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Driver Management That Drives Carrier Performance

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The trucking industry provides the majority of transportation services in the United States. Truck drivers, particularly their driving performance, which influences how customers perceive motor carriers, are integral to the success of their firms. Hence, driver management is a topic of great interest to the trucking industry, logistics practitioners, and logistics researchers. Although the logistics literature does address issues relating to driver management, advice is scarce regarding how motor carriers might manage drivers to improve operational performance and thus the bottom line. Our results shed light on the processes whereby some formal controls directly influence operational performance, whereas others indirectly influence operational performance; that is, in the latter case, the influence of formal controls on operational performance is mediated by certain informal controls. According to our findings, motor carrier firms that employ a combination of formal and informal controls perform better operationally than firms that do not do so. And, thus, those employing such a combination of controls will realize a larger market share.

Keywords: survey; structural equation modeling; mediation; trucking; logistics; control theory; truck driver

INTRODUCTION

The trucking industry provides the majority of transportation services in the United States (U.S. Department of Transportation 2012) and is almost always the service provider in the "last mile" solution to the customer. According to previous research, firms that provide both reliable and on-time delivery services and are responsive to customer requests will ultimately increase their market share (Stank et al. 1999, 2003). That the delivery service provided by any given motor carrier depends to a great extent on the performance of its truck drivers is undeniable. How drivers operate their trucks directly affects fuel efficiency, operating costs, and delivery performance, which in turn affects customers' perceptions of a given carrier's service quality and consequently influences that carrier's competitiveness (Keller and Ozment 1999). Due to a lack of direct supervision, truck drivers characteristically have considerable control over their work (Belman and Monaco 2001). Therefore, managers in charge of truck driver operations at for-hire motor carrier firms and private fleets seeking to improve drivers' performance and ultimately carrier performance cannot depend on direct supervision strategies.

The central thesis of this study is that the key to improving drivers' performance and thus operational performance and eventually carrier market performance lies in implementing a combination of formal and informal controls. Formal controls are written management-initiated mechanisms designed to align employees' behavior with firm objectives, whereas informal controls are unwritten, employee-initiated, and influence their behavior (Jaworski 1988). Mello and Hunt (2009) extend control theory from the salesperson control literature to develop a comprehensive framework of truck driver control. In their view, strategies that incorporate both formal and informal controls can have a positive impact on motor carrier operational performance with regard to critical operational metrics, such as reliable, on-time delivery, and responsiveness to customers. However, the logistics literature does not address how such strategies designed to control drivers' performance affect these critical operational measures. These measures can directly impact customer satisfaction and thus market performance (Stank et al. 2003). It is, therefore, necessary to investigate the effects that driver control strategies have on carriers' operational performance and ultimately carriers' market performance.

The purpose of this research is to answer the question of how formal and informal management strategies designed to control truck drivers' performance affect carriers' operational and market performance across a large and diverse cross-section of motor carrier operations. We build on Mello and Hunt's (2009) theoretic control framework by integrating complementary theoretical perspectives from signaling, social exchange, and social identity theories to empirically test our proposed model for driver control. Next, we develop a theoretical basis for our driver control framework and present a research model with specific hypotheses for testing the effects of driver control strategies on motor carriers' performance. We then present our methodology, including our approach to data collection, scale development, and hypotheses testing using state-of-the-art structural equation model mediation analyses. Finally, we discuss the theoretical and managerial implications of our results and consider directions for future research.

THEORY AND HYPOTHESES

The logistics literature concerning driver control discusses various methods that motor carriers use to influence the actions of their drivers. Some of these methods, for example, standards setting and performance rewards (Keller and Ozment 1999; Cantor et al. 2006) are consistent with management control techniques used to manage employees in other contexts (Jaworski and MacInnis 1989). Logistics methods consistent with informal controls from management theory include providing organizational support and creating a driver-supportive culture (Keller and Ozment 1999; Keller 2002; Williams et al. 2011). The management

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control tradition offers a framework integrating formal and informal controls to explain how effectively controlling driver behavior may improve carrier performance (Mello and Hunt 2009).

We propose a model (Figure 1) that explicates how management's control actions operationalized as formal controls (e.g. activity and output controls) signal to drivers management's encouragement to foster informal controls (as indicated by the red arrows). We draw on the social exchange and social identity theoretical traditions from the management control literature to argue that informal controls, such as perceived organizational support (POS) and professional control influence motor carrier performance (as indicated by the red and blue arrows, respectively). Logistics theory then shows that improvements in operational performance ultimately improve carriers' market performance. In this study, we use the definition of operational performance as presented by Stank et al. (1999, 2003) to measure delivery timeliness, delivery reliability, and responsiveness to customer requests.

Formal controls

Formal controls are written management-initiated mechanisms designed to increase the probability that employees will behave in ways that support the firm's objectives (Jaworski et al. 1993). Formal controls influence a variety of important organizational outcomes, such as operational performance, financial performance (Anderson and Oliver 1987; Jaworski 1988; Jaworski et al. 1993; Baldauf et al. 2005), and market performance (Futrell et al. 1976; Jaworski et al. 1993; Lin and Germain 2003). Research on formal controls distinguishes between activity control and output control (Jaworski et al. 1993).

Activity controls

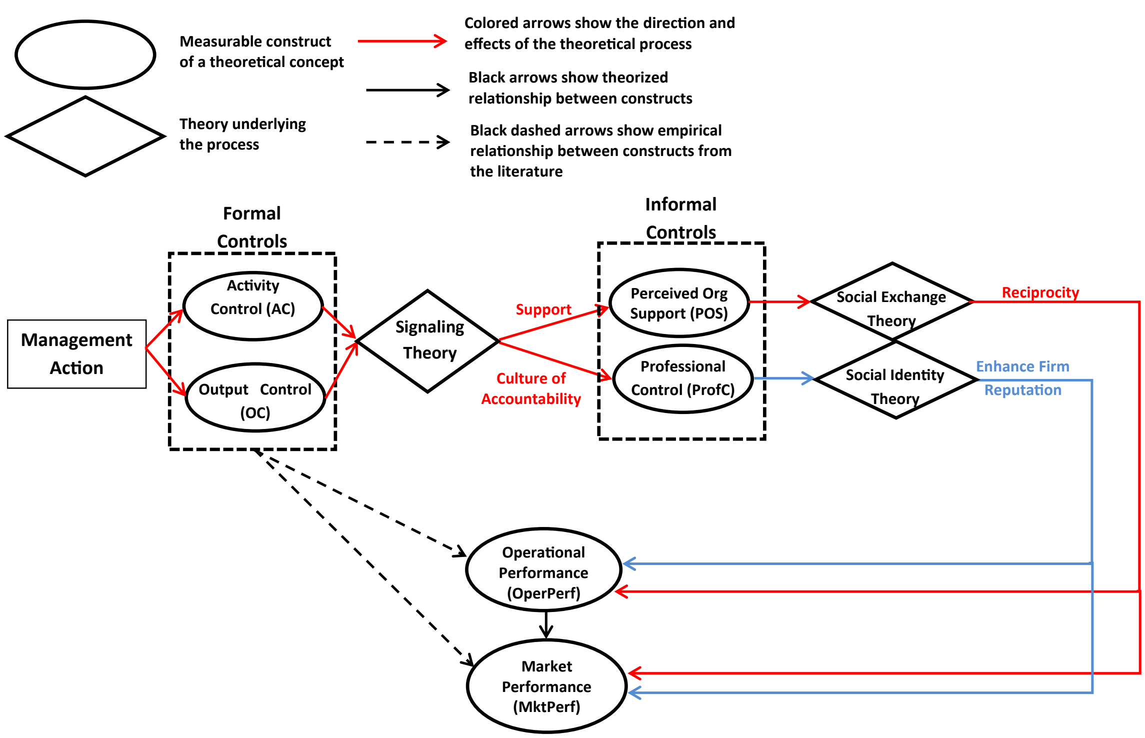
Activity controls reduce opportunism by specifying rules and detailing behaviors (Floyd and Lane 2000; Pappas et al. 2007), which help employees organize and engage in job activities that promote good job performance (Piercy et al. 2006) and firm performance (Fang et al. 2005). Motor carriers typically employ activity control mechanisms when their management organizes and schedules drivers' work activities and procedures (Mello and Hunt 2009). This can take the form of detailing idling procedures and setting out strict routing rules. For example, United Parcel Service (UPS) requires its delivery drivers to follow routes that eliminate left turns to reduce idling time, thereby saving fuel and improving delivery reliability.

