. RESULTS

Performing Bruno's routine was run through the three time-series model as stated above. The corrected Least Square Dummy Variable dynamic estimation yielded the following Nickell's bias-corrected NEDOL coefficients

Table 4: XTLSDVC output

	Anderson and Hsiao	Arellano and Bond	Blundell and Bond [24]
NEDOL	0.180159	0.181185	0.18148
P>|z|	0.004	0.004	0.004

The three bias correction estimates generated significant and very similar coefficients, highlighting the robustness of the model. The actual Stata output is offered in Appendix III. Further tests for unit root, autocorrelation and heteroskedasticity specific to dynamic panel data are conducted to ascertain this robustness. The descriptive statistics are shown in Table 5 below.

Table 5: Descriptive Statistics

Chain	Ticker Symbol	M&R DOL	Exp DOL	NEDOL Obs[25]	NEDOL			NER		
					Mean	Median	Stdev	Mean	Median	Stdev
Marriott International Inc	MAR	0.64	0.53	34	11.4%	21.6%	30.3%	-0.2%	-0.9%	13.2%
American Real Estate Partners	ACP	0.43	0.46	37	3.6%	4.9%	24.7%	-6.9%	0.7%	55.3%
Cendant Corp	CAR	0.74	0.80	30	5.5%	-4.0%	32.8%	6.3%	-3.8%	65.7%
Choice Hotels International Inc	CHH	0.33	0.30	31	3.0%	6.1%	19.7%	1.4%	1.1%	36.9%
ILX Resorts Inc	ILX	0.71	0.75	32	-3.9%	3.1%	22.5%	2.8%	0.4%	26.1%
Monarch Casino & Resort Inc	MCRI.O	1.42	1.41	30	99.0%	52.7%	128.0%	-4.8%	-3.1%	35.9%
Trump Entertainment Resorts Inc	TRMP.O	1.03	1.32	30	0.0%	-49.5%	105.0%	1.3%	-6.3%	53.8%
Hilton Hotels Corp	HLT	0.93	1.04	33	10.5%	-8.8%	53.3%	-1.8%	-1.7%	17.5%
MGM Mirage	MGM	0.95	1.05	39	10.6%	-0.7%	44.4%	1.7%	1.5%	17.0%
Silverleaf Resorts Inc	SLV	0.78	1.28	32	49.9%	3.8%	106.3%	-10.3%	-45.8%	144.9%

[24] The Anderson-Hsiao estimator, with the dependent variable lagged two times, used as an instrument for the first-differenced model with no intercept. This uses Stata's IVREG command to perform instrument variable regression. Arellano-Bond is a standard one-step estimator with no intercept and uses Stata's XTABOND command. Blundell-Bond is standard estimator with no intercept.

[25] Number of NEDOL observations out of 44 NER observations in the panel. Missing values related to negative EBITs.

Testing the basic assumptions

Comparing our LSDV corrected coefficients we see that their magnitude is very similar. In a Two-Stage Least Square (TSLS) regression, the Anderson and Hsiao method used the twice lagged independent variable as the instrument estimating the coefficient to be 0.1801. Claiming gain in efficiency, the Arellano and Bond method replaced the TSLS approach with GMM resulting in an estimate of 0.1811. Finally, the Blundell and Bond method addressed a possible sampling bias in the presence of weak instruments and uses the GMM estimation approach with instruments in first differences, since our data are in levels, resulting in an estimated coefficient of 0.1814, a slight increase over Arellano and Bond. While these approaches address Nickell's bias with finite sample of data, the explanatory variables should be strictly exogenous to be used as instruments, i.e. the lagged NER and NEDOL should not be correlated with the error term. At this stage, the model could suffer from weak endogeneity. While the Blundell and Bond test addressed sampling bias and weakness of instruments, further testing is required.

Because the Arellano and Bond method uses Two-Stage Least Square, it tested for autocorrelation assuming that the NEDOL variable is not correlated with future errors. In a dynamic setting, future values of NEDOL do not depend on future errors. The Arellano and Bond technique is an alternative to the Durbin-Watson and Baltagi tests for autocorrelation in unbalanced panels. From the output, we obtained a *z*-score of –5.01 with lagged-once residuals and a *z*-score of –3.03 with the lagged-twice residuals allowing us to infer that no autocorrelation is present with a confidence level in excess of 99%.

