Accepted Manuscript
Version of record at: https://doi.org/10.1108/IJPDLM-04-2025-0164

Relative performance feedback in the trucking industry: How rank information affects drivers' fuel efficiency

Abstract

Purpose – Trucking companies often use relative performance feedback (RPF) to promote fuel-efficient driving. Building on prior, largely experimental research, we examine the effects of RPF on fuel efficiency performance in the trucking industry. In so doing, we consider how ranking information conveyed to drivers in RPF impacts their subsequent miles per gallon (MPG). Further, we hypothesize that drivers interpret such ranking information in a temporal context such that recent improvements or deteriorations in their rank moderate the rank-MPG relationship.

Design/methodology/approach – We analyze a driver-week-level panel dataset obtained from a US-based trucking company. We implement various regression analyses to estimate the hypothesized effects and ascertain the robustness of our findings. Potential endogeneity concerns are addressed as well.

Findings – We find that that truck drivers' fuel efficiency performance increases (declines) after receiving RPF indicating a higher (lower) rank. This effect, however, is not uniform across all drivers—it is observed for top- and bottom-ranked drivers but less pronounced for middle-ranked drivers. Additionally, both week-over-week deteriorations and improvements in drivers' rankings over time can diminish the impact of RPF on fuel efficiency.

Originality – Our work offers nuanced insights into how RPF affects truck drivers' fuel efficiency. We also contribute to the trucking-focused literature by highlighting feedback as a mechanism to alter operator behavior and efficiency. We similarly add to social comparison theory and prior RPF literature by documenting that temporal changes in relative performance—both improvements and deteriorations in a driver's rank—can moderate the way RPF affects subsequent performance. These insights collectively help inform the design of motor carriers' performance feedback strategies.

Keywords Trucking, ranking, performance feedback, fuel efficiency

Paper type Research paper

1. Introduction

With fuel accounting for over one third of trucking companies' total operating expenses,[1] on average, most carriers engage in various efforts aimed at increasing fuel efficiency. Besides mechanical factors like engine efficiency, vehicle weight, and aerodynamics, driver behavior is a critical determinant of fuel

[1] https://ecapital.com/blog/controlling-your-trucking-companys-cost-of-fuel/

consumption (Phares & Balthrop, 2022; Thijssen et al., 2014). To motivate drivers to operate trucks in a fuel-saving manner, many carriers share relative performance feedback (RPF)—ranking truck drivers' fuel efficiency relative to their peers—and offer incentives and rewards for superior performance. For example, Mesilla Valley Transportation awards its drivers with the highest miles per gallon (MPG) a brand-new car and a $25,000 bonus every three months.[2] A similar RPF-based incentive program has generated nearly $2 million in annual fuel cost savings for full-service truckload carrier Artur Express.[3] RPF is a highly effective tool to promote efficiency and compliance with operational policies in the trucking context since drivers have substantial autonomy on the road (Mello & Hunt, 2009). Indeed, RPF is an integral part of carriers' remuneration and incentive schemes and a means to retain qualified drivers against the backdrop of high turnover rates (Kemp et al., 2013; LeMay & Keller, 2019; Miller et al., 2021).

Despite the widespread use of RPF in the trucking industry and anecdotal evidence of its effectiveness, it is unclear whether RPF consistently produces the desired benefits for motor carriers. This question arises as some prior research—conducted in healthcare, retail, and accounting settings, for example—reports insignificant or even adverse effects of RPF (e.g., Eriksson et al., 2009; Hannan et al., 2008). Other studies, in turn, indicate that RPF enhances worker performance (e.g., Lourenço et al., 2018; Song et al., 2018; Zhang et al., 2022). The findings of most of these studies may not extend to the trucking context as they largely depend on experiments and stylized tasks like word-spotting or simulated decision making to examine the effects of RPF (e.g., Gill et al., 2019; Hannan et al., 2008). Furthermore, some studies have been conducted at the team or firm level (e.g., Bandiera et al., 2013; Casas-Arce and Martínez-Jerez, 2009) rather than at the individual level. Finally, much of the RPF literature is based on settings where subjects receive performance feedback over a limited number of periods (Vidal and Nossol, 2011). In the motor carrier industry, in turn, many companies share RPF specific to each driver and their driving activity on an ongoing basis and with high frequency (e.g., weekly). The high autonomy, distinct demographics, and unique incentive structures of drivers further differentiate the trucking context from the healthcare, retail, and accounting settings that have typically been used in prior RPF research (Phares and Balthrop, 2022). This presents an opportunity not only to examine the effects of RPF in the trucking context but also to take a dynamic perspective and investigate how changes in drivers' relative rank over time modulate their subsequent effort and outcomes.

Drawing on insights from social comparison theory and psychology literature, we examine (1) how ranking information conveyed in RPF impacts drivers' subsequent fuel efficiency performance and

[2] https://afdc.energy.gov/conserve/driving-behavior
[3] https://www.fleetowner.com/emissions-efficiency/fuel-economy/article/21254828/performance-based-driver-incentives-help-fleet-save-2m-in-fuel-costs

(2) how changes in drivers' relative rank over time moderate this effect. We test the associated hypotheses using data obtained from a midsized for-hire trucking company offering truckload, intermodal, and logistics services to a broad range of manufacturing and retail clients across the U.S. The company informs drivers on a weekly basis where they rank in a peer group of drivers operating the same year, make, and model truck and offers financial bonuses to drivers who achieve the highest MPG.

Our study makes several contributions to literature and offers practical insights. First, it advances social comparison theory and the literature on relative performance feedback (RPF) by showing that temporal changes in relative performance—both improvements and deteriorations—moderate how feedback influences subsequent performance. This perspective moves beyond the traditional static view of performance feedback and provides a more dynamic behavioral account of its effects. Second, we contribute to the burgeoning research on people-centric operations (Boudreau et al., 2003; Roels and Staats, 2021) by demonstrating how feedback mechanisms can shape truck driver behavior and impact fuel efficiency in in a transportation and logistics context. Finally, we contribute to the trucking literature which has largely emphasized technological innovations such as real-time tracking and route optimization as drivers of operational efficiency (Feng and Ye, 2021; Zhou and Wan, 2022). In turn, we highlight performance feedback as a conditional performance-enhancing mechanism. The insights shared in this study collectively help inform the design of effective motor carriers' performance feedback strategies.

2. Literature

Our research on how feedback-driven interventions impacts truck drivers' performance draws on and contributes to the literature on people-centric operations, studies of the trucking industry as well as research on performance feedback. We provide an overview of these streams and outline how our work builds on and complements them.