The theoretical tradition on formal management control suggests a strong link between activity control and market performance (Sujan et al. 1994; Fang et al. 2005). On the other hand, the effect of activity control on operational performance has not been examined in the literature. This omission is striking, as activity control is relevant to managing and directing the operational routines and day-to-day activities of employees (truck drivers) and aligning those routines and activities with the firm's interests (Challagalla and Shervani 1996). Sujan et al. (1994) suggest that a high level of activity control focuses the employee (driver) on job strategies that can lead to improved performance in daily routines. Therefore, it is likely that such an improvement facilitated by activity controls leads to improved operational performance. We, therefore, posit that

H_{1a}: *High levels of activity control are related to high levels of operational performance.*

H_{1b}: *High levels of activity control are related to high levels of market performance.*

Figure 1: Theoretical model of control effects on performance as explained by signaling, social exchange and social identity theories.



Output controls

Output controls include setting standards, then monitoring and comparing results with those standards in order to evaluate performance (Jaworski and MacInnis 1989). Management uses output controls to evaluate the extent to which employees meet set standards of performance in terms of results rather than in terms of whether employees exhibit specific behaviors (Jaworski and MacInnis 1989). Output controls ensure that employees receive feedback on their performance from the firm, which itself may lead to higher profits (Jaworski et al. 1993). Control systems that emphasize the achievement of outputs have been shown to improve employees' goal achievement and the overall market performance of firms (Cravens et al. 1993; Fang et al. 2005; Evans et al. 2007).

Mello and Hunt (2009) consider output control an important tool for ensuring satisfactory truck driver performance, which may lead to improved carrier-level operational and market performance. Consider the UPS example: output controls measuring drivers' fuel efficiency and delivery performance are likely to lead to more reliable delivery. On the basis of the literature, we expect motor carriers that emphasize output control systems designed to monitor and influence drivers to exhibit better operational and market performance than carriers that do not. We, therefore, posit that

H_{2a}: *High levels of output control are related to high levels of operational performance.*

H_{2b}: *High levels of output control are related to high levels of market performance.*

Operational and market performance

Stank et al. (1999) show that operational performance has a significant effect on customer satisfaction and loyalty, which in turn affect market performance (Stank et al. 2003). Moreover, a motor carrier's raison d'être derives from its customers' need for transportation services, and its success is predicated on meeting that need. Thus, the ability of any given motor carrier to compete in the market is the measure of how consistently and efficiently it fulfills its customers' requirements. Based on findings presented by Stank et al. (1999, 2003), it is reasonable to expect a relationship between operational performance and market performance. We propose that a motor carrier's operational performance is a direct antecedent of its market performance. We, therefore, posit that

H_3: *High levels of operational performance are related to high levels of market performance.*

Operational performance as a mediator

As discussed in the theoretical conceptualization and as proposed in H_{1a} and H_{2a}, it is reasonable to expect operational-level formal activity and output control variables to have a more salient relationship with operational performance than with market performance. In addition, the literature shows that operational performance has an effect on market performance (Stank et al. 1999, 2003). Taken together, H_{1a}, H_{2a}, and H_3 suggest that operational performance can act as a mediating variable whereby formal controls affect market performance through operational performance. We, therefore, posit that

H_{4a}: *Operational performance mediates the effect of activity control on market performance.*

H_{4b}: *Operational performance mediates the effect of output control on market performance.*

Mello and Hunt (2009) observe that formal controls send signals that influence employees' internalization of informal controls, such as practices the firm wishes to encourage and ways in which the firm supports them. Signaling theory suggests that individuals use various clues, dropped by the firm, to draw conclusions about the firm's intentions or actions (Srivastava and Lurie 2001). According to the literature on signaling theory, firms take actions that, whether intended or not, serve as signals to their employees (Srivastava and Lurie 2001). The present study uses signaling theory to explain how drivers view formal controls as a sign of encouragement to develop informal controls (as shown by the red arrows in Figure 1).

Informal controls

Informal controls are unwritten, often employee-initiated, mechanisms that influence employees' behavior (Jaworski et al. 1993), organizational citizenship behavior, and functional performance (Jaworski 1988; Baldauf et al. 2005; Piercy et al. 2006). Different types of informal control types have been conceptualized (Jaworski et al. 1993), including POS and professional controls, which are prevalent in logistics settings (Mello and Hunt 2009; Williams et al. 2011).

Perceived organizational support

Eisenberger et al. (1986) define POS as a global belief within a firm concerning the extent to which that firm values its employees' contributions and cares about their well-being. One way in which a firm can develop high POS over time is by signaling its concern for employee welfare through frequent employee–management interactions (Stamper and Johlke 2003; Valentine et al. 2006; Williams et al. 2011). Organizational support of employees is expressed through various types of management communications, such as conveying the firm's values (Valentine et al. 2006) and informing employees about organizational policies and practices designed to uphold those values (Guzzo et al. 1994; Valentine et al. 2006).

Formal controls are management-initiated (Baldauf et al. 2005); therefore, employees are likely to perceive them as providing credible information about the values and priorities of the firm (Erdem and Swait 1998). Research has linked POS to certain types of formal controls including activity and output controls (Masterson et al. 2000; Piercy et al. 2006). Activity control mechanisms signal to employees a firm's intentions (values) and actions (how it intends to uphold those values) (Srivastava and Lurie 2001). Output controls signal what a firm values by ensuring that drivers receive rewards when and as long as they meet all the output requirements (Atuahene-Gima and Li 2002).

Furthermore, a firm that establishes formal controls by explicitly specifying job activities and rewarding job outcomes may be perceived by employees as taking most of the performance risk (Cravens et al. 1993). Employees may take this assumption of risk as signaling the firm's concern for and support of its workforce. Accordingly, we expect to find that carriers can signal organizational support to their drivers by specifying the work activities in which drivers must engage to meet performance expectations and by rewarding drivers based on outputs that meet those expectations. We, therefore, posit that

H_{5a}: *High levels of activity control are related to high levels of driver POS.*

H_{5b}: *High levels of output controls are related to high levels of driver POS.*

Professional controls

Representing the degree of interaction, feedback, and evaluation among peers, professional controls thus stress group discussion and cooperation (Flaherty et al. 2007). The fundamental concept of professional control is that employees evaluate each other (Jaworski and MacInnis 1989), which Mello and Hunt (2009) observe as drivers influencing the behavior of their peers.

Research suggests that formal control systems predict high levels of professional controls (Agarwal and Ramaswami 1993; Jaworski et al. 1993; Hartline and Ferrell 1996). This is particularly true of control systems that include activity controls. Formal control systems that include activity controls have been shown to predict high levels of professional control (Jaworski et al. 1993). High formalization in an organizational structure indicates a high level of activity control, which is itself associated with an increase in work group socialization that is akin to professional control (Agarwal and Ramaswami 1993; Hartline and Ferrell 1996). Consequently, by adopting activity controls, firms can encourage a culture of accountability wherein drivers are likely to come together informally to motivate each other.

According to Mello and Hunt (2009), the managerial practice of displaying driver performance metrics in terminals where drivers can see them provide opportunities for drivers to practice professional control by informally evaluating the performance of their peers. Standardization, whereby all drivers are evaluated using the same formal criteria, indicates a high level of output control, which leads to a high level of professional control (Stonich 1981). Thus, it follows that motor carriers would do well to encourage the development of professional control, thereby fostering a culture of accountability via formal evaluation (Figure 1). We, therefore, posit that

H_{6a}: *High levels of activity control are related to high levels of driver professional control.*

H_{6b}: *High levels of output control are related to high levels of driver professional control.*

The effect of informal control on performance

As illustrated in Figure 1, we use social exchange theory (SET) to explain the effect of POS on performance (red arrows) because of the norm of reciprocity, and we use social identity theory (SIT) to explain the effect of professional control on performance (blue arrows) by way of enhanced firm reputation.

Norm of reciprocity

SET proposes that actors in exchange relationships attempt to obtain desirable results from these relationships by maximizing rewards and minimizing costs (Thibaut and Kelley 1959). According to this norm of reciprocity, as long as one party in an exchange meets the expectations of the other, the latter usually reciprocates (Gouldner 1960). Williams et al. (2011) find this to be true with truck drivers.