Using the Modified Wald test for groupwise heteroskedasticity in our panel analysis with fixed-effects, we obtained a $\chi^2_{\text{MWald}} = 77373.72$ test statistic, allowing us to reject the hypothesis that heteroskedasticity is present in our results. Thus, there seems to be no signs of heteroskedasticity in the error term and no evidence of increasing variance with higher values of NER or NEDOL variables.

However, we cannot make any inferences regarding homoskedasiticity as further test are required, as suggested by Long and Ervin (2000).

With respect to stationarity, the Fisher-Augmented Dickey-Fuller and Fisher-Philips-Perron tests allowed us to infer that our series are do not contain a unit root, providing evidence that a spurious regression has not been performed. The Fisher-Augmented Dickey-Fuller in one lag with $\chi^2_{\text{Fisher-ADF}} = 251.8854$ statistic and the Fisher-PP in two lags with $\chi^2_{\text{Fisher-PP}} = 558.2804$ statistic were both significant with a confidence level in excess of 99%.

The Wilcoxon Signed Rank sum test is used when the assumption of normal distribution between the two variables does not hold. It's the non-parametric version of a paired samples *t*-test and tests whether the difference between the M&R elasticity ratio and the rolling log-linear DOL are significant. The output form the equality of distributions test for matched pairs of observations is presented a *z*-score of 2.315 and a *p*-value of 2.05% leading to a conclusion that the M&R elasticity ration and linear DOL are statistically significant. The results indicate that there is a statistically significant difference between the log-linear DOL_{jt} estimation and the average linear, a proxy for $E_{t-1}\left(DOL_t\right)$.

In the previous sections, we delved extensively into the microeconomic foundations of the degree of operating leverage and derived and discussed the different approximations of the degree of operating leverage. The core methodology, however, focused on assessing the impact of the non-expected degree of operating leverage on non-expected stock returns using a corrected Least Square Dummy Variable panel data. By taking the non-expected returns instead of the actual returns on both stocks and the degree operating leverage, the trends have been removed from the series, and we can conclude that the dynamic panel estimation is robust. This is confirmed by the analyzing the Mahalanobis Distance graph found in the appendices, from which it is evident that there are few observations with large values. This indicates that overall, individual observations have a relatively small impact on the estimated coefficients.

VI. SUMMARY AND INTERPRETATION

Our empirical findings suggest that the degree of operating leverage explain a large proportion in the variation of stock return. In accordance with de Medeiros et al. (2006), we find support for the hypothesized positive association between operating leverage and stock returns. The conjecture that hotel firms engage in trade-offs between fixed and variable costs seems to have gained strong empirical evidence in our study. The different degree of operating values across our sample of ten hotel chains motivates our understanding in the risk difference and heterogeneity in expected returns across firms operating in the same industry in similar markets.

After testing our model's assumptions, our estimates seem to produce more consistent results when compared with those obtained by de Medeiros et al. In their case, the estimated coefficient of NEDOL on NER was at most 0.0757 using a fixed-effects approach, and 0.0846 using a random-effects approach. While their random-effects estimate was superior to their fixed-effects estimate, possibly suggesting that Nickell's bias was ameliorated, our analysis result in higher estimates. Comparing Anderson and Hsiao's estimate with de Medeiros et al. fixed-effects estimate, we observe an improvement of almost of 138% in magnitude. After correcting for weak instruments, comparing that result with the Blundell and Bond, we obtain an almost 140% increase in the estimate. Additionally, Wilcoxon's test provided support that the difference between log-linear estimates of DOL and the linear average is statistically significant, thus giving support that our estimates are more consistent.