2.1. Literature on People-Centric Operations in Logistics Research

The pursuit of greater efficiency, sustainability, flexibility, and resiliency amidst growing supply chain complexity as well as customer demand and pressures (Scott & Davis-Sramek, 2023) places rising expectations on the performance of human capital, particularly frontline workers like truck drivers. The people-centric operations literature emphasizes such role of individuals in shaping the performance of operational processes. For instance, Roels and Staats (2021) highlight that workers are embedded in systems where their actions—often discretionary and evolving over time—significantly impact outcomes. Donohue et al. (2020) similarly stress the importance of understanding human behavior in operations, arguing that cognitive biases and social preferences heavily influence process performance. In this vein, de Vries et al. (2016) find that a worker's regulatory focus—whether prevention- or promotion-oriented—leads to better performance when aligned with a cooperation-based rather than competition-based incentive system. Individuals' behavior and motivation, thus, are key considerations in the design of operations strategies to enhance performance.

Several studies have examined the operational outcomes of human-centric strategies in the context of warehousing. Winkelhaus (2022) analyze how changes in work characteristics affect worker satisfaction, emphasizing the alignment of system performance objectives with employee needs. Sheu and Choi (2023) investigate intelligent logistics, demonstrating that human-robot coordination in warehouses can improve order fulfillment. Additionally, Zhang et al. (2022) find that providing feedback to warehouse pickers enhances performance without sacrificing quality. In sum, prior research on people-centric operations in various logistics contexts suggests that mechanisms designed to improve the human element in operations can lead to better overall outcomes. Our research contributes to this burgeoning people-centric supply chain literature examining how human experiences and interactions influence operational performance (Bendoly et al., 2010; Boudreau et al., 2003) in a logistics context.

2.2. Literature on the Trucking Industry

While prior research on people-centric operations has provided valuable insights, it is unclear if these findings apply to the trucking sector since truck drivers, unlike other logistics workforce such as warehouse workers, operate with great autonomy and only intermittent managerial oversight (Phares and Balthrop, 2022). Yet, the trucking industry plays a crucial role in operations management, and the well-being of drivers is a key driver of motor carriers' efficiency (Kemp et al., 2013).

Our study specifically delves into the commercial trucking sector, the primary provider of transportation services in the United States (U.S. Department of Transportation, 2012). How drivers operate their trucks has a direct impact on fuel efficiency, operating costs, and customers' perceptions of service quality, thereby influencing the carrier's competitive edge (Davis-Sramek et al., 2020; Keller & Ozment, 2009). In particular, fuel efficiency not only affects the cost-effectiveness of trucking operations but also reflects the company's commitment to reducing its carbon footprint, which is essential for firms looking to enhance their environmental credentials and comply with increasingly stringent regulations and customer requirements (Davis-Sramek et al., 2020).

This literature discusses various approaches trucking companies adopt to influence truck drivers' behavior. For instance, researchers have explored how technology and formal control mechanisms (e.g., activity and process control) influence firm performance (Miller et al., 2013). Others have studied the factors that contribute to driver turnover (Cantor et al., 2011; Miller et al., 2017), burnout (Thomas et al., 2020), and safe driving (Cantor et al., 2006, 2016). While these studies shed light on important aspects of driver management, there has been a notable dearth of research specifically focusing on fuel efficiency in this context. One of the few exceptions is Jazairy et al. (2023) who explore the motivations behind truck

Accepted Manuscript
Version of record at: https://doi.org/10.1108/IJPDLM-04-2025-0164

drivers' adoption of eco-driving practices, revealing that drivers' intended and actual eco-driving behaviors are influenced by their attitudes, subjective norms, and perceived behavioral control.

Our study examines how feedback-driven interventions impact truck drivers' fuel efficiency performance, thereby contributing to the trucking literature. Specifically, we investigate how RPF affects truck drivers and their fuel efficiency, offering data-driven insights into how such operational interventions can be effectively designed and implemented to enhance operational performance among highly autonomous and logistics workers.

2.3. Literature on the Effects of Performance Feedback

Performance feedback is commonly used to affirm successful practices or promote behavioral change among employees (Bendoly et al., 2010). RPF compares an individual's performance against that of others (Song et al., 2018) and is often communicated in the form of a worker's rank relative to peers (i.e., rank-order feedback) (Eriksson et al., 2009; Genakos and Pagliero, 2012). RPF is the basis for incentive schemes that reward relatively greater performance (Lambert et al., 1993).

Previous research on the effects of RPF has produced mixed results. Some studies suggest that RPF can boost performance. In the context of healthcare operations, Song et al. (2018) find that public disclosure of peer performance allows physicians to identify and adopt best practices from top performers, leading to a significant increase in physician productivity and overall efficiency. Similarly, there is evidence that RPF leads to a large and long-lasting increase in worker productivity in warehouse picking operations (Vidal and Nossol, 2011; Zhang et al., 2022). Conversely, some studies document insignificant and negative effects of providing RPF using real-effort experiments. Eriksson et al., (2009), for example, conduct a laboratory experiment with a piece-rate pay scheme and find that RPF provision does not significantly affect outcomes. Hannan et al. (2008), in turn, observe that providing RPF can even lead to a decline in performance. In their field experiment of team-based incentives, Bandiera et al. (2013) similarly find that ranking feedback reduces average productivity, especially for low-ranked individuals.

A growing body of literature has examined how feedback content influences feedback recipients' performance. Studies exploring the effects of RPF in the form of ranking information have yielded inconclusive findings (Casas-Arce and Martínez-Jerez, 2009; Charness et al., 2014; Genakos and Pagliero, 2012; Gill et al., 2019). There is evidence that individuals become increasingly motivated and make greater effort as RPF conveys greater relative performance (Eriksson et al., 2009). Yet, such feedback can have a demotivating effect, leading individuals to 'rest on their laurels' and resulting in reduced performance (Eriksson et al., 2009). Some studies suggest that RPF indicating extreme levels of relative (non-)performance engenders differential reactions as compared to RPF that places subjects at moderate relative performance levels (Gill et al., 2019). Casas-Arce and Martínez-Jerez (2009), for example, find that leading retailers in a sales tournament reduce their effort as the lead increases, and

Accepted Manuscript
Version of record at: https://doi.org/10.1108/IJPDLM-04-2025-0164

trailing retailers diminish their effort as the distance to the winning position increases. Charness et al. (2014), on the other hand, provide evidence that individuals with lower ranks exert greater subsequent efforts, and Gill et al. (2019) find that both first- and last-ranked subjects make the greatest effort. Other studies emphasize the role of individuals' expectations. Azmat et al. (2019) and Kuhnen and Tymula (2012), for example, report that individuals tend to improve their performance when RPF indicates worse-than-expected outcomes but reduce their effort when RPF reveals better-than-expected performance. These findings collectively highlight the inconsistent effects of RPF—and ranking information specifically—suggesting the need for an empirical study of how truck drivers react to ranking feedback in the unique trucking context.

