THE IMPACT OF MULTIPLE WORK ARRANGEMENTS ON LABOR PRODUCTIVITY

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ABSTRACT

Measuring productivity is an important performance measure for decision making and resource allocation in managerial accounting. One factor which may affect labor productivity is the use of multiple work arrangements (MWA) such as fulltime employees, contract workers and independent contractors. Most of the prior research in accounting on MWA focused on the behavioral aspects of different work scenarios. There has been limited research in managerial accounting about the impact of MWA on the economics of labor productivity which is the focus of this study.

This paper examines the economic impact of MWA in long haul trucking companies. Specifically, we investigated the use of independent contractors (owner-operator drivers) versus fulltime company drivers and their impact on labor productivity. In a managerial context, owner-operators represent soft capacity and company drivers represent hard capacity. Our results indicate that owner-operators will improve the productivity of the company. There is a significant and positive association between the use of owner-operators and labor productivity. Prior studies did not find this positive relationship. Our results indicate that owner-operators can influence the variance of labor productivity either positively or negatively. However, there is more variability associated with the performance of owner-operators than there is with company drivers.

INTRODUCTION

This study investigates the influence of multiple work arrangements (MWA) such as full-time employees and independent contractors on the labor productivity in long-haul trucking companies. Specifically, we examine whether the levels of soft capacity in production affect the levels and the variances of labor productivity. Balakrishnan and Sivaramakrishnan (2002) define soft capacity as the resources having constraints that can be relaxed with a premium and hard capacity as the resources having constraints that cannot be relaxed in the short run. In this study, the independent contractors are considered as flexible resources (acquired as used and needed). Using the Motor Carrier Financial & Operating Information database, we compare the level and the variance of labor productivity across firms with different levels of soft capacity usage. The findings suggest that the level and the variance of labor productivity are significantly associated with the soft capacity ratio. Ittner and Larcker (1998b) suggest that there are many firm-specific, structural and environmental factors affecting the use and performance consequences of performance measures. These results provide empirical evidence that production capacity based on multiple work arrangements affects labor productivity as a performance measure. We show that the measure of multiple employment arrangements such as the soft capacity ratio associates negatively with the variance of labor productivity and positively with the level of labor productivity. The findings can help owners increase the congruence of the performance measures to management objectives and improve investors' understanding of the information content of labor productivity as a non-financial performance measure in the firm's valuation process.

In recent years, using multiple work arrangements (MWA) such as full-time employees, contract workers and independent contractors has become a prominent way of organizing production capacity for companies in different industries and professions (Lepak et al.. 2003; Matusik and Hill 1998; Davis-Blake and Uzzi 1993). For instance, according to the Current Population Survey (CPS) conducted by the Bureau of Census, 10.3 million people or 7.4 percent of the employed were working as independent contractors in February 2005. The proportion of nonstandard workers to the total employed in the U.S. is estimated to be as high as 26.3 percent in February 1995 (Houseman and Polivka 1999). Kalleberg, Reskin and Hudson, 2000, define standard employment arrangements as "the exchange of a worker's labor for monetary compensation from an employer, with work done on a fixed schedule, usually full-time, at the employer's place of business, under the employer's control, and with the mutual expectation of continued employment." As this discernible trend towards the nonstandard work arrangements and MWA becomes more diffuse and diverse, it is important for both internal and external decision makers to understand more about the implications of the employers' labor utilization or production capacity strategy on labor productivity.

Among different performance measures, productivity measures have historically received little attention in the existing accounting research [see Banker, Datar and Kaplan (1989) and Callen, Morel and Fader (2005)]. However, productivity is one of the most important performance measures used by corporate managers in making investment decisions and decisions regarding the utilization of both tangible and intangible assets. Banker, Datar and Kaplan (1989) suggest that productivity improvement can come from intangibles such as efficient labor use; new capital investment; or process improvement efforts. Productivity improvement is generally regarded as a driver of a firm's long-term profitability and value and, therefore, productivity improvement is an important leading indicator of a firm's performance (Kaplan 1983). To date, however, there is little or no empirical research in accounting about the impact of MWA on labor productivity. The fact that little is known about the factors that affect the information content of labor productivity measures may limit firms from fully utilizing productivity measurements to monitor and evaluate managers for internal control and contracting purposes. Also, companies may not be able to design effective labor productivity improvement programs if they do not understand the potential factors that affect labor productivity. This would likely have a negative impact on the firms' sustainable competitiveness and their future performance. Moreover, it may affect their use of labor productivity measurements to assess a firm's expected future payoff by potential investors.

This study proceeds as follows. We will review the literature related to the study and provide an overview of the trucking industry and the van truckload business segment. Then we discuss the development of our hypothesis, research methodology and describe the data. Next, the results of hypothesis testing are reported and discussed. Finally, we summarize our conclusions.

LITERATURE REVIEW

Multiple work arrangements are the various combinations of standard (i.e. full time, continue indefinitely and under the employer's supervision) and non-standard (i.e. part-time, temporary and independent contractor work) employment relationships in organizations (Kalleberg 2000, 2001). The use of MWA is increasingly widespread (Houseman 2001). For example, from 1972 to 2000, the personnel supply employment (temporary workers) grew more than 10 times from 0.27 percent to 2.81 percent while the total nonfarm employment only increased less than 2 times from 71 million to 127 million workers (Wenger and Kalleberg 2006). The proportion of nonstandard workers to the total employed in the U.S. is estimated to be as high as 26.3 percent in February 1995 (Houseman and Polivka 1999).

The study of the consequences and implications of MWA focuses on the differences that MWA bring to the workplace. Broschak and Davis-Blake (2006) show that higher proportions of nonstandard workers such as part-time and temporary workers are associated more with unfavorable attitudes toward supervisors and co-workers, higher turnover intentions and lower job-related helping behaviors. Houseman and Polivka (1999) note nonstandard workers, except for independent contractors, do not have the same job stability as the standard workers. Matusik and Hill (1998) suggest that MWA can accumulate and create valuable knowledge for organizations and provide a competitive advantage in a dynamic environment. Smith, 2002 suggests that MWA can be potentially beneficial for all employees. Lepak et al. (2003) show the levels of knowledge-based employment and contract work are positively related to future firm performance. However, other studies also show that firms depending on independent contractors are significantly less profitable than firms depending completely on standard employees (Corsi and Grimm1987; Ozment et al. 2002). To our best knowledge, empirical studies about the potential impact of independent contractors on labor productivity do not exist.