Based on the norm of reciprocity, employees (drivers) who perceive a high level of organizational support for their well-being feel a reciprocal sense of obligation for the firm's well-being such that they work hard to meet the firm's goals (Aselage and Eisenberger 2003; Fuller et al. 2006). High POS is associated with high employee performance (Wayne et al. 1997; Chen et al. 2009). Hence, employees who feel that the organization is supporting them appropriately tend to reciprocate by performing better than employees who do not consider this to be the case. We expect drivers who perceive their firm as supporting them to be more likely to reciprocate by expending their best effort to meet the firm's objectives, thus leading to a higher level of firm performance. Improved driver performance will lead to improved operational performance (Ouellet 1994; Keller and Ozment 1999; Keller 2002; Mello and Hunt 2009), which we can reasonably expect to lead to improved motor carrier market performance (see H_3). We, therefore, posit that

H_{7a}: *High levels of driver POS are related to high levels of operational performance.*

H_{7b}: *High levels of driver POS are related to high levels of market performance.*

Enhanced firm reputation

According to SIT, individuals classify themselves on the basis of various social factors including where they work, and membership in these social categories influences their self-concept (Ashforth and Mael 1989; Dutton et al. 1994). Employees working for successful firms with good reputations derive certain benefits in terms of their self-esteem (Stets and Burke 2000). With regard to SIT, this phenomenon can be explained in reference to individuals' (e.g., drivers') self-concept as derived from their membership in certain social groups, including the organizations they work for (Tajfel 1982).

According to the literature, we can expect the successes that enhance an organization's reputation to contribute to the self-concept of its drivers (Underwood et al. 2001; Williams et al. 2011). Drivers who belong to successful organizations may engage in downward comparisons whereby their self-esteem is boosted by comparing their organization to organizations they perceive as lesser quality (Stets and Burke 2000). Furthermore, employees who identify with a group through interactions with its members experience enhanced feelings of belonging that contribute to the formation of cohesive units, that is, teams, that support members' efforts to achieve the firm's objectives (Agarwal and Ramaswami 1993; Gundlach et al. 2006). Consequently, employees (drivers) who identify with a team, such as one fostered by the firm's encouragement of professional control, perform well such that the firm likewise performs well (Lembke and Wilson 1998; Cravens et al. 2004).

Given the high self-esteem that comes with working for a successful carrier (Williams et al. 2011), professional control can be understood as effecting a high level of accountability with regard to individual performance among members of a group. On this basis, we contend that professional control encourages drivers to weigh their effort and focus through the lens of past and anticipated future exchanges that intrinsically motivate them to perform better at their jobs. A high level of motivation on the part of the drivers leads to a high level of performance, which in turn results in high firm performance that subsequently improves its reputation. Improved firm reputation will in turn further bolster drivers' self-esteem. We, therefore, suggest that a high level of professional control intrinsically motivates drivers to expend the effort necessary to effect a high level of operational performance on the part of the motor carrier they work for, thus also effecting a high level of market performance. We, therefore, posit that

H_{8a}: *High levels of professional control are related to high levels of operational performance.*
H_{8b}: *High levels of professional control are related to high levels of market performance.*

The mediating effect of informal controls

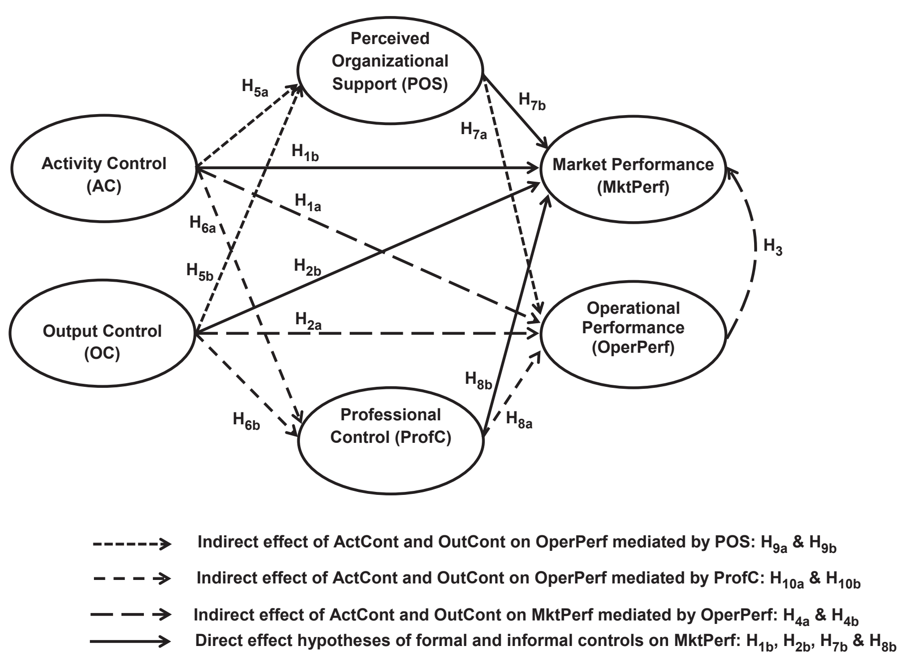
Findings pertaining to establishing a direct relationship between formal controls and performance are inconsistent (Oliver and Anderson 1994; Challagalla and Shervani 1996; Baldauf et al. 2005). Therefore, in the present study, we integrate the hypotheses proposed herein so far and argue that formal controls through their effect on informal controls influence operational performance. In essence, to the extent that formal controls can increase the level of informal controls, formal controls will improve driver performance. Even in cases where there is no empirical support for a direct effect from either activity or output controls on operational performance, Hayes (2009) argues that contrary to Baron and Kenny's (1986) requirement for mediation, the independent variables (activity and output controls) can have an indirect effect on the dependent variable (operational performance). Hayes (2009) argues that such an indirect effect can occur through the mediators (POS and professional control) in the absence of a direct effect between the independent and dependent variables.

Using our theoretical framework, we argue that when a firm uses activity controls, such as setting drivers' work procedures and using output controls to measure drivers' performance and reward them accordingly, it sends a strong signal of support to its drivers. Such perceived support should motivate drivers to reciprocate by performing in such a way as to meet the firm's objectives, which in turn improves operational performance. We, therefore, posit that

H_{9a}: *POS mediates the effect of activity control on operational performance.*
H_{9b}: *POS mediates the effect of output control on operational performance.*

We use Hartline and Ferrell's (1996) finding that increasing the formalization of the organizational structure by, for example, setting strict work procedures leads to greater professional control. In addition, Stonich's (1981) findings suggest that stringent performance evaluation leads to a high level of professional control. We contend that professional control fosters positive peer pressure, which motivates drivers to perform at a higher level than they otherwise would, and that this higher level

Figure 2: Research hypotheses.



of performance on the part of drivers leads to a higher level of operational performance. We, therefore, posit that

H_{10a}: *Professional control mediates the effect of activity control on operational performance.*

H_{10b}: *Professional control mediates the effect of output control on operational performance.*

Figure 2 summarizes our hypotheses with regard to the structure of dependence relationships developed through our discussion of the theoretical concepts in the management control literature.

METHODOLOGY

The objective of this research is to test a theory of management strategies for controlling driver activities to achieve desired outcomes. Therefore, the unit of analysis is the motor carrier firm. We conducted a national survey to measure carrier performance and the formal and informal driver controls used by firms to manage their drivers. Empirically verifying the impact of driver control on performance across a large and significantly more diverse sample than has been used before will expand the field's ability to understand these relationships and to generalize strategies for effectively dealing with performance issues. We, therefore, follow Garver et al.'s (2008) recommendation to include drivers from a variety of contexts. Hence, this study includes motor carriers providing over-the-road, for-hire road-haulage services, and carriers that maintain a private truck fleet for their in-house transportation requirements. The principal informants for this study are professionals responsible for driver management at each firm who are well-placed to respond to questions about the firm's driver control practices and operational and market performance.

Scale development

The measurement instrument was developed using existing scale items from the literature. See Appendix A for detailed information regarding the sources, measures, and scales used for each item. We used a 7-point Likert-type scale to measure all the control items and a 7-point semantic differential scale ranging from "much better" to "much worse" to measure the performance items.

We adapted the items through a series of iterations for the trucking industry. First, we consulted 12 driver-management experts from the trucking industry. We asked them to record their responses using a draft online survey instrument. Over subsequent discussions, we used their feedback to refine the language of the measures to more appropriately capture the measurements of driver control and carrier performance in the trucking industry. For example, we ensured that the language used for the items measuring market performance would convey the correct meaning to private fleets. On the surface, private fleet managers do not have any obvious competitors or market- or revenue-growth aspirations. However, through our conversations with the industry experts, we became aware that carriers with private fleets frequently benchmark their practices against those of national motor carriers. In fact, it is a common practice in large private fleets (typically over 50 vehicles) to compete with bids from national motor carriers for a share of the parent firm's business. Consequently, we refined the language of the market-performance items to ensure accurate measurement of both for-hire and private-fleet performance. In addition, to accommodate private fleets and maintain a diverse sample, we limited our sample to firms with more than 50 vehicles.