2.4. Performance Feedback in the Trucking Context: Addressing a Critical Gap

While there is ample RPF research in the broader management literature, few studies have examined the effects of performance feedback in a trucking context. Most research on performance feedback in the transportation sector focuses on the role of performance feedback in altering driving behavior and performance in a non-commercial setting. In a field experiment with drivers of personal vehicles, Choudhury et al. (2022) observe that individual performance feedback showing personal best and personal average driving scores can improve safe driving performance. Chen et al. (2017) similarly find that providing RPF showing average performance as compared to similar drivers can reduce the number of traffic rule violations by 5 to 6%. Rolim et al. (2016), in turn, observe an increase in fuel consumption for personal drivers receiving individual performance feedback. Choudhary et al. (2021) also document an overall negative effect of individual performance feedback on driver performance in terms of accident rates even though strong negative feedback can have a positive impact on drivers' short-term safety performance.

There remains an opportunity to examine how RPF conveying ranking information affects subsequent performance in a commercial trucking context. Commercial trucking operations differ from personal transportation settings in several critical respects: Truck drivers spend more time on the road (Walton, 1999) and operate vehicles with different driving characteristics (Fors et al., 2015). Importantly, they typically face the pressure of strict delivery schedules. Without incentives or demands from their employers for fuel efficiency, truck drivers might see little reason to alter their driving habits to conserve fuel (Fors et al., 2015). Our study contributes to extant literature by exploring how RPF—including the level and week-over-week change of relative performance information it conveys—affects truck drivers' subsequent fuel efficiency. To address this gap, we draw on and extend social comparison theory (Festinger, 1954) which posits that individuals evaluate their own abilities in comparison to others. Specifically, while prior studies have predominantly focused on an individual's static relative position (e.g., being ranked top or last at one point in time), there is a critical gap in our understanding of the interactive effects of dynamic rank changes—such as an improvement or deterioration in period-over-period rank. By distinguishing the effects of rank level from rank change, we aim to provide a more granular understanding of how dynamic social comparison information impacts effort and behavior in a critical operational context, offering guidance for trucking companies' managers in designing more effective feedback systems.

3. Theory & Hypothesis Development

Building on prior literature, we submit that RPF is a crucial determinant of truck drivers' subsequent fuel performance. RPF indicated to individuals their relative performance, thereby activating social comparison processes. According to social comparison theory (SCT; Festinger, 1954), individuals evaluate their relative standing with other people (Redersdorff and Guimond, 2005) and use this comparison to anticipate future outcomes (Suls et al., 2002) and adjust their effort accordingly. Individuals compare themselves to similar peers and derive psychological utility from better performance. That is, when individuals receive social comparison information that indicates greater relative performance, this higher comparative position in a group evokes positive emotions such as higher self-esteem as well as greater perceived influence and respect from others (Fiske, 1991; Anderson et al., 2001; Berger et al., 1980). Conversely, having a lower relative rank may elicit negative emotions and impair performance (Kemper, 1991; Marr and Thau, 2014), potentially leading to feelings of shame, discouragement, and envy.

In organizational contexts, employees compare themselves against coworkers operating at the same hierarchical levels and functions and derive utility from favorable comparisons in terms of performance, salary, benefits, or their career progression (Lam et al., 2011). SCT further posits that individuals are motivated to reach a higher relative position, either by improving their own performance through increased effort (Kuhnen and Tymula, 2012) or, in adverse scenarios, by engaging in detrimental actions such as cheating and sabotage to lower competitors' standing (Charness et al., 2014). Indeed, an extensive body of research in social psychology and economics shows that social comparisons and benchmarks can substantially influence employee motivation and actions (Falk and Ichino, 2021; Kluger and DeNisi, 1996; Szymanski and Harkins, 1987).

While our primary focus is on the psychological mechanisms of SCT, it is worth noting that tournament theory (Lazear and Rosen, 1981) provides a complementary perspective rooted in microeconomic theory. Tournament theory suggests that competition for monetary rewards based on relative performance strengthens individuals' motivation (e.g., Casas-Arce and Martínez-Jerez, 2009; Eriksson et al., 2009; Hannan et al., 2008) and, thus, highlights the value of RPF as a reference for evaluating and rewarding individuals (Lazear and Rosen, 1981). In our development of Hypothesis 1, we emphasize the various psychological mechanisms of SCT, while acknowledging that economic incentives can reinforce the effects of ranking information.

Traditional SCT focuses on static comparisons at one point in time (Redersdorff and Guimond, 2005) and later studies extend this viewpoint to incorporate the temporal dimension of social comparison capturing individuals' present standing relative to their past standing (Albert, 1977; Reh et al., 2018). Such a temporal view is particularly relevant in organizational contexts where employees receive frequent feedback, making them well aware of how their relative positions have evolved. Reh et al. (2022), for instance, present evidence that employees compare the trajectory of their own position relative to that of their coworkers and use it to project their future performance. The direction and magnitude of change in individuals' ranking trajectories are key temporal social comparison markers (Reh et al., 2022). This dynamic perspective is also consistent with the work of Choudhary et al. (2021) who stress the importance of considering how individuals' performance has improved or deteriorated over time.

Building on these insights, we further theorize that the ranking information contained in RPF is interpreted in the context of drivers' historical rankings such that the effect of RPF on subsequent fuel performance is contingent on recent changes in drivers' rankings, as detailed in Hypothesis 2a and 2b. This temporal context is particularly salient in the trucking context where feedback is often provided with high frequency (i.e., weekly). Such frequent RPF indicates the effectiveness of a driver's effort in response to previous ranking information and, thus, contextualizes the current ranking information provided in RPF. By integrating static and dynamic social comparisons, we extend SCT to explore their interplay in the setting of the trucking industry.

3.1. Effects of Current Rank on Driver's Subsequent Fuel Efficiency Performance

Drawing from SCT, we contend that a driver's current rank as conveyed through RPF significantly affects the driver's subsequent fuel efficiency. The provision of RPF triggers social comparisons with peers and various psychological and motivational responses. Rank-order feedback fosters performance through competition that is stoked via social comparisons, peer pressure and monitoring (Falk and Ichino, 2021; Festinger, 1954; Roels and Su, 2014). Individuals are intrinsically motivated to outperform others even when their performance is not linked to financial rewards (Kuhnen and Tymula, 2012). That is, humans derive utility from the mere knowledge that they attain a higher rank (Dohmen et al., 2011; Zizzo, 2002), and this utility drives goal commitment (Locke and Latham, 1990), motivates greater effort (Bendoly et al., 2010; Kandel and Lazear, 1992), and ultimately produces superior outcomes. In the trucking context, drivers who receive RPF that implies a favorable relative standing derive positive psychological utility from this information. This motivates them to sustain and expand their performance advantage and, thus, operate in a manner that increases their fuel efficiency.