Traditionally, financial performance measures (FPMs) have been used to monitor and evaluate managers or firms. However, these measures have been criticized as lagging indicators that encourage shortsighted effort and discourage farsighted financial performance in companies. More specifically, these measures assess only the utilization of tangible assets in prior periods. As companies build their strategies and operations around intangible assets, such as business processes and human resources, many researchers and practitioners argue that non-financial performance measures (NFPMs) may be better measures for assessing managerial performance. These measures are purported to better measure the creation and deployment of these intangible assets, and may be better, more relevant indicators of long-term corporate health than the traditional accounting metrics.

Productivity is considered to be one of the key drivers of firm value by both economists and accountants (Baily et al. 1981, Bao and Bao 1989). Productivity measures are ratios of outputs to inputs that allow users to compare and understand differences in the physical use of resources within companies at different time periods or across different companies in the same industry at the same time. There are two types of productivity measures: total factor productivity, which measures the ratios of total outputs to total inputs; partial productivity, which measures the ratios of the outputs to a specific input.

Kaplan (1983) contends that firm-level productivity measurements can provide information about a firm's comprehensive measure of the real efficiency gains, which allow users to separate the unsustainable value created by the changes in relative costs and prices from the sustainable value gained by real improvement in efficiency in financial performance measurements. This suggests that the net benefits from investments in productivity may not be fully captured in contemporaneous FPMs because improvement in productivity is assumed to be sustainable into the future. It also implies that a productivity measure can provide information about the manager's action that may affect future profitability. Said, HassabElnaby and Wier (2003) report that when firms employ both financial and nonfinancial performance measures such as productivity in their compensation contracts, they have significantly higher firm performance.

In general, there are only limited empirical studies of the MWA's impact on firm level performance. Ozment, Spraggins and Tokar (2002) study the effects of independent contractors (owner-operators) usage by truckload carriers on productivity and profitability. They suggest that the carriers relying on standard employment (company drivers) have better performance than the carriers relying on the nonstandard employment (owner-operators). They also suggest that carriers depending on company drivers are more profitable because these companies can charge a premium for their service when compared to the carriers relying on owner-operators.

Corsi and Stowers (1991) suggest that carriers relying on owner-operators (independent contractors in the trucking industry) are less competitive because of higher insurance costs, lower service quality and reliability, and more safety problems associated with the owner-operators. They also suggest that the carriers' operational strategy, regulatory environment and industry life cycle are the determinants of MWA. They argue that as carriers compete on both costs and service levels, carriers will use fewer owner-operators.

Overall, these empirical studies presented mixed evidence on the MWA's impact on firm performance. On one hand, the studies that show a positive relationship between MWA and firm performance tend to suggest firm performance is associated with the competitive advantage of flexibility provided by the use of MWA (Wright and Snell, 1998). On the other hand, studies that show a negative relationship between MWA and firm performance tend to suggest that transaction costs of MWA outweigh its benefits, and therefore have a negative impact on firm performance. Also, most of these studies, except Lepak et al. (2003), do not investigate the factors that may enhance or diminish MWA's impact on firm performance.

TRUCKING INDUSTRY

Since companies' operating data generally are not accessible, archival studies on MWA and labor productivity are rare. However, the trucking industry provides an excellent opportunity to study these topics because Federal regulations require all trucking companies with adjusted annual operating revenue of three million dollars or more to file Motor Carrier Financial & Operating Information with the Federal Motor Carrier Safely Administration. Therefore, data for the FPMs and NFPMs of both publicly-traded and privately-held trucking companies were available from the Department of Transportation.

The trucking industry can be sub-divided into three major segments. One is the segment separated by the length of haul. Trucking companies can be categorized into ones that provide primarily intercity services (long haul) and the ones that provide services within-city (short haul). Second is the segment divided by the availability to the public. Trucking companies can either move the goods of others for payment (for-hire) or move their own goods primarily (private-carriage). Third is the segment separated by the lot size. Within the for-hire segments, companies can either move truckloads lots (TL) of goods from origin to destination directly, or companies can consolidate and move less-than-truckload lots (LTL) of goods through a network of terminals.

The trucking industry was highly regulated between 1935 and 1980. The Motor Carrier Act of 1980 changed the industry tremendously. It eliminated the regulatory barriers to entry, particularly the requirement for a route and commodity-specific operating requirement. It lifted the pricing restrictions and allowed companies to develop their operating capacity without restrictions. It provided the opportunity to the truckload (TL) sector to become the biggest segment in the industry. The trucking industry has evolved into a mature, highly competitive and fragmented industry since deregulation in 1980.

Although deregulation brought competition and huge gains in productivity to the industry, it also posed many challenges to the industry. As trucking rates per mile declined significantly, so did profit margins. Publicly traded truckload carriers, on average, can only make around a five percent profit margin. Trucking companies compete with each other mainly on the basis of operation efficiency and utilization of existing resources; however, the investment and development of new resource positions are crucial for firms to achieve sustained growth (Pettus 2003).

The TL segment of the trucking industry was selected for analysis for several reasons. First, compared to $27 billion revenue in the less-than-truckload (LTL) sector, the TL segment, with total revenue of $110 billion, is the largest for-hire industry segment in terms of total revenue. There are about 53,000 TL firms, of which 40,000 are very small, with five or fewer tractors. The remaining 13,000 TL companies, a large number compared to any other segments of the for-hire business, generate about 91 percent of sector revenue.

Second, the TL segment is quite homogeneous in its operating characteristics and market structure, but is different from the operating structure faced by the LTL sector and the private carriage sector. According to the U.S. Department of Transportation, 43 percent of the total TL revenue is with small and middle-sized TL firms (firms with fewer than 100 tractors), while 88 percent of the total TL revenue is from long-haul service. Boyer and Burks (2003) suggest that in order to measure the productivity in the trucking industry correctly, it is important to control for the equipment type and the heterogeneity of the sector. The TL sector, therefore, offers an opportunity to focus on relatively homogeneous outputs and equipment. Measuring productivity of the trucking companies by the standard ton-mile measure per truck or per driver in the TL sector will have less measurement error caused by the factors such as drivers' wages, fuel costs and geographic locations.

Third, high driver turnover is a serious problem faced by the TL carriers. This is because TL drivers have irregular and shifting work times, long working hours on the road, and long periods of time away from home. In order to alleviate the problem of high driver turnover, many TL companies use owner-operators (independent contractors). In addition, managers can improve companies' performance and productivity by contracting or outsourcing more owner-operator drivers in their operations. There are approximately 300,000 owner-operators in total. Most of them are working under contracts to larger TL companies.