Businesses change the level of output to increase the rate of return. This can be done either by selling more units or avoiding producing units which cannot be sold without a rate-of-return-reducing reduction in price. In the hospitality industry, output is a constant. The whole inventory (total number of rooms) is available for sale every day. Hence, hotel operators need to adjust the rooms pricing strategy to meet the daily demand. In the competitive market hotels operate in, managers seek to maximize their profits by selling the optimal number of rooms within the market structure they operate in. Once managers reach their fair market share, i.e a hotel's own capacity with respect to the market's aggregate capacity, where marginal profits are neglected, other methods are employed to enhance both the occupancy level and average daily rate.

In the case of a downturn, a high operating leverage hotel has to sell additional rooms to cover the high fixed costs. Microeconomic intuition pushes the manager to lower the room's average daily rate. Lowering price reduces the room unit contribution margin and lifts the operating breakeven point further up, reaching the desired earnings to pay fixed charges becomes even more difficult.

The degree of operating leverage is a double-edged sword: a high DOL yields higher returns in good times and lower returns in bad times. Hotel firms with high DOLs, like Trump and Monarch, observe higher volatility in their operating earnings which translated in a higher intrinsic business risk and raise the cost of debt financing. Hence, ambitions related to growth through leverage, or fast growth, could be scaled down, in line with the capital structure theory. Intuitively, when demand for hotel rooms decrease, stock returns fall. If the fixed costs are proportional to book-value, the risk of hotel firms increases because of their higher operating leverage. Although in this study we do not address business cycles directly, the operating-leverage mechanism is likely to cause high fixed cost hotels to be more affected by negative aggregate shocks than lower fixed costs hotels.

Firms differ in their operating leverage because fixed costs are determined by previous investment decisions. Additionally, the resulting increase in physical capital may generate operating leverage through long-term obligations, including the fixed operating costs of a larger plant, wage contracts, and commitments to suppliers. It is natural to conclude that expected returns might relate to current and historical investment decisions of the firm.

Although the direct operating leverage – the proportion of fixed to variable costs – is not directly observed to outside investors, managers are concerned by changes in their companies cost structure. For instance, the decision of opening a new hotel could raise the degree of operating leverage (Nicolau (2003)); should the hotel firm observe a high degree of financial leverage, a high degree of fixed costs can be a handicap if the company is going in a down cycle and has to meet creditor's obligations.

Hedging a high operating leverage is a challenging exercise. A hotel manager is better off lowering the fixed-cost component through inventive business modeling and negotiation: increase the share of temporary labor, flexible lease schemes for equipment and machinery, or renegotiate short-term debt. Although the proportion of variable-to-fixed costs is relatively hard to alter, we suspect managerial decisions related to delays in payments, such as facility repairs, supplies, staff bonuses, to preserve liquid resources and/or show better profits to meet analysts' earning forecasts. However, the manager's attitude to defer payments is countered by a loss in productivity and reduction of the hotel property asset life, offsetting the possible increase in expected returns. In the bottom line, a lower operating leverage will decrease the unlevered beta component of the discount rate, and, all factors remaining equal increase the hotel's financial valuation.

VII. CONCLUSION

In this paper, we developed on the topic of operating leverage and used it to analyze the hotel industry. Microeconomics provided the general framework to understand firm behavior, especially with respect to its cost-structure and how it evolves over time. We found a significant relationship between the Mandelker and Rhee proxy and the conventional fixed and variable approach to estimate the degree of operating leverage for hotels.

We developed our analysis into assessing the impact of the DOL on stock returns; covering a sample of 10 U.S. listed lodging firms. From a corrected dynamic LSDV model, the statistical significance of our estimates and the robustness of the model allowed us to conclude that the relationship between the stock returns and operating leverage exists in the selected sample of US firms in the hotel industry. Using three approaches to correct for Nickell's bias and sample selection, we obtained estimates that greatly improved on previous studies and led to gains in estimate consistency.

VIII. SUGGESTION FOR FURTHER RESEARCH

In our paper, we discussed the concerns by Lord (1999) regarding the techniques to measure operating leverage. The techniques need to further take into account the cost-structure dynamics and the downward bias present in the estimates.