Conversely, unfavorable social comparisons resulting from a lower rank can elicit negative emotions and lead to reduced effort. Effort and performance often decline when goals are deemed unattainable (Casas-Arce and Martínez-Jerez, 2009; Hannan et al., 2008; Locke and Latham, 1990). In this vein, prior studies find that when workers learn of their relatively poor performance, they tend to exert less effort and may even give up (Ashraf et al., 2014; Bandiera et al., 2013; Barankay, 2012). For truck drivers, lower rank can diminish their motivation to strive for better fuel performance. In the absence of this motivation to compete or improve their rank, such drivers may revert to less fuel-conscious behaviors. This is consistent with findings showing that truck drivers express a preference for positive feedback while becoming less engaged when feedback is negative (Huang et al., 2005).

Besides these psychological mechanisms, tournament theory offers additional insights suggesting that economic incentives based on relative performance can also affect employees' efforts and associated outcomes. Tournament theory builds on the fundamental tenet that effort is costly and, therefore, a function of expected rewards—the product of the likelihood of winning a tournament and the size of the prize (Lazear and Rosen, 1981). RPF provides an indication of the likelihood of earning bonuses, pay raises, or other economic rewards that are competitively awarded by organizations. As the rank and the likelihood of winning increase, employees are further motivated to expend greater effort (Hannan et al., 2008). In this vein, Awaysheh et al. (2023), find that some warehouse workers increase their effort when presented with performance information that suggests greater marginal return on incremental effort. Contrarily, drivers who receive RPF that conveys a lower rank have no reasonable expectation of earning any of the rewards offered to higher-ranked performers. In the absence of the prospect of fiduciary rewards, such drivers may engage in fuel-consuming behaviors like speeding and idling that offer the appeal of shortening total trip time, lowering the likelihood of incurring penalties for late deliveries, and increasing driver comfort. These economic incentives can reinforce the motivational effects of social comparison, affecting truck drivers' responses to RPF.

Based on the above arguments, we expect that drivers' effort and subsequent fuel efficiency performance increase with the rank conveyed in RPF and hypothesize that:

H1: The higher the rank (as conveyed in RPF), the greater the truck drivers' subsequent fuel efficiency performance.

3.2. Moderating Effects of Temporal Rank Change

Building on the dynamic perspective of SCT, we hypothesize that the effect of rank information on drivers' subsequent fuel efficiency performance (H1) is moderated by drivers' temporal rank change. (Kluger and DeNisi, 1996). In particular, we conjecture that an improvement in a driver's rank over time strengthens the positive impact of having a higher current rank on subsequent effort and fuel efficiency. In such a scenario, drivers likely attribute the achievement of a higher current rank to their fuel-conserving efforts, reinforcing the perception that these efforts are effective (Lam et al., 2011) and magnifying the motivational effect of higher current ranks. Indeed, prior research suggests that individuals are motivated to work harder when they believe that higher efforts will lead to improved performance outcomes, particularly when there is evidence of progress in terms of positive changes in their relative standing (Vroom, 1964). Furthermore, as individuals improve their rank over time, their self-efficacy (Bandura et al., 1999) increases, enhancing their belief in their ability as well as motivation to perform well in the future. Consequently, rank improvement strengthens the motivational effects of a high current rank on drivers' subsequent performance.

H2a: RPF conveying greater week-over-week improvement in a driver's rank strengthens the positive effects of current rank on the truck driver's subsequent fuel efficiency performance.

We also anticipate that rank deterioration reduces the positive effects of a current rank on subsequent effort and performance. As their rank decreases, drivers experience deteriorated self-efficacy (Bandura et al., 1999) making them less confident in their ability to sustain and improve performance. Rank deterioration can also send a signal to the drivers that their effort does not result in better performance, leading them to disengage from tasks and divert their focus from expending effort to maintain high performance (Vroom, 1964). Barankay (2012) for example, observe that salespeople reduce their effort and have lower subsequent performance when they receive negative feedback showing a decrease in historical performance in their field experiment. In the context of our research, current rank information may be less effective in enhancing performance as drivers feel discouraged by their recent rank decline. As such, rank deterioration dampens the motivational effects of higher current rank.

H2b: RPF conveying greater week-over-week deterioration in a driver's rank weakens the positive effects of current rank on the truck driver's subsequent fuel efficiency performance.

4. Research Setting, Data, and Econometric Models

4.1. Research Setting

We test our hypotheses using data obtained from a U.S.-based midsized for-hire trucking company offering truckload, intermodal, and logistics services across the manufacturing, retail, and automotive sectors. The company's trucks are fitted with Qualcomm satellite communication devices through which driving performance is captured and RPF is shared. As drivers are required to sign in before operating the trucks, they can be associated with trucks in specific time periods.

The company operates a bonus program whereby drivers can earn monthly, quarterly, and annual bonuses based on their relative fuel efficiency. Drivers are ranked within groups of peers operating the same year, make and model trucks, and the average peer group size is 153. Those with relatively greater performance are awarded a variety of prizes like cash payments, iPhones, iPads, and gift cards. The company provides drivers with weekly performance reports, including the driver MPG, the count of all drivers in their peer group, and their rankings within the peer group.

4.2. Data

4.2.1. Data Cleaning

We obtained weekly truck-level data for a 29-week period from May to December 2016. The dataset is not balanced since not all trucks are continuously operated. We start with a sample of 17,891 driver-week observations pertaining to 2,661 drivers and driver pairs. We take the following data cleaning steps:

- Since we are interested in the effects of RPF on driver performance, we restrict our analysis to single drivers and remove truck-week observations pertaining to driver pairs.
- A total of 201 driver/driver pairs (7.5%) switch trucks during the studied time period. We retain only the longest driver-truck-level time series and examine if truck switching affects performance in the robustness check section.
- We remove observations with missing data on any of the variables detailed below.

Our final dataset used to test our hypotheses contains 8,130 truck-driver-week observations pertaining to 552 drivers. We conduct additional robustness checks using a larger, less restrictive sample to ensure our findings are consistent.

4.2.2. Variable Descriptions

Dependent variable

The main dependent variable of interest is the driver's fuel efficiency performance as measured by miles per gallon (MPG), the ratio between the traveled distance and total fuel used in a given week (Mane et al., 2021).

Independent and control variables

We use a driver's rank, i.e., a driver's position in terms of fuel efficiency relative to their peers in the same group as a basis for the measurement of our key independent variables. This rank is scaled such that drivers with lower (higher) fuel efficiency are assigned a lower (higher) rank score. To control for variations in peer group size, we divide this score by the total number of drivers in the peer group to obtain the standardized rank (*StdRank*). For example, a driver ranked at number 20 among 40 peers will have a standardized rank score of 0.5, placing the driver in the 'middle of the pack.' In turn, a driver with a rank score of 20 in a group of only 20 peers will have a score of 1, thus making them the top-ranked driver. We evaluate the sensitivity of the results with respect to variations in the operationalization of the *Rank* variable in Section 6.2 and note that our *StdRank* (*Rank*) variables are consistent with the RPF information the carrier shared with its drivers.