The owner-operator drivers are considered as the soft capacity, which does not require commitment in investment in both equipment (tangible assets) and management (intangible assets) relative to the decision of employing company-hired drivers, which requires investment and commitment in both capital assets and human resources. However, owner-operator drivers in general are considered to be less loyal (the turnover is higher) and less cooperative and provide less customer satisfaction compared to the company-hired drivers. Although the owner-operators are considered as part of the capacity of those companies, they are different from the capacity provided by the company-hired drivers in terms of quality of service, dependability, consistency, risk-sharing properties and profitability.

Moreover, capacity utilization is crucial to the survival of a TL company. Since individual shippers usually do not require round trip service and individual drivers do not know all the routes equally well, high capacity utilization depends largely on a firm's ability to identify and organize demands of two or more shippers for individual trucks and trips, and to match an appropriate driver with the right trip and route. A TL company's dispatching staff constantly tries to allocate optimally the company's equipment and drivers, both company drivers and owner-operators, to the available loads, within a host of cost considerations. Since owner-operators are not employees of a trucking company, they have full discretion in accepting a job assignment (haul) and undertaking any activities to maximize the return from each job. The company drivers, however, usually have much less discretion in picking the haul and selecting their routes and stops. The usage of owner-operators may present a variable in maximizing a trucking company's capacity utilization and labor productivity. The capacity decision between hiring company drivers and contracting with owner-operators in the TL firms, therefore, provide an opportunity to investigate whether labor productivity is related to the types of capacity.

HYPOTHESIS DEVELOPMENT

We argue that the information content of productivity measurements is related to MWA decisions. Generally, MWA can be a strategic decision of the production capacity modes, i.e., the soft capacity and hard capacity, which will not only affect the production cost behavior, but also the productivity, especially labor productivity. Labor productivity is an important performance measure that assesses the utilization of intangible assets such as human resources management practices which can be a source of sustained competitive advantage and can impact a firms' performance (Wright and McMahan 1992; Wright et al. 1994; Huselid 1995). MWA has a direct impact on the production capacity in many industries. In some cases, it not only affects the composition of direct labor used in production, it also affects the investment of production assets. These influences are reflected in the labor productivity measure.

From the production perspective, the main differences between soft capacity and hard capacity are in the levels of control, stability and flexibility. The hard capacity can provide higher levels of control and stability to the production of a company over the soft capacity while the soft capacity can increase a firm's flexibility in terms of product variety and production quantity.

Companies usually have better control over hard capacity because the company can give specific work instructions to the employees, make plans and arrangements for asset usage, monitor labor and asset utilization and make necessary adjustments and corrections. When companies use soft capacities such as independent contractors, they externalize administrative control over both the labor and the operating assets and do not make day-to-day work arrangements for the independent contractors. So it seems that a more stable production is related to the use of more homogeneous hard capacity because companies' internal labor market can increase employees' performance stability (Sorensen 1983), and companies' systematic asset management practice, e.g. scheduled maintenance, can decrease equipment breakdowns in the production process and therefore the variance of labor productivity.

However, it is also possible that the proportion of soft (hard) capacity used by a company can decrease (increase) the variance of labor productivity. For example, when companies with a high proportion of hard capacity face decreases (increases) in demand, they are less flexible to cut down (increase) their hard capacity immediately. This will result in a higher variance of labor productivity. So it follows that the variance in labor productivity is likely to be a function of companies' capacity choice, but whether the relationship is positive or negative is an empirical question. Therefore, we hypothesize the following:

Hypothesis 1: The variance in labor productivity changes with the proportion of soft capacity.

Some studies in the trucking industry suggest that employing company drivers can lead to high levels of asset utilization and therefore increase productivity and reduce operating expense (Corsi and Grimm 1989). However, as the authors point out, these findings should be interpreted with caution because possible confounding factors such as the technology are not controlled. Based on the following arguments, we suggest that compared to the companies with low levels of soft capacity, companies with high levels of soft capacity would have higher average labor productivity. First, the soft capacity offers companies a way to better match different production resources to different products' production requirements. For example, a trucking company can utilize its owner-operators more in the long-haul service since the owner-operators prefer long-hauls to short-hauls. As the soft capacity is arranged to specialize more in providing a specific product or service, there is a positive influence on the soft capacity's productivity. Second, based on the assumption that independent contractors are less risk averse than the average employee, it is less costly to motivate the independent contractors to work hard. In other words, given the same level of incentive, the independent contractors are more likely to exert more effort than the employees. These arguments suggest that the average labor productivity is likely to be a positive function of companies' capacity choices since soft capacity is likely to allow specialization and the entrepreneur motivation. We, therefore, make the following hypothesis:

Hypothesis 2: The average labor productivity of companies increases with the levels of soft capacity.

DATA AND RESEARCH METHODOLOGY

We begin with all 12069 observations of 3769 trucking companies that filed Motor Carrier Financial & Operating Information with the Federal Motor Carrier Safety Administration (FMCSA) from 1999 to 2003. Federal regulation requires all trucking companies with adjusted annual operating revenue over $3 million to file this report annually. Until 2003, the FMCSA made the data available in electronic form. Since 2004, the data is collected is but is no longer available in electronic form. The FMCSA collects financial data such as balance sheet and income statement data along with operating information such as tonnage, mileage, employees and transportation equipment. All motor carriers are required to use Generally Accepted Accounting Principles in reporting their financial data and they are required to follow specific guidelines in reporting their financial and operating information.

We select all the truckload firms from the 3769 trucking companies. A total of 6513 observations of 2167 firms are included in the initial sample. The range of sales revenue of these firms is between 3 million to over 2 billion dollars. In order to make the sample firms more comparable, we exclude 5707 observations of 1875 firms that have less than 30 million in sales revenue from the sample.

Table 1 Sample Selection Criteria for Analysis from Year 1999-2003 and Descriptive Statistics

Panel A: Sample Selection Procedure

Full Sample	# of Obs	# of firms
Firms in the Motor Carrier Financial & Operating Information	12069	3769
Exclusion of firms that are not in the truckload (TL) segment	5556	1602
Exclusion of firms that have less than 30 million dollars of sales revenue	5707	1875
Exclusion of firms that do not have 4 or more consecutive years records	336	192
Exclusion of firms that are NFH, LTL or have errors	91	19
Total:	379	81

NFL= Not for hired, LTL= Less than truckload.