The items used to measure POS were modified to report POS provided by the firm to the drivers from the manager's perspective. In making this modification, we limited our survey to a single principal informant from each company who was knowledgeable about both driver-control practices and firm-level performance, thus keeping the survey administration within our budget constraints. Our use of a single key informant is consistent with the protocol used by most research studies in the field—a protocol followed largely because of budget constraints (Van Bruggen et al. 2002). Previous research has successfully measured managers' perceptions of formal and informal control effects at the employee level (Piercy et al. 2006; Flaherty et al. 2007). In addition, studies have consistently found that self-reported and manager-reported measures are highly correlated (Churchill et al. 1985).

Pilot test

After refining the measurement items and scales based on the initial interviews, we conducted a pilot test. Our sampling frame was developed with a systematic random sample drawn from FleetSeek (http://www.FleetSeek.com), the U.S. National Motor Carrier database, and the Private Fleet database. Professional phone interviewers prequalified the potential respondents. Trained and retained by a university research center responsible for research with human subjects, the interviewers were required to adhere to strict protocols. For example, they were trained not to interpret or reword items, such that when asked to clarify an item they simply repeated the item in its entirety. All clarifications and inquiries were logged to aid with measurement refinement, if necessary, after the pilot was complete.

To qualify the respondents for participation, interviewers asked them to confirm that they were responsible for driver management at the firm and, therefore, able to respond to questions about the firm's driver-control practices and market performance. Qualified respondents were asked to complete the survey over the phone with an interviewer. To accommodate the respondents' schedules, the interviewers scheduled callbacks and as a last resort allowed respondents to independently complete an identical survey online. The interviewers' central purpose was to prequalify principal informants and administer the survey in a way that would be most convenient to the respondents. We designed this data collection strategy consistent with Armstrong and Overton's dictum whereby the "most commonly recommended protection against nonresponse bias [is] … the reduction in nonresponse itself" (1977, 396 cited in Wagner and Kemmerling 2010, 359).

The interviewers had contacted 1,254 firms by the end of spring 2011. Of these, the driver managers of 680 firms were qualified as principal informants. Of the managers from these 680 firms, 121 completed the survey for an effective response rate of 17.8%. The interviewers recorded disposition codes for the other prequalified participants who had not responded either because of a company policy against such participation, because they were not interested in the study, or because they did not have time to take part, among other stated reasons. In addition, a number of prequalified respondents scheduled callbacks, but proved unreachable after the initial contact and thus were recorded as nonrespondents.

We used the data from the pilot to conduct a variety of tests. We conducted an ANOVA to determine whether there were differences in measurement across what turned out to be four groups based on combinations of response formats and populations within our sample: interviewer-administered for-hire, interviewer-administered private fleet, self-administered for-hire, and self-administered private fleet. None of the measures showed significant differences among the groups, indicating a minimal risk of using the two response formats and combining private and for-hire fleets in the sample. We conducted a confirmatory factor analysis (CFA) to ensure measurement validity. All measures exhibited unidimensionality, reliability, and convergent and discriminant validity. After reviewing the logged feedback from the interviewers during the pilot test, we consulted five of the original 12 industry experts to further refine the language of a few measures before commencing the main data collection. On the basis of the logged feedback from the interviewers and from the five industry experts, we made slight alterations to the wording of the three output control measures, not to change the meaning of the items, but to achieve greater precision and clarity (Appendix A).

Main survey

We drew a second systematic random sample from the FleetSeek database to develop our sampling frame for the main survey. By the end of summer 2011, we had contacted a total of 3,838 firms, of which 2,464 respondents were prequalified and 573 responded to the survey for an effective response rate of 23.25%. The nonrespondents did not respond for reasons already outlined for the pilot test. As the measures used for the pilot test do not differ substantively from the instrument used for the main data collection, the pilot test responses are included in the analysis. The effective response rate for the combined data set is 22.1%.

The use of data collected from different groups, that is, response formats, populations, and waves, for structural equation modeling raises the concern of measurement equivalence—a concern that arises because item measures and factor loadings may differ across groups (Jöreskog 1971; Steenkamp and Baumgartner 1998). Thus, it is necessary to establish the invariance of factor loading pattern and the measurement invariance or configural and metric invariance among the groups, as the absence of these gives rise to the risk that systematic biases will be introduced (Steenkamp and Baumgartner 1998). Steenkamp and Baumgartner (1998, 78) recommend Jöreskog's (1971) multigroup invariance checks, which other studies combining different populations and groups have employed successfully (Mishra et al. 1998; Cannon and Homburg 2001). We used Chen's (2007) approach as advocated by Byrne (2009) and Marsh et al. (2009) wherein absence of invariance is indicated by a change in comparative fit index (CFI) $\geq -.010$, root mean square error of approximation (RMSEA) $\geq .015$, and standardized root mean square residual (SRMR) $\geq .030$. The results of the invariance tests support configural and metric invariance among the different populations and groups (Table 1). As the factor loading patterns and the item loadings on the underlying constructs do not differ significantly among the groups, the risk of introducing systematic biases by combining the groups is minimal.

Response bias

We used the characteristic comparison method demonstrated by Lambert and Harrington (1990) to test nonresponse bias. We tested for nonresponse bias by comparing the characteristics of respondents and nonrespondents across three demographic variables (Table 2).

Chi-square tests of association among the respondents and nonrespondents for region (χ^2 = 12.07, df = 8, *p*-value = .148), fleet size (χ^2 = 2.70, df = 6, *p*-value = .845), and revenue (χ^2 = 2.40, df = 6, *p*-value = .879) are reported in Table 2. On the basis of these results, we are confident that the risk of nonresponse bias is minimal for this data set. The configural and metric invariance between the pilot and the main survey groups conducted over two distinct time periods provide further evidence that nonresponse bias is unlikely to have affected our results (Table 1).

In addition, in an effort to rule out informant bias, we looked at the characteristics of the principal informants to check for respondent competency (Table 3). The majority of respondents hold management positions, such that they are responsible for setting and reviewing the policies relating to managing the drivers. In addition, they reported spending an average of 14.2 years in their current positions and 19.2 years at their current companies. Hence, we are confident that the respondents are very knowledgeable about driver-management practices and performance at their firms. Informant bias, therefore, does not pose a serious threat.

RESULTS

Measurement model

We used LISREL 8.8 (Scientific Software International, Inc., Skokie, IL) to perform a CFA to determine construct validity, including testing for unidimensionality, reliability, convergent validity, and discriminant validity (see Appendix B for the covariance and correlation matrix). To assess unidimensionality and convergent validity, we considered the direction, magnitude, and significance ($\alpha \leq .05$) of each item and its focal construct (Table 4). And, to test for construct reliability, we used composite reliability and average variance extracted (AVE). The AVE, interconstruct correlations, and the chi-square difference test formed the basis for establishing discriminant validity (Table 4).

All item loadings were significant at $\alpha \leq .05$. One item (ProfC1) was dropped because of very low standardized loadings (.33) and an erratic pattern of high modification indices and standardized residuals. Two other scale items (OC2, ProfC4) exhibited standardized loadings lower than the .5 minimum recommended by Hair et al. (2010). An examination of the standardized residuals and modifications indices for these items,

Table 1: Multigroup invariance tests

	1. Pilot (n = 121) versus 2. Main (n = 573)			1. NMC (n = 444) versus 2. PF (n = 250)			1. Self (n = 219) versus 2. Interviewer (n = 475)		
	CFI	**RMSEA**	**SRMR**	**CFI**	**RMSEA**	**SRMR**	**CFI**	**RMSEA**	**SRMR**
Separate groups									
1.	.9744	.0403	.0399	.9710	.0431	.0448	.9671	.0554	.0557
2.	.9181	.0809	.0756	.9585	.0512	.0521	.9663	.0408	.0438
Configural Invar	.9616	.0498	.0756	.9665	.0462	.0521	.9666	.0459	.0438
Metric Invar	.9565	.0516	.0985	.9629	.0472	.0597	.9670	.0446	.0450
Δ Fit Index	−.0051	.0018	.0229	−.0036	.0010	.0076	.0004	−.0013	.0012

Notes: CFI, comparative fit index; RMSEA, root mean square error of approximation, SRMR, standardized root mean square residual.