We capture the week-over-week change in a driver's rank as an indicator of the improvement or deterioration of their performance. Specifically, we subtract each driver's standardized rank score in week *t* from that in week *t-1*, and then split rank changes into rank improvement and deterioration scores following Choudhary et al. (2021):

Let $Delta_t = StdRank_t - StdRank_{t-1}$, then

$$\begin{cases} RankImprovement_t = \ Delta_t \ if \ Delta_t > 0 \ and \\ RankImprovement_t = \ 0 \ otherwise \end{cases}$$

$$\begin{cases} RankDeterioration_t = \ |Delta_t| \ if \ Delta_t < 0 \ and \\ RankDeterioration_t = \ 0 \ otherwise \end{cases}$$

We also include the logarithm of weekly distance traveled *(Distance*), a key trip characteristic, as a control variable. Weekly fixed effects account for time-specific weather and driving conditions that might affect drivers' fuel efficiency. Driver-truck fixed effects, finally, capture otherwise unobserved time-invariant driver- or truck-specific characteristics (e.g., drivers' general aptitude and driving style or the driving conditions in the geographic region within which they tend to operate; trucks' technical characteristics and levels of wear and tear).

All variables are winsorized at the 1st and 99th percentiles to reduce the effects of outliers. We also mean-center all our independent variables to facilitate the interpretation of the results in the presence of interaction effects.

Descriptive statistics and correlations

Table 1 presents the descriptive statistics and pairwise correlations of all variables. Multicollinearity does not appear to be a significant concern as all variance inflation factors are well below the threshold recommended by Hair et al. (2010).

Table 1. Descriptive Statistics and Pairwise Correlations (n = 8,130)

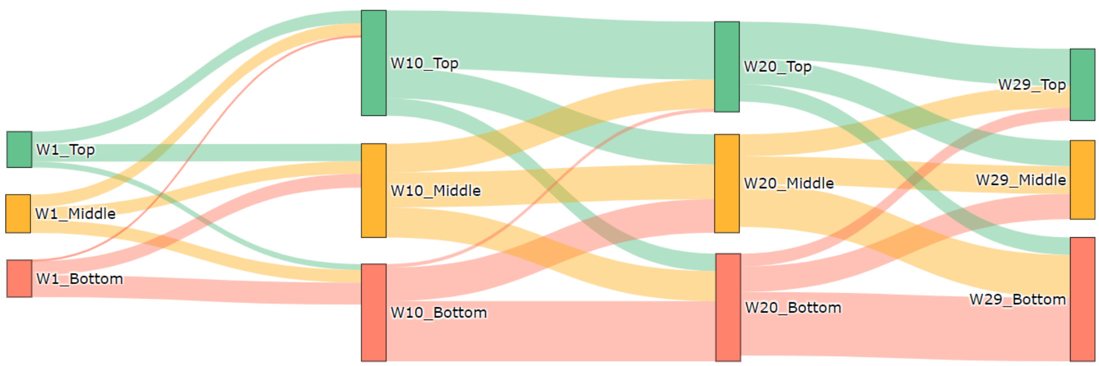
Variables	Mean	Std. Dev.	(1)	(2)	(3)	(4)
(1) MPG	7.731	.748				
(2) StdRank	.476	.288	.540			
(3) RankImprovement	.092	.151	.055	.385		
(4) RankDeterioration	.092	.150	.001	-.338	-.373	
(5) LogDistance	7.588	.495	.139	.038	-.008	.035

Note: All correlation coefficients with an absolute value greater than .055 are statistically significant at $p<.05$.
Source: Authors' own elaboration.

We note that there are significant fluctuations in drivers' performance over time. Across the 29-week sample period, drivers' standardized rank (ranging from 0 to 1) exhibits an average standard deviation of 0.288. Correspondingly, their unstandardized rank varies by an average of 60.09 positions. To visually demonstrate these performance and rank variations over time, Figure 1 illustrates the movement of drivers between the bottom, middle, and top terciles of the rank distribution across Weeks 1, 10, 20,

Accepted Manuscript
Version of record at: https://doi.org/10.1108/IJPDLM-04-2025-0164

and 29. The thickness of each flow line in the diagram is proportional to the number of drivers making that specific transition, with thicker lines indicating a greater number of drivers. Figure 1 demonstrates significant temporal shifts in driver performance, indicating that top-ranked drivers can transition to middle or bottom tiers and vice versa over time. This dynamic characteristic of driver performance serves as an important condition for our subsequent analyses of the effects of ranking feedback.



Source: Authors' own elaboration.

Figure 1. Driver Rank Transitions Across Weeks 1-10-20-29

4.3. Econometric Model

We use panel regression analyses to test our hypotheses. Specifically, we estimate fixed effects models to address potential endogeneity concerns that may arise due to unobserved variables (Certo et al., 2017; Halaby, 2004). By using fixed effects models, we control for time-invariant driver-level characteristics that may affect the level of their driving performance. In turn, this approach enables us to examine the effects of ranking information that varies over time while holding driver-level (truck-level) factors constant. Stated differently, the fixed effects estimation focuses on within-driver variance and allows us to capture how changes in a given driver's rank feedback result in changes in subsequent fuel efficiency performance for the same driver (Certo et al., 2017).

Our data exhibits both heteroskedasticity and first-order autocorrelation as indicated by the Wald test ($\chi^2(552) = 10{,}611, p = 0.000$) and the Wooldridge test ($F(1{,}512) = 415{,}81, p = 0.000$). We therefore employ robust standard errors clustered at the driver-truck level. We also estimate feasible generalized least squares models addressing both heteroskedasticity and panel-specific autocorrelation in the robustness check section. To ensure a strict temporal sequence between the independent variables of interest and the outcome, we lag all ranking feedback-related variables by one period relative to the dependent variable (MPG). While we strive to alleviate endogeneity concerns with our fixed effects-based estimation and the temporal lag structure, we further address endogeneity using a system generalized method of moments (GMM) estimation in the robustness check section.

The direct effects model specified in Equation (1) is used to test Hypothesis 1, and the interaction terms between *StdRank* and *RankImprovement* / *RankDeterioration* are added in Equation (2) and used to test Hypotheses 2a/b. In line with our contention that RPF will affect subsequent performance, all RPF-based variables are lagged by one week as mentioned above.

$$MPG_{it+1} = \beta_0 + \beta_1 StdRank_{it} + \beta_2 RankImprovement_{it} + \beta_3 RankDeterioration_{it} + \beta_4 LogDistance_{it+1} + \varphi_i + \theta_{t+1} + e_{it+1} \quad (1)$$

$$MPG_{it+1} = \beta_0 + \beta_1 StdRank_{it} + \beta_2 RankImprovement_{it} + \beta_3 RankDeterioration_{it} + \beta_4 StdRank_{it} * RankImprovement_{it} + \beta_5 StdRank_{it} * RankDeterioration_{it} + \beta_6 LogDistance_{it+1} + \varphi_i + \theta_{t+1} + e_{it+1} \quad (2)$$

where φ_i captures driver fixed effects and θ_{t+1} captures time fixed effects, and e_{it+1} is the error term.