Panel B: Descriptive Statistics for all variables tested in the TL Carriers Samples

Variables	Mean	Median	Minimum	Maximum	Std Dev
SCR (n=379)	0.282	0.1617	0	1	0.308
TRAC (n=377)	839.3024	314	0	10649	1547
CID (n=271)	0.0644	0.0388	-0.5683	1.1158	0.1751
PROD (n=344)	98918	99149	26110	204271	26775
TRL (n=370)	2.0819	2.0162	0	8.2513	1.1285
MSS (n=375)	0.1544	0.0745	0.0137	0.9397	0.1769
WAGES (n=361)	35472	36598	0	62162	11928
PTR (n=375)	0.0737	0.013	-0.0024	0.8372	0.128
VPROD (n=260)	151399233	33282910	21812.87	5161606684	394091420
LSCR (n=297)	0.2874	0.1802	0	1	0.3072
CWPD (n=279)	0.0311	0.0158	-0.5257	0.9521	0.1572
CRPM (n=263)	0.0304	0.0274	-1.3532	1.2341	0.1916
CTND (n=298)	69.31	6.3489	-1424	6058	430.37

The 30 million sales revenue cutoff point is selected for two reasons. First, according to the American Trucking Association, firms with sales revenue of less than thirty million are considered to be small trucking companies. Second, the smallest sales revenue of a public trucking company reported in the sample is about $31 million dollars. To control for the possibility of unusual management behavior and firm performance due to bankruptcy or takeover, we removed 336 observations of 192 firms that do not have at least four consecutive years of records in the sample. We further dropped 9 firms that are private carriers or semi-private carriers, 1 truck-rental firm, 1 less-than-truckload trucking firm, and 6 firms that have errors in their operating information. We also consolidate the records of 3 subsidiaries into one for the analysis. Since the US DOT has not been very strict in enforcing its reporting requirement, some carriers only report limited data. We adopted the following remedies for missing data. First, in order to maintain internal consistency, we use related information from the same firm-year report to compute or estimate the missing data for 6 firm-year observations. Second, for the publicly-traded carriers, we fill out some of the missing information of 17 firm-year observations from their corresponding annual financial reports 10-K and Other Definitive Proxy Statements Def-14A. Since our hypotheses require different sets of variables, we kept the firm observations that have all variables for at least one hypothesis testing. Finally, in order to remove the effects of outliers from the data, we drop observations with the highest and lowest 0.5 percent of the values for each variable in each year (Kothari and Zimmerman 1995). The final sample includes 379 observations of 81 firms. The sample selection procedures are summarized in Table 1.

RESEARCH METHODOLOGY

To test whether the variance of labor productivity of TL carriers is affected by the proportional use of soft capacity, we estimate the following regression model across all TL carriers for H1:

$$VPROD_{it} = \alpha_t + \beta_1 SCR_{it} + \beta_2 LSCR_{it} + \beta_3 CID_{it} + \beta_4 CTND_{it} + \beta_5 CWPD_{it} + \beta_6 CRPM_{it} + \beta_7 TRL_{it} + e_{it}, \tag{1}$$

where
i = trucking company index;
t = year index for 1999 to 2003;
VPROD = variance in labor productivity, measured by the square of changes in average labor productivity, which is the change in the average miles driven by a driver;
SCR = the soft capacity ratio, total number of owner-operators scaled by the total number of drivers (both owner-operators and company drivers);
LSCR = the lagged SCR; (SCR = total number of owner-operators scaled by the total number of drivers)
CWPD = the change in average wages per company driver;
CTND = the change in the total number of drivers
CRPM = the change in average revenue per mile;
CID = changes in total miles driven;
TRL = the average number of trailers available per driver;
e = error term.

The coefficient of interest is β_1, in model 1. We expect that the coefficient is significantly different from zero if the variance of productivity is associated with the levels of soft capacity used by a carrier. In general, the variance of labor productivity is assumed to be related to the change in market demand (Lenz and Bricker 1983), and the change in the quantity of labor (CTND). However, factors such as operation strategies (Corsi and Grimm 1991), financial incentives (Durant et al 2006) and capital substitution (Dupuy and de Grip 2006) also affect the variance of labor productivity.

CID and CTND are included to control for differences in the change in demand of the carriers and the change of the number of drivers. We do not make a prediction for the coefficients on CID and CTND because the changes in demand and number of drivers can be either positive or negative. So even the magnitude of CID and CTND may be positively related to the variance, whether the coefficients are positive or zero is an empirical question.

SCR is a measurement of the proportion of soft capacity we use to test our hypothesis. As we discussed in the section of hypothesis development, the influence of the levels of SCR on the variance of labor productivity can be either positive or negative, therefore, we do not make a prediction for the coefficient on SCR. Although there may exist a non-linear relationship between the variance of labor productivity and the levels of SCR, we do not consider that special functional form in this exploratory study.

LSCR is included to control for the difference in the lagged soft capacity. Together with the current soft capacity, the LSCR also provides information about the change in SCR. We do not make a prediction for this coefficient because it can be either positive or negative.

CWPD is included to control for the differences in the change of average wages per company driver. The level of average wages per company driver can be a proxy of the effectiveness of the carriers to manage and motivate their employees to work and therefore is negatively associated with the variance of labor productivity. We do not make a prediction for the coefficient on CWPD because the change can be either positive or negative.

CRPM is included to control for the differences in the change of market position and operating strategies among the carriers. We do not make a prediction for the coefficient on CRPM because on one hand, the higher the revenue generated per mile, the more value added by carrier on average. It is more likely that carriers need to provide consistent services through more efficient management of their production resources to control the variability in the overall performance of its drivers. On the other hand, if only the owner-operators in companies can reap the benefits from the higher revenue generated per mile, and the rest of the drivers do not share the benefit, the high CRPM will create a differential motivation effect on owner-operators and company drivers, and therefore can be associated with a high level of variance in labor productivity.

TRL is included to control the degree of substituting labor with capital in carriers' operations. The coefficient on TRL should be negative if the number of trailers available per driver can make the drivers' performance become more uniform across both company drivers and owner-operators.

To test whether the average labor productivity of the firms increases with the proportion of soft capacity, we estimate the following regression model across all TL carriers for H2:

$$PROD_{it} = \alpha_t + \beta_1 SCR_{it} + \beta_2 TRL_{it} + \beta_3 MSS_{it} + \beta_4 WAGES_{it} + \beta_5 ASSETS_{it} + \beta_6 PTR_{it} + \beta_7 TRAC + e_{it}, \qquad (2)$$

where
i = trucking company index;
t = year index for 1999 to 2003
PROD = the average labor productivity, average ton miles driven by a driver;
SCR = the soft capacity ratio, total number of owner-operators
scaled by the total number of drivers (both owner-operators and company drivers);
TRL = the average number of trailers available per driver;
TRAC = the number of tractors owned or leased by a carrier at the beginning of the period;
WAGES= the average wages per company driver
PTR = the purchased transportation services from the third parties;
ASSETS = the natural log of total assets;
MSS = market share of a firm in the state where its primary operation is located;
e = error term.