Table 2: Nonresponse bias test using geographic, revenue, and fleet-size characteristic comparisons

Census region	**Sample**	**Nonrespondents**
N. ENG	16	108
MID ATL	75	344
E.N. CNTR	169	648
W.N. CNTR	68	325
S ATL	97	543
E.S. CNTR	64	242
W.S. CNTR	83	376
MTN	49	204
PAC	73	354
Totals	694.0	3,144.0
Q = 12.07	p-value = .148	
$\chi^2(8)$ = 13.36		
Fleet size	**Sample**	**Nonrespondents**
50	29	139
100	331	1,517
250	201	869
500	69	292
1,000	33	151
5,000	27	142
>5,000	4	34
Q = 2.70	p-value = .845	
$\chi^2(6)$ = 10.645		
Revenue	**Sample**	**Nonrespondents**
<$1 million	8	33
$25 million	506	2,321
$50 million	81	355
$100 million	52	196
$500 million	36	184
$1,000 million	7	30
>$1,000 million	4	25
Q = 2.40	p-value = .879	
$\chi^2(6)$ = 10.645		

Table 3: Titles of respondents

Position	**Frequency**	**Percentage**
Owner	67	9.7%
President	333	48.0%
CEO, COO	29	4.2%
VP	16	2.3%
Director	13	1.9%
Fleet Manager	127	18.3%
Manager	67	9.7%
Other	42	6.1%
Total	694	

however, indicated no justification for dropping them. With the exceptions of Output Control (OC) and Professional Control (ProfC), all the constructs exhibited high AVE, above the .5 recommended by Hair et al. (2010). Dropping OC2 and ProfC4 would have slightly increased the AVE of OC and ProfC (OC = .47, ProfC = .42), respectively. However, there is a strong substantive justification for retaining these two measures: OC2 refers to the extent to which pay increases are influenced by achieving performance goals, and ProfC4 refers to the extent to which department members are familiar with each other's work. After considering all the evidence, particularly, the existing measurement theory (Behrman and Perreault 1982; Ramaswami 1996; Baldauf and Cravens 2002), we decided to retain these two items on the strength of face validity and the global model fit indices (Rodrigues et al. 2004). The global model fit indices indicate a good or better than recommended fit of the model to the data (Garver and Mentzer 1999; Hair et al. 2010).

Most of the composite reliabilities (Table 4) are higher than the .7 recommended by Hair et al. (2010). And, although OC and ProfC exhibit lower reliability measures, these are still higher than the .6 considered acceptable by Hair et al. (2010). The square-root of the AVE is provided on the diagonal of the construct correlation matrix in Table 4. A comparison of these values with the corresponding row and/or column correlations indicates that most of the constructs exhibit good discriminant

Table 4: Construct reliability and convergent and discriminant validity

	AC	OC	OperPerf	MktPerf	POS	ProfC	*t*-value	$\Theta\delta$
AC1	.77						22.10	.41
AC2	.79						23.02	.37
AC3	.78						22.60	.39
AC4	.63						17.20	.6
OC1		.7					17.17	.51
OC2		.49					11.65	.76
OC3		.67					16.46	.55
MktPerf1			.62				16.02	.61
MkTPerf2			.84				22.00	.29
MktPerf3			.68				17.73	.53
OperPerf1				.79			20.38	.38
OperPerf2				.65			16.56	.58
OperPerf3				.66			16.99	.56
POS1					.73		20.27	.46
POS2					.73		20.08	.47
POS3					.74		20.48	.45
ProfC2						.59	14.55	.65
ProfC3						.74	18.02	.46
ProfC4						.41	9.64	.83
AVE	.56	.39	.52	.49	.54	.36		
Comp. Rel.	.83	.66	.76	.74	.79	.61		

Construct correlations**

	AC	OC	OperPerf	MktPerf	POS	ProfC
AC	.75*					
OC	.27	.63*				
OperPerf	.11	.28	.72*			
MktPerf	.19‡	.28	.46	.70*		
POS	.19	.65	.31	.38	.73*	
ProfC	.21	.62	.3	.47	.73	.60*

Overall model fit statistics

χ^2: 308.74, df = 137, *p*-value <.0001
RMSEA: .041
SRMR: .039
χ^2/df: 2.25
NFI: .96
NNFI: .97
CFI: .97
IFI: .97

Notes: AVE, average variance extracted; CFI, comparative fit index; IFI, incremental fit index, NFI, normed fit index; NNFI, nonnormed fit index; RMSEA, root mean square error of approximation; SRMR, standardized root mean square residual.
*Sqrt(AVE).
**All correlations are significant at $p < .01$ except when indicated by ‡ where $p < .05$.

validity. The exceptions (underlined in the construct correlation matrix in Table 4) are OC, which does not exhibit good discrimination from POS, and ProfC, which does not show good discrimination from either POS or OC. Hence, we used the chi-square difference test of nested models, which separately fixes each value of the construct correlation matrix to 1.0 (i.e., testing $\mathbf{H_0}$: the two constructs are the same). To ensure an overall $\alpha_0 = .05$ for the family of tests, the 15 individual tests were adjusted as $\alpha_i = .003$ ($\alpha_0 = (1-(1-\alpha_i)^{15}$. All the chi-square difference tests were significant, including for the three correlations in question ($\rho_{OC,POS}$: $\Delta\chi^2(1) = 110.8$, $\rho_{OC,ProfC}$: $\Delta\chi^2(1) = 83.6$, $\rho_{POS,ProfC}$: $\Delta\chi^2(1) = 69.9$); thus, we rejected $\mathbf{H_0}$, which held that any of these three pairs of constructs would be the same. Overall, the measurement model shows good convergent and discriminant validity.

Structural model

Without informal controls

We first specified the structural model of the theoretical framework without the informal controls (ProfC and POS). The model is specified with direct structural relationships between the formal controls (AC, OC) and carrier performance (MktPerf, OperPerf). The structural model (Table 5) exhibits good fit to the data (χ^2 = 128.6, df = 59, RMSEA = .039, SRMR = .037, χ^2/df = 2.18, normed fit index [NFI] = .96, CFI = .98, incremental fit index (IFI) = .98).

There is no support for H_{1b}; however, all the other hypotheses are significant. These results in isolation suggest that activity control only affects operational performance (H_{1a}) and not market performance (H_{1b}). In addition, without further analysis, we could conclude that market and operational performance are directly affected by output control (H_{2a}, H_{2b}), precluding the existence of any underlying processes that might play a role in explaining these relationships. To determine any underlying processes, we examine the model for mediation effects that may shed more light on these relationships.

The nonnormal sampling distribution of the product of the two indirect pathways used to estimate the indirect mediation effect precludes the use of Sobel's z test to establish mediation (Preacher and Hayes 2004; Zhao et al. 2010; Preacher and Kelley 2011). Zhao et al. (2010, 204) strongly recommend that "only one test: the bootstrap test of the indirect effect" be used to establish mediation.

Consequently, we used Shrout and Bolger's (2002) bias-corrected bootstrap methods implemented in AMOS 19.0 (Preacher and Hayes 2008). Five thousand resamples with replacement were used to empirically represent the sampling distribution of the indirect effects (Hayes 2009). By this method, we determined the product of the constituent mediation pathways by estimating the indirect effect in the population sampled and thereby generate a 95% confidence interval. According to Zhao et al. (2010), "to establish mediation, all that matters is that the indirect effect is significant" (p. 204). We report these indirect effects for the base model without informal control mediators in Table 5.

The paths for output control to operational performance and market performance and those from operational performance to market performance (H_3) are all significant. In addition, the indirect effect from output control to market performance through operational performance (H_{4b}) is significant, indicating complementary mediation (Zhao et al. 2010). Hence, we can conclude that although operational performance is a mediator for the effect of output control on market performance, the theoretical framework is incomplete, as there is likely to be another mediator present in the theoretical framework (Zhao et al. 2010). On the other hand, for activity control, the path to market performance is insignificant (H_{1b}), whereas the path to operational performance is significant (H_{1a}). In addition, the indirect path from activity control to market performance through operational performance (H_{4a}) is significant, indicating the presence of indirect mediation and the absence of any additional mediators (Zhao et al. 2010).