5. Empirical Results

5.1. Main Estimation Results

Table 2 presents the fixed effects regression results. Model (1) includes only the direct effects, and the interaction terms between *StdRank* and *RankImprovement* as well as *RankDeterioration* are added in Model (2). With respect to the control variable, there is a marginally significant positive effect of distance on fuel efficiency ($\beta = 0.039, p = 0.088$), indicating that greater distance driven is associated with greater MPG. As for the weekly fixed effects, which we do not report in the interest of brevity, we find that fuel efficiency tends to be lower in November and December relative to June. This may be attributable to factors such as increased air density, higher rolling resistance, and longer engine warm-up times in colder weather.

Regarding the direct effect of our main independent and moderating variables, we observe a positive and significant coefficient estimate for *StdRank* ($\beta = 0.391, p = 0.000$) in Model 1. In periods where a given driver's rank is greater than their average rank across the 29-week study period, their subsequent fuel efficiency performance increases. This result aligns with H1. Furthermore, *RankImprovement* carries a negative coefficient ($\beta = -0.144, p = 0.002$), whereas *RankDeterioration* carries a positive coefficient ($\beta = 0.113, p = 0.014$). These findings suggest that drivers' fuel efficiency performance increases (decreases) following RPF conveying relatively greater deterioration (improvement) in rank over the prior period.

We interact *StdRank* with *RankImprovement* and *RankDeterioration* to test Hypotheses 2a and 2b. The coefficient for *StdRank*RankImprovement* interaction term is marginally significant and negative ($\beta = -0.341, p = 0.072$), such that Hypothesis 2a is not supported. This unexpected negative interaction suggests that the motivational effects of a high current rank might be somewhat weakened when coupled with strong recent rank improvement. One possible behavioral explanation is that drivers who have just significantly improved their rank might be complacent or feel less motivated to sustain their effort, leading to a diminished response to their current high rank. Offering support for Hypothesis 2b, the interaction with *RankDeterioration* carries a negative coefficient estimate ($\beta = -0.436, p = 0.039$). This result indicates that the aforementioned positive effect of *StdRank* on a driver's subsequent fuel efficiency performance decreases in magnitude when the driver's rank recently declined to a relatively greater extent. This finding indicates that negative rank changes can significantly dampen the positive impact of a high rank level.

5.2. Heterogeneous Effects of StdRank

The analyses presented above constrain the effect of *StdRank* to be constant across the entire performance spectrum. To explore how the effects of RPF may vary for different groups of truck drivers, we split the sample into top-ranked (*Top*), middle-ranked (*Middle*) and bottom-ranked (*Bottom*) truck drivers based on their weekly *StdRank* (Vidal and Nossol, 2011). We then replicate our main analyses for each of the three subsamples of truck drivers. The results are presented in Table 3. The coefficients of *StdRank* in Models (1), (2), and (3) indicate that higher ranks are associated with greater subsequent fuel efficiency for top- and bottom-ranked driver groups, while the effect appears less discernible for middle-ranked performers.

To further explore any nonlinear effects of rank on subsequent fuel efficiency, we include quadradic (*StdRank_SQ*) and cubic (*StdRank_CUB*) terms of *StdRank*. As shown in Column (1) of Table 4, the coefficient for *StdRank_SQ* is not significant ($\beta = -0.002,\ p = 0.987$). However, the coefficient for *StdRank_CUB*, presented in Column (2), is significantly positive ($\beta = 0.965,\ p = 0.011$), providing support for a non-linear relationship where the effect of rank on subsequent performance is not constant across the entire distribution. Figure 2 plots the marginal effects of *StdRank* across its range based on this cubic model. Consistent with the tercile regressions presented in Table 3, Figure 2 demonstrates that the effect of *StdRank* is most pronounced at the lower and upper ends of the rank distribution, with the effect remaining positive but diminishing in magnitude in the middle range.

Collectively, this evidence suggests an overall positive effect of ranking that is greatest for top- and bottom-ranked drivers and less pronounced for those in the middle of the ranking distribution.

Accepted Manuscript
Version of record at: https://doi.org/10.1108/IJPDLM-04-2025-0164

Table 2. Fixed Effects Regression Results (DV: MPG)

	(1)		(2)	
	Coef.	Robust std. error	Coef.	Robust std. error
StdRank	0.391**	(0.050)	0.368**	(0.048)
RankImprovement	-0.144**	(0.047)	-0.088	(0.060)
RankDeterioration	0.113*	(0.045)	0.045	(0.060)
StdRank*RankImprovement			-0.341#	(0.189)
StdRank*RankDeterioration			-0.436*	(0.211)
LogDistance	0.039#	(0.023)	0.038#	(0.023)
Week dummies	Yes		Yes	
Constant	7.760**	(0.183)	7.267**	(0.183)
Observations	8,130		8,130	
Number of drivers	552		552	
R-squared (within)	0.132		0.133	

** p<0.01, * p<0.05, # p<0.1. Feedback variables and the associated interaction terms are lagged by one week.
Source: Authors' own elaboration.

Table 3. Split-Sample Fixed Effects Regression Results (DV: MPG)

	Top (1)		**Middle (2)**		**Bottom (3)**	
	Coef.	Robust std. error	Coef.	Robust std. error	Coef.	Robust std. error
StdRank	0.438**	(0.167)	0.092	(0.112)	0.490**	(0.156)
RankImprovement	0.129#	(0.069)	-0.070	(0.085)	-0.152	(0.200)
RankDeterioration	0.307	(0.231)	-0.052	(0.087)	-0.049	(0.062)
LogDistance	0.009	(0.045)	0.049	(0.039)	0.064#	(0.037)
Week dummies	Yes		Yes		Yes	
Constant	8.064**	(0.096)	7.925**	(0.080)	7.404**	(0.087)
Observations	2,355		2,656		3,119	
R-squared (within)	0.128		0.114		0.127	