TRL is included to control the degree of substituting labor with capital in carriers' operations. The coefficient on TRL should be positive if the number of trailers available per driver can decrease the drivers' down time and increase their driving hours on the road.

TRAC is included to control for the differences in the production capacity available for the company drivers. We expect this coefficient to be negative because if a carrier has more tractors, they will have more company drivers. This variable can provide information about the level of standard employees in MWA, while the SCR can provide the proportion of owner-operators in MWA. Since the number of tractors available can also represent the amount of spare equipment available for the company drivers, the bigger the base of tractors, the better support the company drivers can get to improve their productivity. In other words, the negative impact of TRAC on PROD may be offset by the positive impact; therefore we do not expect the coefficient to be of much practical significance.

WAGES is included to control for differences in company drivers financial incentives to work. We expect this coefficient to be positive. Although the effect of diminishing marginal utility of financial incentives may influence company drivers' motivation, the nonlinear impact of financial incentives on labor productivity is not modeled in this study.

ASSETS is included to control for the differences in size of the carriers. We expect this coefficient to be positive because large companies usually have more resources and better infrastructure to support their employees. For example, large companies can improve their labor productivity by optimizing both load assignments and trailer usage among their large numbers of drivers and trailers through their sophisticated dispatching technology and systems. The effect of diseconomies of scale is not considered in the model.

PTR is included to control for the effects of different levels of outsourcing on labor productivity. We expect the coefficient on PTR to be positive because if the external party can provide more efficient and productive transportation service than the carrier, then the carrier would prefer outsourcing to in-house production. The carrier will keep depending on outsourcing until the marginal productivity of both outsourcing and in-house-production become the same. In other words, we expect the labor productivity should be at least as good as the external parties. So we expect that the more purchased transportation from external parties, the higher the internal labor productivity on average. MSS is included to control for the difference in market share of the carriers. It is the sales of the sample carrier divided by the total sales reported in the same state as the sample carrier is located. We expect the coefficient on MSS to be negative because on average the larger the carrier's market share then, generally, the carrier serves more customers. Supply of heterogeneous services, in general, has a negative impact on productivity. Also, carriers with large market share may have relatively high production slack which may drive down the average labor productivity.

EMPIRICAL RESULTS

We first discuss the univariate analysis and then the multiple regression results of individual hypothesis. Table 2 presents details on correlations among all the variables used in the analysis of the impact of the levels of the soft capacity ratio on the variance and level of labor productivity (H1 and H2). It shows that among all the independent variables, only CID and TRL are significantly correlated with the VPROD. As expected, TRL is negatively and significantly correlated with VPROD ($\rho = -0.1366$) while CID is positively and significantly correlated with VPROD ($\rho = 0.1644$). The correlation between CRPM and VPROD is almost zero ($\rho = 0.0014$). It suggests that the operating strategy may not affect the variance of labor productivity. Both SCR and LSCR are positively correlated with VPROD, but not significantly. Both CWPD and CTND are negatively correlated with the VPROD, but not significantly.

The correlations between CTND, CWPD and CID are significant at the 0.05 level, while CID and CRPM are significantly negatively correlated ($\rho = -0.5683$) at less than the 0.01 level. Also, SCR and LSCR are positively and significantly correlated at less than the 0.01 level ($\rho = 0.9893$). The results suggest that multicollinearity is a concern in the multiple regression analysis. Overall, the correlations between the independent variables and VPROD do not provide preliminary support for H1.

The correlations between CTND, CWPD and CID are significant at the 0.05 level, while CID and CRPM are significantly negatively correlated ($\rho = -0.5683$) at less than the 0.01 level. Also, SCR and LSCR are positively and significantly correlated at less than the 0.01 level ($\rho = 0.9893$). The results suggest that multicollinearity is a concern in the multiple regression analysis. Overall, the correlations between the independent variables and VPROD do not provide preliminary support for H1.

Table 2: Sample Correlations: Variables tested in Hypothesis 1 and Hypothesis 2													
	PROD	SCR	TRL	MSS	WAGES	ASSETS	TRAC	PTR	VPROD	CID	CWPD	CRPM	CTND
PROD													
SCR	0.1846												
sig	-0.0006												
n	344												
TRL	0.0630	-0.1356											
sig	-0.2460	-0.0090											
n	341	370											
MSS	-0.1865	-0.0527	0.1078										
sig	-0.0005	-0.3086	-0.0393										
n	341	375	366										
WAGES	-0.0224	-0.4697	0.1106	0.0586									
sig	-0.6841	0.0000	-0.0364	-0.2696									
n	334	361	358	357									
ASSETS	0.0206	-0.2932	0.1642	0.5030	0.1571								
sig	-0.7052	0.0000	-0.0017	0.0000	-0.0030								
n	341	373	364	369	355								
TRAC	0.0639	-0.0441	-0.0018	0.0487	0.0191	0.6568							
sig	-0.2383	-0.3936	-0.9730	0.0000	-0.7181	0.0000							
n	342	377	368	373	359	371							
PTR	-0.0487	-0.0372	0.1103	0.1848	0.2494	0.2494	0.0663						
sig	-0.3710	-0.4733	-0.0348	-0.0003	0.0000	0.0000	-0.2016						
n	340	375	366	371	357	357	373						
VPROD	-0.0265	0.0364	-0.1366	-0.0654	-0.0529	-0.0905	-0.0725	0.0372					
sig	-0.6710	-0.5579	-0.0277	-0.2961	-0.4025	-0.1471	-0.2460	-0.5532					
n	259	261	260	257	253	258	258	257					
CID	0.0364	0.0219	-0.1115	0.0367	0.0581	-0.0576	-0.0592	-0.0404	0.1644				
sig	-0.5572	-0.7193	-0.0685	-0.5505	-0.3498	0.3469	-0.3332	-0.5111	-0.0078				
n	263	271	268	267	261	269	269	267	261				
CWPD	0.1188	0.0582	0.0562	-0.0407	0.2197	-0.0307	-0.0324	0.0224	-0.0685	0.1250			
sig	-0.0571	-0.3332	-0.3504	-0.5017	-0.0002	-0.6121	-0.5919	-0.7118	-0.2806	-0.0449			
n	257	279	278	275	277	275	277	275	250	258			
CRPM	-0.1143	-0.0503	0.0544	0.0402	0.0335	0.0784	0.0284	0.0935	0.0014	-0.5683	-0.0583		
sig	-0.0673	-0.4171	-0.3828	-0.5196	-0.5957	-0.2083	-0.6481	-0.1327	-0.9824	0.0000	-0.3585		
n	257	263	260	259	253	261	261	260	257	263	250		
CTND	0.0134	-0.0757	-0.0071	0.3000	-0.0136	0.2886	0.1389	-0.0124	-0.0208	0.1796	-0.1338	0.0157	
sig	-0.8366	-0.1924	-0.9040	0.0000	-0.8188	0.0000	-0.0168	-0.8323	-0.7381	-0.0030	-0.0254	-0.7995	
n	241	298	293	294	285	294	296	294	260	271	279	263	
LSCR	-0.1720	0.9893	-0.0794	-0.0455	-0.4624	-0.2854	-0.0368	-0.0377	0.0425	0.0045	0.0369	-0.0322	-0.0663
sig	-0.0076	0.0000	-0.1761	-0.4380	0.0000	0.0000	-0.5290	-0.5204	-0.4958	-0.9411	-0.5402	-0.6044	-0.2548
n	240	297	240	293	284	293	295	293	259	270	278	262	297