As regards the dynamic panel data model, Bruno suggests calculating a bootstrap variance-covariance matrix for the corrected LSDV using repetition, like for a Monte Carlo simulation. In Bruno (2005), he claims that his procedure "continues to work also in the presence of gaps in the exogenous variables, although in this case, bootstrap samples for each unit are truncated to the first missing value encountered".

There is a significant lag in literature to measure the impact of the DOL on *growth* and *value* stocks separately. In the spirit of a Fama-French model, further research is required to motivate the relationship of the DOL to market capitalization, leverage ratio (debt-to-equity), and book-to-market value of equity. While observing our sample, we didn't find a significant relationship between the degree of operating leverage and the three factors stated above. Some previous research on other industries found a positive association with firm size and a negative association with the book-to-markets.

BIBLIOGRAPHY

Ahmed F., Zaidi J.A., Chawla M.A., (2004). “Lodging Industry Rating Methodology” JCR-VIS Credit Rating Company Limited, Karachi, Pakistan

Anderson, Theodore W. and Chen Hsiao (1982). “Formulation and Estimation of Dynamic Models Using Panel Data.” *Journal of Econometrics*, 18,570-606.

Arellano, Manuel and Stephen Bond (1991). “Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations.” *Review of Economic Studies*, 58, 277-297.

Ball, R. and P. Brown (1966). “An Empirical Evaluation of Accounting Income Numbers”, *Journal of Accounting Research*, 6, 6, 159-178.

Blundell, R. and S. Bond. (1998). “Initial Conditions and Moment Restrictions in Dynamic Panel Data Models.” *Journal of Econometrics*, 87, 115–143.

Bruno, G. S. F. (2004). “Approximating the Bias of the LSDV Estimator for Dynamic Unbalanced Panel Data Models.” CESPRI Working Paper no. 159, available at: http://www.cespri.unibocconi.it/.

Bruno, G. S. F. (2005). “Estimation and Inference in Dynamic Unbalanced Panel Data Models with a Small Number of Individuals.” CESPRI Working Paper no. 165, available at: http://www.cespri.unibocconi.it/.

Bun, Maurice and Jan Kiviet (2001). “The Accuracy of Inference in Small Samples of Dynamic Panel Data Models.” Tinbergen Institute Discussion Paper TI 2001-006/4.

Bun, M. J. G. and J. F. Kiviet (2003). “On the diminishing returns of higher order terms in asymptotic expansions of bias”. *Economics Letters,* 79, 2, 145-152.

Canning, John B. (1929). The Economics of Accountancy. New York: The Ronald Press Co.

Chung, K.H. (1989). “The Impact Of The Demand Volatility And Leverages On The Systematic Risk Of Common Stocks.” *Journal of Business Finance and Accounting*, 16, 3, 343-360.

Coombs P., (2003). IT Project Estimation, Cambridge University Press.

Dugan, M.T., Minyard, D.H. and Shriver, K.A. (1994). “A re-examination of the operating leverage-financial leverage tradeoff hypothesis.” *The Quarterly Review of Economics and Finance,* 34, 3, 327-334.

Dugan, M.T. and Shriver, K.A. (1992). “An empirical comparison of alternative methods for the estimation of the degree of operating leverage.” *The Financial Review,* 27, 2, 309-321.

Elgonemy A., (1999). “The Pricing of Lodging Stocks: A Reality Check” Hotel Online Special Report, PKF Consulting.

Földvári, Péter (2006). “A Quantitative Analysis of Foreign Trade and Foreign Direct Investments” Universiteit Utrecht Netherlands , PhD. Thesis

Gahlon, J. M. and J. A. Gentry (1982). “On the relationship between systematic risk and the degree of operating and financial leverage.” *Financial Management*, 11, 15-23.

Gourio, François (2005). “Operating Leverage, Stock Market Cyclicality, and the Cross-Section of Returns.” University of Chicago Manuscript.

Graham, I. C., and Harris, P. J. (1999). “Development of a profit planning framework in an international hotel chain: A case study.” *International Journal of Contemporary Hospitality Management*, 11(5), 198–204.

Griffin, H. F. and Dugan, M.T. (2003). “Systematic risk and revenue volatility.” *The Journal of Financial Research*, 26, 2, 179-189.