With informal controls

In Table 6, we present the results of the full structural model, including the informal controls (ProfC and POS). Using SEM to fit a multiple mediator model, we freely estimate the covariance of the residuals associated with the mediators, POS and ProfC, as recommended by Preacher and Hayes (2008). The overall model fit statistics, which are the same as those reported for the CFA in Table 4, indicate good model fit. The results of the analysis indicate no support for the direct relationships posited by H_{1b}, H_{2a}, H_{2b}, H_{5a}, H_{6a}, H_{7a}, H_{7b}, and H_{8b}. Neither formal nor informal controls have a direct effect on market performance. Activity control does not affect the informal controls, and POS has no direct effect on operational performance and no direct or indirect effect on market performance. As pointed out with regard to the results of the first model presented in this article (without informal controls), the conclusions drawn from these results are very different from those that accrued from also investigating the mediation effects. For example, based solely on the results of the unmediated model, we could have erroneously concluded that output control does not affect operational and market performance. We, therefore, examine the indirect mediation effects next to uncover the underlying process for these effects.

These results confirm our conclusions from the results of the previous model (Table 5), that is, that additional mediators may be necessary to explain the effect of output control on market performance. The paths from output control to operational per-

Table 5: Structural equation model results, without informal control mediators

Structural path	Hypothesis	Effect	SE	*t*-value	*p*-value	UCL*	LCL*
AC → OperPerf	H_{1a}	.12	.05	2.52	.012	–	–
AC → MktPerf	H_{1b}	−.01	.04	−.27	.787	–	–
OC → OperPerf	H_{2a}	.23	.06	3.61	.000	–	–
OC → MktPerf	H_{2b}	.14	.05	2.83	.005	–	–
OperPerf →MktPerf	H_3	.36	.05	7.51	.000	–	–
AC → OperPerf →MktPerf	H_{4a}	.04	.02	–	.007	.02	.08
OC → OperPerf →MktPerf	H_{4b}	.08	.03	–	.001	.04	.13

Note: *Bootstrap upper and lower confidence intervals for the indirect effects.

Table 6: Structural equation model results with informal control mediators

Structural path	Hypothesis	Effect	SE	*t*-value	*p*-value	UCL*	LCL*
AC → OperPerf	H_{1a}	.09	.05	2.03	.043	–	–
AC → MktPerf	H_{1b}	−.01	.04	.18	.857	–	–
OC → OperPerf	H_{2a}	−.08	.08	.98	.327	–	–
OC → MktPerf	H_{2b}	.1	.06	1.61	.108	–	–
OperPerf → MktPerf	H_3	.34	.05	6.45	.000	–	–
AC → OperPerf → MktPerf	H_{4a}	.03	.02	–	.049	.000	.067
OC → OperPerf →MktPerf	H_{4b}	−.03	.03	–	.304	−.100	.025
AC → POS	H_{5a}	.01	.03	.34	.734	–	–
OC → POS	H_{5b}	.44	.04	9.98	.000	–	–
AC → ProfC	H_{6a}	.03	.03	1.03	.303	–	–
OC → ProfC	H_{6b}	.39	.05	8.33	.000	–	–
POS → OperPerf	H_{7a}	.14	.14	1.06	.290	–	–
POS → MktPerf	H_{7b}	.11	.11	1.07	.285	–	–
ProfC → OperPerf	H_{8a}	.63	.16	3.95	.000	–	–
ProfC → MktPerf	H_{8b}	−.05	.13	.42	.675	–	–
AC → POS → OperPerf	H_{9a}	.00	.01	–	.551	−.01	.03
OC → POS → OperPerf	H_{9b}	.06	.08	–	.412	−.11	.21
AC → ProfC → OperPerf	H_{10a}	.02	.03	–	.342	−.03	.10
OC → ProfC → OperPerf	H_{10b}	.25	.09	–	.000	.12	.47

Note: *Bootstrap upper and lower confidence intervals for the indirect effects.

formance to market performance are now not significant. The paths from output control to professional control to operational performance, however, are significant. More importantly, the bias-corrected bootstrap confidence interval for the indirect effect of output control on operational performance through professional control is significant. And, thus, the mediation H_{10b} is supported. Hence, our results indicate that mediation does take place and that professional control is likely to be the only mediator necessary to explain the effect of output control on operational performance. This is confirmed by the insignificant indirect effect of output control on market performance through operational performance (H_{4b}). Considering all these results along with the significant effect of operational performance on market performance (H_3), it is reasonable to infer that output control, through its effect on operational performance mediated by professional control, affects market performance. The results of the bootstrap confidence intervals for the indirect path from output control to market performance through professional control and operational performance indicate a significant effect (.08, *p*-value <.001) and a bias-corrected confidence interval of (.04, .19). Our results, therefore, support the position that output control affects market performance through professional control and operational performance.

Activity control has no significant effect on any of the informal controls (H_{5a}, H_{6a}). The direct and indirect effects of activity control on operational and market performance, respectively (H_{1a}, H_{4a}), remain unchanged from the first model, which excludes the informal controls as mediators. Due to the insignificant effect of POS on performance (H_{7a}, H_{7b}), our results do not support H_{9a} or H_{9b}, both of which posit POS as a mediator of the formal controls on operational performance.

In summary, the results of our analysis show that activity control through its effect on operational performance affects market performance. And, output control affects POS (H_{5b}) and professional control (H_{6b}), the latter of which is the only mediator necessary to explain the effect of output control on operational performance and, therefore, market performance.

DISCUSSION

The findings from our study extend the literature by demonstrating empirical support for the relationships between specific driver control strategies and carrier performance. Our study provides a theoretical rationale for how the combinations of formal and informal controls in our study influence motor carrier performance. In addition, the current study informs practitioners of the impact that management actions in support of formal and informal driver control can have on carrier performance across diverse motor carrier settings. Although we examined the phenomenon of management control in the trucking industry, our results may also be applicable to other logistics contexts, such as managing autonomous vehicle operators of other transportation modes and managing remote autonomous employees and business units.

Theoretical implications

This study represents the first effort to integrate complementary theoretical perspectives to explain the antecedent effect of formal controls on informal controls and ultimately firm performance. Research from marketing and logistics suggests that formal controls influence informal controls (Jaworski et al. 1993; Mello and Hunt 2009). In addition, the organizational literature discusses the benefits of using more formal and informal controls (Cravens et al. 2004; Baldauf et al. 2005). However, the signaling effect of formal controls on informal controls and subsequently performance has not been investigated before. The results of our analyses provide the first empirical evidence that formal control (output control) affects informal controls (POS and professional control). On the other hand, despite theoretical support, our results do not indicate that there is a direct effect of activity control on informal controls.

The results of our analyses present a new process whereby formal and informal controls affect market performance. To explain how formal and informal controls affect market performance, we integrated logistics knowledge about the operational performance effects on market performance into our model (Stank et al. 1999, 2003; Inman et al. 2011). The results of our study also support the logistics literature, wherein it is held that operational performance affects market performance even across a large and diverse sample of motor carriers.

Previous research examining activity control does not show evidence of a link between activity control and market performance (Jaworski et al. 1993; Oliver and Anderson 1994; Challagalla and Shervani 1996). Our research, then, is the first to provide any empirical support for the idea that formal controls affect market performance by influencing operational performance. Our results show weak support for the direct effect of activity control on operational performance; however, we show strong support for the indirect effect of activity control on market performance through operational performance. From the results of the mediation analyses, using the mediation framework provided by Zhao et al. (2010) we can see that in the current theoretical framework operational performance is the lone mediator of the effect of activity control on market performance.

This study constitutes the first endeavor to empirically test the effects of informal control on operational performance. It is surprising that POS does not affect operational performance; however, we did find that professional control has a significant effect on operational performance. Professional control effects on organizational performance are well understood in the marketing and sales literature (Agarwal and Ramaswami 1993; Lembke and Wilson 1998). However, our study extends the literature, as the first to show that professional control has a significant effect on market performance through operational performance.

In addition, our study examines the mediating effects of informal controls, such as how professional control mediates the effect of output control on firm performance. Studies from marketing and sales have resulted in inconsistent findings with regard to the effect of formal controls on market performance (Baldauf et al. 2005). The results of our study provide empirical support for the mediating role of an informal control, that is, professional control, on the relationship between output control and operational performance. Neither we did not find that POS acted as a mediator nor did we find the effect of activity control on operational performance to be mediated by the informal controls included in our study. Furthermore, new methodological advances allowed for enhanced mediation analyses that enabled us to test indirect effects that had previously been unavailable. And, although we did not directly hypothesize about the indirect effects of output control on market performance, we can infer this effect from the serial mediation effects. Hence, the results of our bootstrapping mediation analyses provide empirical support for the position that the effect of output control on market performance is mediated through professional control and operational performance. As a result, our study provides the first evidence of a process by which output control influences market performance. We hope that this provides a foundation for future research to build on in efforts to develop a theory about the effects of formal controls on performance.