Variable Definitions:
VPROD = variance in labor productivity, measured by the square of changes in average labor productivity, which is the change in the average miles driven by a driver; SCR = the soft capacity ratio, total number of owner-operators scaled by the total number of drivers (both owner-operators and company drivers); LSCR = the lagged SCR; CWPD = the change in average wages per company driver; CTND = the change in the total number of drivers; CRPM = the change in average revenue per mile; CID = changes in total miles driven; TRL = the average number of trailers available per driver; PROD = the average labor productivity, average ton miles driven by a driver; TRAC = the number of tractors owned or leased by a carrier at the beginning of the period; WAGES = the average wages per company driver; PTR = the purchased transportation services from the third parties; ASSETS = the natural log of total assets; MSS = market share of a firm in the state where its primary operation is located

As expected, SCR is significantly positively correlated with PROD (ρ = 0.1866). MSS is significantly and negatively correlated with the PROD (ρ = -0.1865), while all other control variables such as TRAC, WAGES, and PTR are negatively correlated with the PROD, but not significantly. TRL and ASSETS are positively correlated with PROD, but not significantly. Many correlations between the independent variables are significant. For example, the correlations between ASSETS and MSS (ρ = 0.5030), ASSETS and TRAC (ρ = 0.6568), MSS and TRAC (ρ = 0.4873), SCR and WAGES (ρ = -0.4697) are significant at the 0.01 level. The results suggest that multicollinearity is a concern in the multiple regression analysis. Overall, the significant positive correlation between SCR and PROD provides some preliminary support for H2.

In Panel A of Table 3, we present the OLS results for the pooled cross-sectional regression model presented in Equation (1), in which the variance in labor productivity is regressed on the soft capacity ratio, lagged soft capacity ratio, change in demand and change in number of drivers and other economic determinants. There are 243 firm-year observations used in estimation. The model is explanatory with an adjusted R^2 of 20.58%. The coefficient on SCR is negative. The results suggest that variance in labor productivity decreases 342.81 miles per driver as the proportion of soft capacity increases by 1 percent, holding other variables constant.

Table 3: Tests of Impacts of SCR on Productivity for the TL carriers

Panel A: Pooled cross-sectional OLS regressions of VPROD using 243 observations for 81 TL carriers in the period of 1999 – 2003

Model: $VPROD_{it} = \alpha_t + \beta_1 SCR_{it} + \beta_2 LSCR_{it} + \beta_3 CID_{it} + \beta_4 CTND_{it} + \beta_5 CWPD_{it} + \beta_6 CRPM_{it} + \beta_7 TRL_{it} + e_{it}$, (1)

	Variables	Predicted Sign	Coefficient Estimates	t-statistic	p-value[a]
	INTERCEPT		120055692	2.25	0.0256
	SCR	?	-1.175E+09	-2.08	0.0384
	LSCR	?	1.232E+09	2.18	0.0303
	CID	?	897430145	4.96	0
	CTND	?	-83747	-1.7	0.0906
	CWPD	?	93685862	0.66	0.5073
	CRPM	?	-327668403	-2.22	0.0277
	TRL	-	-26110918	-1.41	0.0795
	Adj. R^2		0.2058		0
	No. of Obs.		243		

[a] All p-value are based on one-tailed t-tests when the coefficient sign is predicted, and based on two-tailed t-tests otherwise.
Variable Definitions: VPROD is the variance in labor productivity, measured by the square of changes in average labor productivity, which is the change in the average miles driven by a driver. SCR is the soft capacity ratio, the total number of owner-operators scaled by the total number of drivers (both owner-operators and company drivers). LSCR is the lagged SCR. CWPD is the change in average wages per company driver. CTND is the change in the total number of drivers. CRPM is the change in average revenue per mile.CID is changes in total miles driven. TRL is the average number of trailers available per driver.e is the error term.

Panel B: Cross-sectional regressions of VPROD by year for the period of 1999 – 2003

OSL estimation: Model: $VPROD_i = \alpha_t + \beta_1 SCR_i + \beta_2 LSCR_i + \beta_3 CID_i + \beta_4 CTND_i + \beta_5 CWPD_i + \beta_6 CRPM_i + \beta_7 TRL_i + e_i$, (1)