Hamada, R. S. (1972). “The Effects of the Firm's Capital Structure on the Systematic Risk of Common Stocks.” *Journal of Finance*, 27, 435-452.

Hanson B. (2004). “U.S. Lodging Industry Briefing and Forecast.” *Global Hospitality Industry Leader*, PriceWaterhouseCoopers LLP

Huffman, S.P. (1989). “The impact of the degrees of operating and financial leverage on the systematic risk of common stocks: another look.” *Quarterly Journal of Business and Economics*, 28, 1, 83-100.

Jehle, G.A. and Reny, P.J. (2003). Advanced Microeconomic Theory. 2nd edition, Paperback. Addison-Wesley, Boston.

Judson, R. A. and A. L. Owen (1999). “Estimating dynamic panel data models: a guide for macroeconomists.” *Economics Letters*, 65, 9-15.

Kiviet, J. F. (1995). “On Bias, Inconsistency and Efficiency of Various Estimators in Dynamic Panel Data Models.” *Journal of Econometrics*, 68, 53-78.

Lev, B. (1974). “On the Association between Operating Leverage and Risk”, *The Journal of Financial and Quantitative Analysis*, 9, 4, 627-641.

Lévesque G., Little D., “Characteristics and performance of hotels and motor hotels.” *Service Indicators*, Canadian Minister of Industry. 2000

Lord, R. (1999). “Properties of Time Series Estimates of Degree of Leverage Measures”. SSRN Working Paper.

Mandelker, G. and S. G. Rhee (1984). "The Impact of the Degrees of Operating and Financial Leverage on Systematic Risk of Common Stock" *Journal of Financial and Quantitative Analysis*, 19, 1, 45-57.

McDaniel, W. R. (1984). “Operating Leverage and Operating Risk”, Journal of Business, Finance, and Accounting, 11, 1, 113-125.

de Medeiros, O. R; P. R. Lustosa; and J. A. Dantas (2006). “The Impact of the Degree of Operating Leverage on Stock Returns: An Empirical Study in the Brazilian Market.” SSRN Working Paper

Nickell, Stephen (1981). “Biases in Dynamic Models with Fixed Effects.” *Econometrica*, 49, 6, 1417-1426.

Nicolau, Juan L. (2003). “Leveraging profit from the fixed-variable cost ratio: the case of new hotels in Spain”, *Tourism Management*, 26, 105-111.

O’Brien, T.J. and Vanderheiden, P.A. (1987). “Empirical measurement of operating leverage for growing firms.” *Financial Management*, 16, 2, 45-53.

Presbitero, Andrea F. (2005). “The debt-growth nexus: an empirical analysis” Università Politecnica delle Marche. Preliminary draft.

Rushmore, S. (1994). “An overview of the hotel industry: past, present and future.” *The Real Estate Finance Journal*, Spring, 5-14.

Rushmore, S., and Goldhoff, G. (1997). “Hotel value trends: Yesterday, today and tomorrow.” *Cornell Hotel and Restaurant Administration Quarterly*, 38(6), 18-29.

UK Commission of Competition Reports (2003). “Estimation of the Elasticities of the Residual Supply of Gas”

Wang, X. H. and B. Z. Yang (2001). “Fixed and Sunk Costs Revisited.” *Journal of Economic Education*, 32, 2, 178-185.

APPENDIX I – DERIVATION OF DOL WITH RESPECT TO TIME

Since $DOL_t = \frac{p_t - w_t}{p_t - w_t - \overline{w}_t}$, the derivative of DOL with respect to time is,

- $\dot{DOL}_t = \frac{dDOL_t}{dt} = \frac{\partial DOL_t}{\partial p_t}\frac{dp_t}{dt} + \frac{\partial DOL_t}{\partial w_t}\frac{dw_t}{dt} + \frac{\partial DOL_t}{\partial \overline{w}_t}\frac{d\overline{w}_t}{dt}$