Our initial model, that is, the model without informal controls (Figure 2), follows the existing theoretical control framework. It reveals that both the direct path from output control to market performance and the indirect path through operational performance are positive and significant. Consequently, the mediation framework proposed by Zhao et al. (2010) suggests that such a result indicates an incomplete theoretical framework wherein important mediators are excluded. Following the theoretical direction of Mello and Hunt (2009), our proposed theoretical paradigm includes two informal controls, professional control and POS, as mediators to explain the link between formal controls and performance. Our results indicate that professional control is likely to be the only mediator necessary to explain the link between output control, operational performance, and market performance in our theoretical framework. By demonstrating the mediation effects of informal controls on the effects of formal controls on performance, we are the first to empirically validate the theoretical framework for driver management as set out by Mello and Hunt (2009).

We used two structural models to illustrate the incomplete conclusions that could be drawn should mediators not be included in the theoretical framework. We thereby demonstrated the need for a strong theoretical framework supporting mediation coupled with a rigorous mediation analysis to understand how informal controls influence performance. We consider this demonstration of the use of bias-corrected bootstrap methods to be a major contribution to the field. These bootstrap methods were first advocated by Shrout and Bolger (2002), subsequently implemented by Preacher and Hayes (2008) and Preacher and Kelley (2011), and strongly advocated by Zhao et al. (2010). These methods enable the calculation of indirect effects with bias-corrected confidence intervals to test the significance of complex mediation effects, which offer tremendous potential for investigating the complex relationships inhering in supply chain management.

Managerial implications

Managers may not perceive their actions as having any influence on whether and to what extent positive peer pressure develops among drivers or how drivers perceive organizational support. However, we show that when firms measure and incentivize employees' efforts, they can have a direct impact on employees in two ways: by fostering positive peer pressure among employees and by fostering the perception on the part of employees that the firm is providing them with a high level of organizational support. Likewise, managers may not perceive any benefits from exercising intangible informal controls, such as professional control. However, our results suggest that tangible benefits accrue from informal controls, such as professional control, which are influenced by management actions through implementing formal controls, such as output control.

Logistics managers could use the results of this research to select appropriate policies and procedures in an effort to motivate drivers to behave in ways that support the firm's objectives. Our results demonstrate that management strategies influence firms' operational goals and thus affect the bottom line. Our results suggest that when drivers are encouraged to interact with each other that the resulting positive peer pressure facilitates the full benefit of detailed driver feedback and driving-performance-based incentives on firm performance. Hence, firms that encourage their drivers to interact, cooperate, and discuss their work with each other reinforce the feedback drivers receive and the incentives designed to influence them. Our results suggest that driving-performance-based incentives could lead drivers to discuss feedback they receive from the firm. This could result in improved delivery reliability and responsiveness to customers, which could in turn lead to the firm realizing greater sales growth and market share. For example, a manager could post certain individual driver performance metrics in a prominent location in a terminal. This action could motivate drivers to influence each other through peer pressure, resulting in overall higher performance for all drivers and thus positively driving the bottom-line performance of the firm.

Logistics managers could use the results of this study to gain a better understanding of the importance of scheduling their drivers' work activities, determining work procedures, and regularly monitoring those activities. Our results demonstrate the resulting expected improvements in the reliability of delivery and responsiveness to customer needs for managers wishing to undertake these activities. By taking such steps, managers will position their firms to grow sales and gain a larger market share.

Limitations and future research directions

The results of this study are most applicable to firms with fleet sizes of 50 trucks or more because we excluded smaller fleets after consulting with industry experts. As with all empirical data, our data contains inherently random and nuisance variation. Perceptual data instead of actual performance data were collected to measure firm performance. Although the study could have benefited from drawing on firms' actual performance data such data is hard to come by due to its confidential nature. Perceptual data could cause different data sets to generate different results. However, we minimized this risk by adapting existing validated scale items from the literature. In addition, we specifically chose our methodology to minimize the effects of any spurious variation. Another possible limitation of this research is our use of a single key informant to collect data. Using a single informant from each firm allowed us to manage the cost of data collection; however, each informant was an expert with regard both to management controls and firm-level performance. Using structural equation modeling, we accounted for possible errors in measuring the different constructs and in validating our model's efficacy with regard to uncovering the underlying process. The use of a single respondent may also raise concerns with regard to common method variance, which can result in common method bias (CMB) (e.g. Podsakoff et al. 2003). However, Harman's single-factor test of our data provided evidence that the risk of CMB is minimal. Furthermore, recent simulation studies argue that single-respondent surveys do not exhibit bias (Richardson et al. 2009; Lance et al. 2010). Another possible limitation is our use of two response formats, self-administered and interviewer-administered. However, rigorous tests for multigroup configural and metric invariance showed the risk of bias from using the two response formats to be minimal. There could also be concern that changing the wording of the output control measures between the pilot and the main data collection might have compromised the results. The changes in wording, however, did not alter the meaning of the measures or the results, as evidenced in the results of the full model, for the main sample only (n = 573) (Appendix C).

Given the theoretical support, we were surprised to see no significant effects of POS on either operational or market performance. As our budget constraints dictated, we used the driver manager as the single key informant; however, it is likely that by measuring POS from the manager's perspective, we did not capture the construct effectively. It would be advisable, therefore, for future research to consider a research design and budget that would allow constructs to be measured based on interviews with multiple relevant key informants, such as driver managers and drivers. In general, the direct effects of formal and informal controls on performance were insignificant. Future research could take advantage of methodological advances in moderated mediation structural equation modeling (Preacher et al. 2007) to revisit the moderation effects of environmental factors and task characteristics theorized by Jaworski (1988) and Jaworski and MacInnis (1989). In addition, the field would benefit were future qualitative and quantitative research to be expanded to investigate driver control in a way that included the driver's perspective. For example, integrating the theoretical paradigm suggested in this study with that of Williams et al. (2011) would be useful in efforts to understand the effects that management driver control strategies have on drivers' intentions with regard to whether to stay in the employ of a motor carrier. Furthermore, future research could look at the effects of driver control on motor carrier safety and drivers' turnover intentions. In doing so, we could triangulate the data and compare performance with data from the Federal Motor Carrier Safety Administration safety database.

The model evaluated in this study includes a subset of formal and informal controls that are relevant to our theoretical framework of signaling theory, that is, SET and SIT. Future research could build on the current framework by investigating other formal or informal control strategies associated with other relevant theoretical paradigms. For example, research could investigate the combination of controls implemented by a motor carrier and their influence on how drivers exercise self-control in going about their jobs. Self-control is another type of informal control that could be beneficial in efforts to understand the management control process, especially when measured from the driver's perspective. Researchers could extend this framework to other logistics settings that employ autonomous employees, such as vehicle operators, in other transportation modes or autonomous teams that operate remotely and/or largely unsupervised.

Finally, Mello and Hunt (2009) suggest the use of technology as a complementary control to the formal controls used herein. In this study, our theories precluded consideration of theories from the information technology literature. Consequently, we did not consider the control aspects of recent innovations in QUALCOMM systems, electronic log-books, hand-held devices, or electronic on-board recorders. Future research could build on the results of this study to inform theory regarding and practices associated with the effects of using technology for driver-control purposes.

CONCLUSION

Driver control is crucial to the success of motor carrier operations. This article constitutes a first effort to answer this question: How do management strategies to control truck drivers influence carrier performance? We used multiple complementary theoretical perspectives to build a theoretical framework grounded in the management control literature to explain the process by which formal and informal controls affect firms' operational and market performance. We explicated the process whereby activity controls directly influence operational performance and the process whereby output controls' influence on operational performance is mediated by professional controls. Finally, improved operational performance eventually leads to sales growth and a larger market share. Researchers can continue to build on the theoretical framework developed and tested herein and thus further our knowledge of how management strategies for controlling truck drivers can influence carrier performance. Managers can use these results to select appropriate policies and procedures to influence driver behavior in favor of achieving company goals, thereby making a positive impact on the bottom line.

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APPENDIX A

ITEM MEASURES

Activity Control (AC) (Challagalla and Shervani 1996)
AC1: My company schedules my drivers' work activities.
AC2: My company determines my drivers' work procedures.
AC3: My company organizes my drivers' work as they see best.
AC4: My company makes most of the decisions that affect the way my drivers perform their job.