Table 3: Tests of Impacts of SCR on Productivity for the TL carriers					
Year	Variables	Predicted Sign	Coefficient Estimates	t-statistic	p-value[a]
2000	INTERCEPT		56690595	0.95	0.3453
	SCR	?	-2.234E+09	-4.51	0
	LSCR	?	2.195E+09	4.54	0
	CID	?	105329390	0.53	0.5984
	CTND	?	-47752.5	-1.03	0.3081
	CWPD	?	-110746057	-1.04	0.3025
	CRPM	?	727890072	2.09	0.0426
	TRL	-	-5523205	-0.38	0.3547
	Adj. R^2		0.4383		
	No. of Obs.		50		
[a] All p-value are based on one-tailed t-tests when the coefficient sign is predicted, and based on two-tailed t-tests otherwise.					
Panel B: Cross-sectional WLS regressions of VPROD by year for the period of 1999 – 2003 WLS Estimation: Model: $VPROD_i = \alpha_t + \beta_1 SCR_i + \beta_2 LSCR_i + \beta_3 CID_i + \beta_4 CTND_i + \beta_5 CWPD_i + \beta_6 CRPM_i + \beta_7 TRL_i + e_i$, (1)					
Year	Variables	Predicted Sign	Coefficient Estimates	t-statistic	p-value [a]
2001	INTERCEPT		294296100	2.66	0.0106
	SCR	?	-3.843E+09	-2.62	0.0116
	LSCR	?	3.842E+09	2.64	0.0111
	CID	?	-152896982	-0.33	0.7421
	CTND	?	-363633	-1.17	0.2483
	CWPD	?	-981775744	-2.22	0.0313
	CRPM	?	-162592573	-0.28	0.7789
	TRL	-	-59234060	-1.54	0.0655
	Adj. R^2		0.1749		
	No. of Obs.		58		
2002	INTERCEPT		2789768	0.08	0.9379
	SCR	?	1.187E+09	2.33	0.0236
	LSCR	?	-1.036E+09	-2.1	0.0409
	CID	?	235824572	1.74	0.0868
	CTND	?	-6992.84	-0.27	0.7886
	CWPD	?	699536347	3.56	0.0008
	CRPM	?	-121050377	-0.99	0.3244
	TRL	-	31364562	2.26	0.014
	Adj. R^2		0.318		
	No. of Obs.		61		
2003	INTERCEPT		-98989764	-1.43	0.1632
	SCR	?	-3.093E+09	-2.06	0.0471
	LSCR	?	3.196E+09	2.14	0.0404
	CID	?	1.632E+09	3.25	0.0027
	CTND	?	-37533	-0.15	0.8834
	CWPD	?	-826255888	-2.59	0.0143
	CRPM	?	-339534702	-0.9	0.3726
	TRL	-	31270860	0.8	0.7839
	Adj. R^2		0.2395		
	No. of Obs.		40		
[a] All p-value are based on one-tailed t-tests when the coefficient sign is predicted, and based on two-tailed t-tests otherwise.					

Table 3: Tests of Impacts of SCR on Productivity for the TL carriers

Panel C: Pooled cross-sectional OLS regressions of PROD using 321 observations for 81 TL carriers in the period of 1999 – 2003
Model: $PROD_{it} = \alpha_t + \beta_1 SCR_{it} + \beta_2 TRL_{it} + \beta_3 MSS_{it} + \beta_4 WAGES_{it} + \beta_5 ASSETS_{it} + \beta_6 PTR_{it} + \beta_7 TRAC + e_{it}$, (2)

Variables	Predicted Sign	Coefficient Estimates	t-statistic	p-value [a]	
INTERCEPT		-34603	-1.17	0.2445	
SCR	+	26045	4.75	0	
TRL	+	1395.03	1.1	0.137	
MSS	-	-32788	-3.05	0.0012	
WAGES	+	0.1735	1.25	0.1067	
ASSETS	+	7242.3	4.19	0	
PTR	+	9102.54	0.74	0.2289	
TRAC	-	-3.0815	-2.49	0.0068	
Adj. R^2		0.1062			
No. of Obs.		321			

[a] All p-value are based on one-tailed t-tests when the coefficient sign is predicted, and based on two-tailed t-tests otherwise.

Panel D: Pooled cross-sectional OLS regressions of PROD using 165 observations for 31 TL carriers in the period of 1999 – 2003
Model: $PROD_{it} = \alpha_t + \beta_1 SCR_{it} + \beta_2 TRL_{it} + \beta_3 MSS_{it} + \beta_4 WAGES_{it} + \beta_5 ASSETS_{it} + \beta_6 PTR_{it} + \beta_7 TRAC + e_{it}$, (2)

Variables	Predicted Sign	Coefficient Estimates	t-statistic[a]	p-value[b]	
INTERCEPT		-65893.8	-1.19	0.2349	
SCR	+	18421.08	2.06	0.0206	
TRL	+	10547.56	4.86	0	
MSS	-	-36488.7	-2.72	0.0036	
WAGES	+	0.5397	2.55	0.0059	
ASSETS	+	7283.26	2.49	0.007	
PTR	+	24190.5	0.66	0.2536	
TRAC	-	-3.2525	-1.6	0.0557	
Adj. R^2		0.3746			
No. of Obs.		165			

[a] All t-statistics are based on Newey and West's (1987) heteroscedasticity and autocorrelation consistent standard error estimates
[b] All p-value are based on one-tailed t-tests when the coefficient sign is predicted, and based on two-tailed t-tests otherwise.

Table 3: Tests of Impacts of SCR on Productivity for the TL carriers					
Panel D: Cross-sectional OLS Regression of PROD by Year Model: $PROD_i = \alpha_t + \beta_1 SCR_i + \beta_2 TRL_i + \beta_3 MSS_i + \beta_4 WAGES_i + \beta_5 ASSETS_i + \beta_6 PTR_i + \beta_7 TRAC_i + e_i$					
Year	Variables	Predicted Sign	Coefficient Estimates	t-statistic	p-value [a]
1999	SCR	+	5201.59	0.39	0.351
	TRL	+	2475.14	0.6	0.275
	MSS	-	-68793	-3.94	0.0002
	WAGES	+	0.02	0.04	0.4828
	ASSETS	+	10582	2.81	0.0037
	PTR	+	-20751	-0.9	0.1865
	TRAC	-	-3.04	-1.16	0.1266
	Adj. R^2		0.2876		
	No. of Obs.		52		
2000	SCR	+	20925	1.69	0.0484
	TRL	+	2274.6	0.82	0.2081
	MSS	-	-10664	-0.36	0.3603
	WAGES	+	0.26	0.77	0.2228
	ASSETS	+	8131.47	2.05	0.0221
	PTR	+	6750.43	0.27	0.3944
	TRAC	-	-4.59	-1.38	0.0868
	Adj. R^2		0.0137		
	No. of Obs.		71		
2001	SCR	+	26244	2.22	0.0152
	TRL	+	288.6	0.11	0.4559
	MSS	-	-48711	-2.3	0.0125
	WAGES	+	0.16	0.54	0.2961
	ASSETS	+	10065	2.74	0.004
	PTR	+	24977	1.05	0.1478
	TRAC	-	-3.68	-1.42	0.0799
	Adj. R^2		0.0813		
	No. of Obs.		71		
2002	SCR	+	36024	3.07	0.0017
	TRL	+	3317.65	1.09	0.1409
	MSS	-	-49650	-2.75	0.004
	WAGES	+	0.12	0.41	0.3417
	ASSETS	+	4703.4	1.35	0.0915
	PTR	+	25187	0.68	0.2501
	TRAC	-	-1.36	-0.48	0.3151
	Adj. R^2		0.1418		
	No. of Obs.		68		
2003	SCR	+	51174	3.17	0.0013
	TRL	+	-1557.11	-0.49	0.3135
	MSS	-	-30449	-1.27	0.1058
	WAGES	+	0.29	0.82	0.209
	ASSETS	+	7167.23	1.65	0.0526
	PTR	+	90509	2.03	0.024
	TRAC	-	-5.01	-1.45	0.0764
	Adj. R^2		0.1441		
	No. of Obs.		57		

[a] All p-value are based on one-tailed t-tests when the coefficient sign is predicted, and based on two-tailed t-tests otherwise.