- $\dot{DOL}_t = \frac{p_t - w_t}{(p_t - w_t - \overline{w}_t)^2}\left(\frac{d\overline{w}_t}{dt}\right) - \frac{\overline{w}_t}{(p_t - w_t - \overline{w}_t)^2}\left(\frac{dp_t}{dt}\right) + \frac{\overline{w}_t}{(p_t - w_t - \overline{w}_t)^2}\left(\frac{dw_t}{dt}\right)$

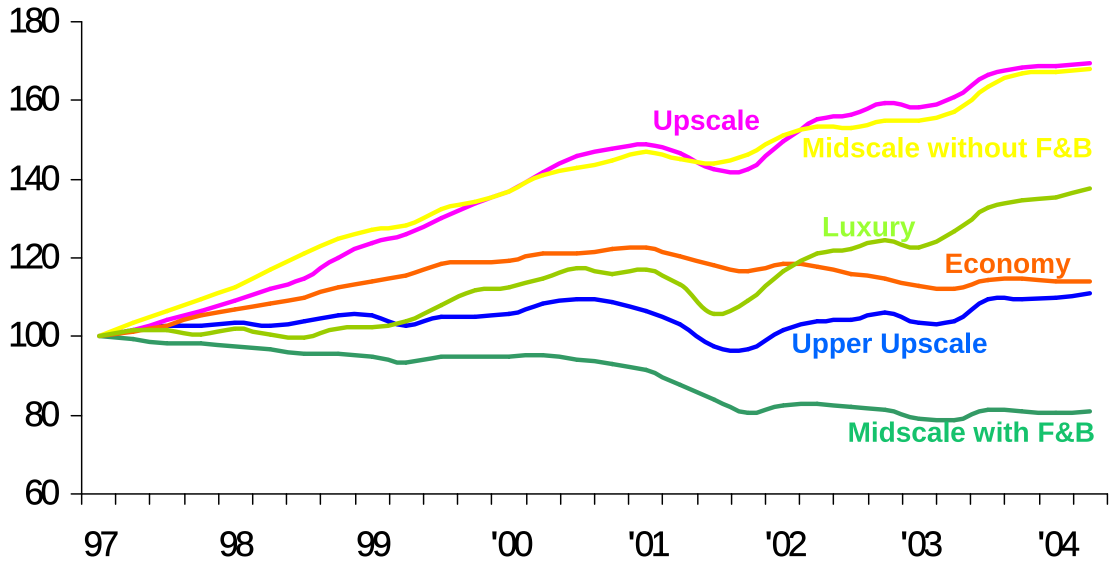
- $\dot{DOL}_t = \frac{1}{(p_t - w_t - \overline{w}_t)^2}\left[(p_t - w_t)\left(\frac{d\overline{w}_t}{dt}\right) - \overline{w}_t\left(\frac{dp_t}{dt}\right) + \overline{w}_t\left(\frac{dw_t}{dt}\right)\right]$
- $\dot{DOL}_t = \frac{1}{(p_t - w_t - \overline{w}_t)^2}\left[(p_t - w_t)\dot{\overline{w}} - \overline{w}_t\dot{p}_t + \overline{w}_t\dot{w}_t\right]$

reaching our desired function (2.8)

$$\mathrm{D\dot{O}L}_t = \frac{(p_t - w_t)\dot{\overline{w}}_t - \overline{w}_t(\dot{p}_t - \dot{w}_t)}{(p_t - w_t - \overline{w}_t)^2}$$