Output Control (OC) (Ramaswami 1996)
OC1: My company provides **detailed** feedback to the drivers concerning the extent to which they achieve their goals.*
OC2: **My drivers'** pay increases are **largely** based on how their performance compares with their goals.*
OC3: My company **sets** specific performance goals for my drivers.*

Perceived Organizational Support (POS)
POS1: My company makes sure that its drivers are aware of the company's values. (Piercy et al. 2006)
POS2: My company makes sure that its drivers feel good about working here. (Eisenberger et al. 1986; Piercy et al. 2006)
POS3: My company makes sure that its drivers are aware of what it considers to be proper behavior for its drivers. (Eisenberger et al. 1986)

Professional Control (ProfC) (Flaherty et al. 2007)
ProfC1: In my company, drivers have a lot of influence on how their fellow drivers perform their jobs.**
ProfC2: My drivers take their jobs very seriously.
ProfC3: The fleet department encourages cooperation among its members.
ProfC4: Most of the members of my department are familiar with each other's work.

Market Performance (MktPerf) (Baldauf and Cravens 2002)
MktPerf1: Market share compared to your major competitor.
MktPerf2: Market share compared to business unit objectives.
MktPerf3: Sales growth compared to business unit objectives.

Operational Performance (OperPerf)
OperPerf1: Reliable delivery of products compared to your company's objectives. (Stank et al. 2003)
OperPerf2: Percentage of late or changed deliveries compared to your company's objectives. (Stank et al. 2003)
OperPerf3: Responsiveness to special delivery requests compared to your company's objectives. (Stank et al. 1999)

Note: *Bolded text was added after the pilot test; **Dropped from the final analysis.

APPENDIX B
COVARIANCE–CORRELATION MATRIX*

	AC1	AC2	AC3	AC4	OC1	OC2	OC3	POS1	POS2	POS3	ProfC1	ProfC2	ProfC3	ProfC4	MktPerf1	MktPerf2	MktPerf3	OperPerf1	OperPerf2	OperPerf3
AC1	**1.6539**	.9174	1.0539	.8123	.1910	.1919	.4668	.0709	.1220	.1699	.1239	.0888	.1832	.0925	.0374	.1578	.0528	.2107	.1216	.1812
AC2	.6251	**1.3020**	.9171	.8485	.1713	.1366	.4155	.1155	.0917	.1749	.1013	.0780	.1813	.0705	.0825	.1620	.1466	.1826	.1375	.1833
AC3	.6092	.5975	**1.8096**	1.0552	.1258	.2100	.4019	.0707	.0825	.1149	.1074	.0201	.1444	.0241	.0287	.0722	.0419	.0809	.1080	.1488
AC4	.4316	.5081	.5360	**2.1418**	.0551	.1328	.4913	.1641	.0780	.1896	.1244	.1318	.2544	.0630	.0418	.0753	.0277	.1619	.1236	.1787
OC1	.1054	.1065	.0664	.1136	**.0551**	.8547	1.0225	.4001	.6210	.3902	.4785	.6416	.4821	.2705	.3115	.2591	.2686	.3020	.2974	.2614
OC2	.0745	.0597	.0779	.0453	.3028	**4.0124**	1.2871	.3950	.5839	.3366	.4626	.3336	.3037	.0662	.1973	.2992	.3554	.2213	.1201	.1231
OC3	.2279	.2286	.1875	.2108	.4555	.4034	**2.5372**	.4767	.4523	.3898	.2774	.4061	.3510	.1689	.1990	.2202	.2823	.2580	.0597	.2549
POS1	.0606	.1113	.0578	.1233	.3121	.2169	.3291	**.8270**	.5497	.3951	.2192	.3278	.3135	.1920	.1276	.1667	.1951	.2092	.1886	.1788
POS2	.0850	.0720	.0550	.0478	.3949	.2612	.2544	.5417	**1.2453**	.4567	.4276	.4077	.4281	.1917	.1880	.2495	.3074	.3442	.2121	.2373
POS3	.1690	.1961	.1093	.1657	.3542	.2150	.3130	.5557	.5235	**.6111**	.1980	.2545	.3215	.1254	.1741	.1560	.1777	.2352	.1717	.1493
ProfC1	.0599	.0552	.0496	.0528	.2110	.1435	.1082	.1498	.2381	.1574	**2.5901**	.3528	.3663	.2572	.1568	.0611	.1670	.0596	.0329	−.0187
ProfC2	.0646	.0640	.0140	.0843	.4264	.1560	.2388	.3376	.3422	.3049	.2053	**1.1397**	.4285	.2374	.1223	.1769	.1338	.2305	.1784	.2017
ProfC3	.1495	.1668	.1126	.1824	.3590	.1591	.2313	.3618	.4026	.4316	.2389	.4212	**.9080**	.3121	.2166	.1907	.1832	.3345	.2514	.2538
ProfC4	.0728	.0626	.0182	.0436	.1944	.0335	.1074	.2139	.1740	.1624	.1619	.2252	.3317	**.9747**	.1484	.1414	.1472	.1969	.2210	.2314
MktPerf1	.0234	.0583	.0172	.0230	.1781	.0794	.1007	.1131	.1357	.1795	.0785	.0923	.1831	.1211	**1.5401**	.7799	.5931	.4212	.2349	.3599
MktPerf2	.1040	.1204	.0455	.0436	.1558	.1266	.1172	.1554	.1896	.1692	.0322	.1405	.1697	.1214	.5327	**1.3916**	.8549	.4189	.2459	.3472
MktPerf3	.0329	.1029	.0249	.0152	.1527	.1421	.1419	.1719	.2206	.1821	.0831	.1004	.1540	.1194	.3828	.5805	**1.5586**	.4519	.2516	.3692
OperPerf1	.1389	.1357	.0510	.0938	.1817	.0937	.1374	.1951	.2616	.2552	.0314	.1831	.2977	.1691	.2878	.3012	.3070	**1.3902**	.7676	.6798
OperPerf2	.0749	.0955	.0636	.0669	.1672	.0475	.0297	.1643	.1506	.1740	.0162	.1324	.2090	.1773	.1500	.1651	.1596	.5158	**1.5931**	.6653
OperPerf3	.1219	.1390	.0958	.1057	.1605	.0532	.1385	.1702	.1840	.1653	−.0101	.1635	.2305	.2029	.2510	.2547	.2559	.4989	.4561	**1.3353**

Note: *Variances (bold) on the diagonal, correlations below, and covariances above.

APPENDIX C
MAIN SAMPLE: FULL MODEL PATH WEIGHTS

Structural Path	Hypothesis	Effect	SE	*t*-value	*p*-value	UCL*	LCL*
AC → OperPerf	H_{1a}	.12	.05	2.35	.019	–	–
AC → MktPerf	H_{1b}	−.01	.04	.22	.826	–	–
OC → OperPerf	H_{2a}	−.03	.08	.29	.769	–	–
OC → MktPerf	H_{2b}	.16	.06	1.67	.096	–	–
OperPerf → MktPerf	H_3	.40	.06	5.79	.000	–	–
AC → OperPerf → MktPerf	H_{4a}	.04	.02	–	.013	.008	.079
OC → OperPerf →MktPerf	H_{4b}	−.01	.03	–	.764	−.083	.051
AC → POS	H_{5a}	−.02	.03	.36	.717	–	–
OC → POS	H_{5b}	.66	.04	9.69	.000	–	–
AC → ProfC	H_{6a}	−.03	.04	.61	.540	–	–
OC → ProfC	H_{6b}	.69	.05	8.88	.000	–	–
POS → OperPerf	H_{7a}	.11	.14	1.10	.272	–	–
POS → MktPerf	H_{7b}	.01	.11	.11	.915	–	–
ProfC → OperPerf	H_{8a}	.37	.17	2.94	.003	–	–
ProfC → MktPerf	H_{8b}	.00	.13	.04	.971	–	–
AC → POS → OperPerf	H_{9a}	.00	.01	–	.418	−.03	.01
OC → POS → OperPerf	H_{9b}	.06	.08	–	.419	−.10	.21
AC → ProfC → OperPerf	H_{10a}	−.01	.02	–	.476	−.07	.03
OC → ProfC → OperPerf	H_{10b}	.20	.10	–	.008	.06	.43

Notes: Chi-square = 272.65, df = 137, *p*-value = .000, CFI = .97, RMSEA = .040
*Bootstrap upper and lower confidence intervals for the indirect effects.

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