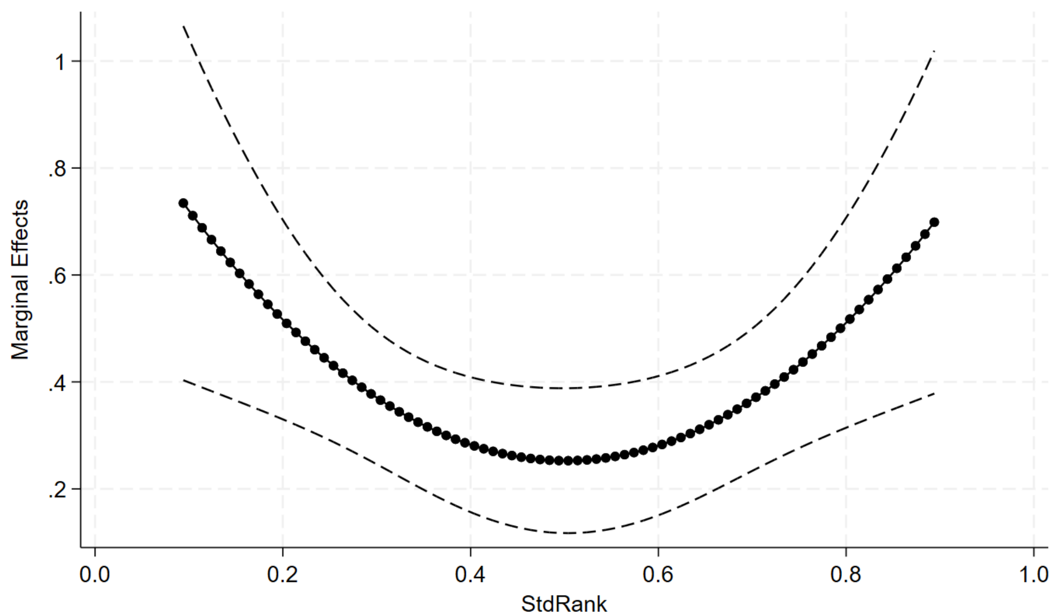
** p<0.01, * p<0.05, # p<0.1. Feedback variables and the associated interaction terms are lagged by one week. Source: Authors' own elaboration.

Accepted Manuscript
Version of record at: https://doi.org/10.1108/IJPDLM-04-2025-0164

Table 4. Nonlinear Fixed Effects Regression Results (DV: MPG)

	(1)		(2)	
	Coef.	Robust std. error	Coef.	Robust std. error
StdRank	0.391**	(0.050)	0.255**	(0.069)
RankImprovement	-0.144**	(0.047)	-0.142**	(0.047)
RankDeterioration	0.113*	(0.046)	0.110*	(0.045)
StdRank_SQ	-0.002	(0.109)	-0.076	(0.111)
StdRank_CUB			0.966*	(0.378)
LogDistance	0.039#	(0.023)	0.039#	(0.023)
Week dummies				
Constant	7.760**	(0.044)	7.765**	(0.044)
Observations	8,130		8,130	
Number of drivers	552		552	
R-squared	0.132		0.133	

** p<0.01, * p<0.05, # p<0.1. Feedback variables and the associated interaction terms are lagged by one week.
Source: Authors' own elaboration.



Note: StdRank on the x-axis ranges from the 10th to the 90th percentiles. The dashed lines represent the 95% confidence interval.
Source: Authors' own elaboration.

Figure 2. Marginal effects of *StdRank*

5.3. RPF and Driving Behavior

The causal mechanism linking RPF to truck drivers' subsequent performance involves a range of driving behaviors that ultimately contribute to fuel efficiency. Such behaviors are often difficult to observe or quantify. Some behaviors—notably, idling and speeding—are, however, commonly tracked by motor carriers. Accordingly, we examine the effects of ranking information in RPF truck drivers' idling and speeding. Idling is defined as the percentage of time a truck is not moving, and the engine is on. Speeding is the percentage of time the vehicle exceeds the defined speed limit. Both idling and speeding significantly affect fuel efficiency according to the U.S. Department of Energy's Argonne National Laboratory, in the United States, idling consumes over six billion gallons of fuel at a cost of more than $20 billion annually (U.S. Department of Energy Report, 2015). Miotti et al. (2021), in turn, indicates that aggressive driving behaviors, such as speeding and abrupt acceleration and braking, can reduce fuel efficiency by 15%–30% at highway speeds and by 10%–40% in stop-and-go traffic.

Table 5 reports the estimation results of regression models similar to those shown in Equations (1) and (2) but with *Idling* and *Speeding* as the respective dependent variables. We find evidence that when truck drivers are presented with RPF that indicates a higher rank, they will subsequently idle less ($\beta = -3.030, p = 0.000$). This result is consistent with prior research highlighting the effectiveness of incentive-based programs and targeted feedback in modifying idling habits (Sigurjonsdottir et al., 2022). Since lower idling is associated with greater fuel efficiency performance, this finding is also in line with H1 and the results discussed in Section 5. We do not find any evidence of significant effects on drivers' speeding behavior, however. As Delhomme et al. (2009) point out, comprehensive interventions including monitoring and enforcement rather than mere feedback and incentive systems may be required to alter speeding habits. Finally, the interactions between *StdRank* and rank change (*RankImprovement*, *RankDeterioration*) do not carry significant coefficient estimates either, suggesting that the adverse moderating effect of negative rank changes on the *StdRank*-fuel efficiency performance link (H2b) involve behaviors other than idling or speeding.

We further examine how RPF may differentially affect idling habits of top-, middle-, and bottom-ranked truck drivers. The results shown in Table 6 indicate that while top- and bottom-ranked drivers significantly reduce idling after receiving RPF conveying higher ranks, such effects are less pronounced for the group of middle-ranked drivers. This aligns with our earlier observation that the middle-ranked group appears to be less affected by ranking information.

Table 5. Fixed Effects Regression Results (DVs: Idling, Speeding)

	Idling				Speeding			
	(1)		(2)		(3)		(4)	
	Coef.	Robust std. error	Coef.	Robust std. error	Coef.	Robust std. error	Coef.	Robust std. error
StdRank	-3.030**	(0.756)	-2.849**	(0.748)	-0.211	(0.460)	-0.169	(0.445)
RankImprovement	2.154**	(0.705)	1.554	(1.068)	0.243	(0.399)	0.069	(0.479)
RankDeterioration	-1.092	(0.739)	-0.693	(0.868)	0.031	(0.314)	0.094	(0.345)
StdRank*RankImprovement			3.176	(2.988)			0.843	(0.999)
StdRank*RankDeterioration			2.956	(2.716)			0.575	(1.373)
LogDistance	-4.741**	(0.364)	-4.738**	(0.365)	0.978**	(0.149)	0.978**	(0.149)
Week dummies								
Constant	26.668**	(0.679)	26.626**	(0.674)	7.686**	(0.276)	7.674**	(0.276)
Observations	8,130		8,130		8,130		8,130	
Number of drivers	552		552		552		552	
R-squared (within)	0.215		0.215		0.027		0.027	

Robust standard errors are reported in parentheses. ** p<0.01, * p<0.05, # p<0.1. Feedback variables and the associated interaction terms are lagged by one week.
Source: Authors' own elaboration.