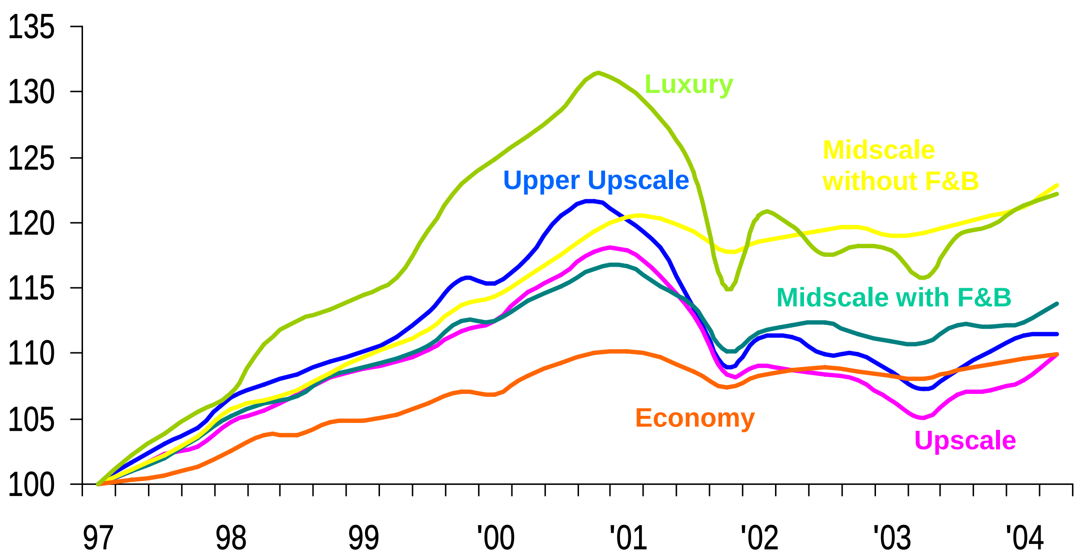
APPENDIX II – SALES AND ADR PER HOTEL CLASS

A - Rooms Sold (Average Daily, Seas. Adj.) in 1997 Q1 = 100



P.S. F&B = Food & Beverage facilities (Restaurants, Bars, Banquets, Dinings, etc)

B - Average Daily Rate (Seas. Adj.) in 1997 Q1 = 100



Source: PricewaterhouseCoopers LLP based on Smith Travel Research data

APPENDIX III – LDSV CORRECTED RESULS AND TEST OUTPUTS

LSDV dynamic regression

ner	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
ner						
L1.	-.2566824	.0803789	-3.19	0.001	-.4142222	-.0991427
nedol	.1801593	.0628212	2.87	0.004	.057032	.3032865

Wilcoxon Signed Rank test[26]

```
unadjusted variance        96.25
adjustment for ties        -1.75
adjustment for zeros        0.00
                         -------
adjusted variance          94.50

Ho: logs = linear
             z =    2.315
    Prob > |z| =    0.0206
```

Arellano-Bond Autocorrelation Test[27]

One-step results

D.ner	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
ner						
LD.	-.3704195	.0950942	-3.90	0.000	-.5568008	-.1840382
nedol						
D1.	.1565943	.0779046	2.01	0.044	.003904	.3092846
_cons	.0136542	.0403607	0.34	0.735	-.0654514	.0927598

```
Sargan test of over-identifying restrictions:
         chi2( 35) =   114.08       Prob > chi2 =  0.0000

Arellano-Bond test that average autocovariance in residuals of order 1 is 0:
         H0: no autocorrelation   z =    -5.01   Pr > z =  0.0000
Arellano-Bond test that average autocovariance in residuals of order 2 is 0:
         H0: no autocorrelation   z =    -3.03   Pr > z =  0.0024
```

[26] The test was performed using Stata's KORNBROT command.
[27] The test was performed using Stata's XTBOND2 command.

Wald Test for Panel Heteroskedasticity[28]

```
Modified Wald test for groupwise heteroskedasticity
in fixed effect regression model

H0: sigma(i)^2 = sigma^2 for all i

chi2 (44)  =    77373.72
Prob>chi2 =       0.0000
```

Fisher-Augmented Dickey-Fuller Unit Root Test [29]

```
Fisher Test for panel unit root using an augmented Dickey-Fuller test (1 lags)

Ho: unit root

          chi2( 88)     =   251.8854
           Prob > chi2  =        0.0000
```

Fisher-Phillips-Perron Unit Root Test

```
Fisher Test for panel unit root using Phillips-Perron test (2 lags)

Ho: unit root

          chi2( 84)     =   558.2804
           Prob > chi2  =        0.0000
```

[28] The test was performed using Stata's XTTEST3 command.
[29] The test was performed using Stata's XTFISHER command.