However, the White's (1980) tests indicate specification and / or heteroscedasticity problems in the sample at less than the 0.05 and 0.01 level (Chi-Square = 50.77 and 225.6). On top of the heteroscedasticity, the error terms in the OLS are also likely to be autocorrelated. As a result, estimation of the standard errors of the estimators in the OLS regression is biased, and the inferences from the F-test or t-tests may be misleading.

To mitigate the influence of heteroscedasticity and autocorrelation, we perform an additional OLS estimation based on a sub-sample. From the original 243 firm-year observations sample, we can only select 34 carriers, a total of 136 firm-year observations that have complete data from 2000 to 2003 for further analysis. The model is not explanatory with an adjusted R^2 of 2.71%. Except for the CID, none of the other independent variables is significantly different from zero at the 0.05 level. Overall, the regression model does not describe the sub-sample well.

However, the cross-sectional regressions by year show that the proportion of independent contractors of a carrier's production capacity has significant explanatory power to the variance of labor productivity of the TL carriers in all four years. The results provide support for the hypothesis that the variance of labor productivity changes with the proportion of soft capacity used by a carrier.

Panel B of Table 3 reports the OLS and the WLS results for the cross-sectional regression model of Equation (1) by year. All cross-sectional regressions models by year are explanatory. The adjusted R^2 for 2000, 2001, 2002 and 2003 are 43.83%, 17.49%, 31.80% and 23.95% respectively. Except for the year 2001, the White's tests do not indicate the presence of heteroscedasticity. The coefficients of SCR in 2000, 2001 and 2003 are negative and significant (t-statistics = -4.51, -2.62 and -2.06 respectively), while it is positive and significant (t-statistics = 2.33) in 2002. At the same time, the coefficients on TRL in 2000, 2001 and 2003 are negative but not significant, and it is positive and significant in 2002. The inconsistent signs of SCR and TRL in 2002 suggest that the carriers' performance in 2002 may be systematically different from other years since the trucking industry started to recover from its depression in 2002. Overall, the results indicate that the effect of SCR on the variance of labor productivity is negative. These results provide consistent evidence for the association between the variance in labor productivity and the proportion of soft capacity. The inconsistent findings between the pooled regression on the sub-sample and the cross-sectional regression by year may be caused by insufficient power to detect the effect.

In Panel C of Table 3, we present the OLS results for the pooled cross-sectional regression model presented in Equation (2), in which levels of labor productivity are regressed on the levels of the soft capacity ratio and other economic determinants across 321 carriers in the sample. The regression is explanatory with an adjusted R^2 of 10.62%. All coefficients have the expected signs. The coefficient on SCR is positive. However, the White's (1980) tests again indicate the presence of specification and / or heteroscedasticity problems in the sample at less than the 1% level (Chi-Square = 58.19 and 164.5) and therefore the estimates of the standard errors are likely to be biased.

In order to mitigate the inference problems caused by heteroscedasticity and potential autocorrelations in the sample, we perform an additional analysis based on a sub-sample and report t-values based on Newey and West's (1987) heteroscedasticity and autocorrelation corrected covariance estimates in the Panel D Table 3. From the original 321 firm-year observations sample, we select 51 carriers that have complete data from 1999 to 2003, a total of 208 firm-year observations, for analysis. The regression model is explanatory with an adjusted R^2 of 37.46%. All coefficients have the expected signs. All, except PTR and TRAC, are significant at the 0.05 level or better. As expected, the coefficient on SCR is significantly positive (t-statistic = 2.06). The results suggest that labor productivity increases 184.21 miles per driver as the proportion of soft capacity increases by 1 percent, holding other variables constant. Overall the OLS pooled regression results provide support to H2 that the average labor productivity of companies increases with the levels of soft capacity. The proportion of soft capacity (SCR) has significant explanatory power to the level of labor productivity among the TL carriers. The cross-sectional regressions by year, except for the year 1999, provide consistent results to support the conclusion. Panel D of Table 3 reports the WLS results for the cross-sectional regression model of Equation (2) by year. The White test for heteroscedasticity is no longer significant in the estimations of these five years. The regression model estimations of 1999, 2002 and 2003 are significant at the 0.05 level. The regression model estimation for 2001 is of marginal significant (F-statistics = 1.89, p-value = 0.0869). Consistent with the results in Panel A, SCR is positively associated with PROD in 2001, 2002 and 2003 at less than the 0.05 level. SCR is positive but not significant in 1999. It is positive and significant in 2000, but the regression model is not significant explanatory (F-statistics = 1.14, p-value = 0.3506). The coefficients on all independent variables maintain the same expected signs as in the pooled regression in all five years except TPD and PDR in 2003 and 1999. Overall, the cross-sectional regression by year provides consistent support to H2 that the average labor productivity of companies increases with the levels of soft capacity.

CONCLUSION

This study investigates the impact of the proportion of soft capacity (SCR) used in operations on the level and variance of labor productivity. We find that the proportion of the soft capacity deployed by the TL carriers is significantly and positively associated with the levels of labor productivity. Our results are in contrast to the prior studies of the TL trucking industry, which suggest that productivity is positively associated with employing company drivers. Our evidence is consistent with our argument that owner-operators are more motivated to work hard because they are less risk averse and more sensitive to pay-for-performance, and therefore the proportion of soft capacity is positively associated with the average labor productivity. We also find that the proportion of soft capacity is significantly associated with the variance in labor productivity. Results from the cross-sectional regression tests by year are consistent with our argument that the influence of the levels of the soft capacity ratio on the variance of labor productivity can be either positive or negative. Owner-operators can be less controllable and more heterogeneous than the company drivers; therefore, more variability is associated with their performance. But at the same time, owner-operators may decrease the variance in the labor productivity because they provide the carriers the flexibility to face fluctuations in the demand. In other words, as customers demands fluctuate, the carrier can effectively meet the customer needs with soft capacity (owner-operators).

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