Table 6. Split-Sample Fixed Effects Regression Results (DV: Idling)

	Top (1)		Middle (2)		Bottom (3)	
	Coef.	Robust std. error	Coef.	Robust std. error	Coef.	Robust std. error
StdRank	-4.038#	(2.101)	0.071	(1.790)	-7.491*	(2.985)
RankImprovement	0.785	(0.927)	1.946	(1.393)	5.355#	(3.191)
RankDeterioration	-2.103	(2.701)	-0.614	(1.214)	0.111	(1.014)
LogDistance	-5.046**	(0.603)	-4.360**	(0.623)	-4.899**	(0.638)
Week dummies						
Constant	24.839**	(1.170)	24.494**	(1.430)	28.811**	(1.419)
Observations	2,355		2,656		3,119	
R-squared (within)	0.265		0.229		0.209	

** p<0.01, * p<0.05, # p<0.1. Feedback variables are lagged by one week.
Source: Authors' own elaboration.

6. Robustness Testing

6.1. Endogeneity

We conduct several additional analyses to ascertain the robustness of our empirical findings. First, we implement a system generalized method of moments (GMM) estimation (Blundell & Bond, 2023) to address potential concerns of dynamic panel bias that may arise as rank information is a function of prior MPG, our dependent variable. Specifically, the inclusion of a variable that is a function of the lagged dependent variable in the model, by construction, leads to a correlation with truck-driver level fixed effects and, thus, gives rise to concerns regarding dynamic panel bias (Halaby, 2004). Another endogeneity concern arises from unobserved factors that might affect both a driver's rank and performance. Whereas the fixed effect regression approach allows us to control for such factors to the extent that they are time-invariant, these fixed effects do not account for time-variant characteristics such as drivers' different rates of learning or motivation across time. We, therefore, implement the System GMM method as outlined in the next paragraph.

The System GMM method is an instrumental variable technique that does not require exogenous instruments. Instead, it uses deeper lags of existing variables as instruments. We implement the System GMM method using Stata's *xtabond2* command with robust standard errors and weekly dummies in all models. To reduce concerns about instrument proliferation, we apply the *collapse* option. The System GMM estimation results are shown in Table 7. The Arellano-Bond test for second-order autocorrelation ($p \geq 0.219$) and the Hansen test of overidentifying restrictions ($p \geq 0.190$) support the validity of our estimation approach. The results reported in Table 7 are consistent with our main findings. Truck drivers' subsequent performance increases following RPF conveying a higher rank ($\beta = 0.680,\ p = 0.006$). Furthermore, greater levels of period-over-period rank deterioration reduce the magnitude of this effect ($\beta = -2.895, p = 0.014$). Contrary to our expectation, greater levels of improvement in historical rank weakens rather than enhances the positive impacts of RPF conveying a higher current rank. We provide further insights regarding this result in the discussion section.

6.2. Additional Robustness Tests

We present several additional analyses to assess the robustness of our statistical findings. First, we present results from alternative model specifications using feasible generalized least squares (FGLS) regressions. These models account for both heteroskedasticity and panel-specific autocorrelation. The associated estimation results are shown in Table 8 and are largely consistent with our main findings.

Second, we explicitly examine the effects of deeper lags of *StdRank* on subsequent fuel efficiency. We re-estimate our models including two-week (L2.StdRank) and three-week (L3.StdRank) lagged *StdRank* in addition to one-week lagged *StdRank*. At the same time, we omit the rank change variables to preempt collinearity concerns. As shown in Table 9, the effect of *StdRank* diminishes with deeper lags and becomes insignificant at the third lag.

Third, we use unstandardized rank (*Rank*) and separately control for the number of peer drivers (*PeerGroupSize*) in lieu of the standardized rank variable *(StdRank)*. Alternative rank improvement and deterioration variables (*AltRankImprovement* and *AltRankDeterioration*) are also generated based on the unstandardized rank instead of the standardized rank. For readability purposes, we multiply MPG by 10,000 (*ScaledMPG)* and use it as an alternative dependent variable. The results shown in Table 10 are, once again, consistent with our main analyses: RPF conveying a higher current rank leads to greater subsequent performance ($\beta = 20.105, p = 0.000$), and this effect is weakened as drivers observe greater deterioration in their rank relative to the prior period ($\beta = -0.106, p = 0.046$).

Finally, we replicate the analysis using an expanded sample. In particular, we relax the restriction that a truck can only be operated by a single driver and that a driver can only be associated with a single truck over the study period of 29 weeks used in our main analysis. The previous construction yields a panel dataset consisting of time series observations at the truck (driver) level but comes at the expense of lost observations. In turn, removing the aforementioned restrictions increases the sample size from 8,130 to 9,448 observations but creates the need to modify the estimation procedure: We use truck-driver random effects and account for dependencies across observations due to shared drivers or trucks by using two-way cluster-robust standard errors (Mackelprang et al., 2015). The statistical results displayed in Table 11 are largely consistent with our main analysis. Feedback showing a higher current rank is associated with greater subsequent performance ($\beta = 0.582, p = 0.000$). Furthermore, the positive effect of a higher current rank is dampened when drivers observe greater deterioration in their rank over the prior period ($\beta = -0.431, p = 0.028$). In this extended analysis, we further flag instances when drivers first switch trucks to investigate if switching trucks impacts performance. As indicated in Column (3) of Table 11, the Switch dummy variable is not statistically significant ($\beta = -0.095, p = 0.421$).

6.3. Falsification Test

To evaluate the possibility that our observed effects are driven by spurious correlations, we conduct a falsification test by arbitrarily shuffling the rank values among drivers within each week. Specifically, for each week, we randomly assign *StdRank* values to drivers (*pseudo StdRank*, *pseudo RankImprovement*, and *pseudo RankDeterioration*). We then re-estimate Equation (1) using these pseudo feedback variables. We conduct 1000 such experiments and present the distribution of the t-values for *pseudo StdRank* in Figure 3 where the red vertical line represents the actual t-value of *StdRan*k (7.76) from Table 2. This value falls outside the 95% confidence interval (CI) of the pseudo t-values, suggesting that the observed association between *StdRank* and subsequent fuel efficiency is not spurious.

Table 7. System GMM Estimation Results (DV: MPG)

	(1)		(2)	
	Coef.	Robust std. error	Coef.	Robust std. error
StdRank	0.680**	(0.245)	0.555*	(0.218)
RankImprovement	-0.154	(0.170)	0.349	(0.261)
RankDeterioration	0.045	(0.148)	-0.264	(0.246)
StdRank*RankImprovement			-2.918*	(1.187)
StdRank*RankDeterioration			-2.895*	(1.175)
LogDistance	0.090	(0.126)	0.020	(0.088)
Week dummies	Yes		Yes	
Constant	7.851**	(0.038)	7.868**	(0.040)
Wald χ^2[p-value]	143015.13 [0.000]		135879.47 [0.000]	
No. of instruments	140		196	
AR1 [p-value]	-4.73 [0.000]		-5.42 [0.000]	
AR2 [p-value]	1.23 [0.219]		1.02 [0.309]	
Hansen test [p-value]	121.75 [0.190]		171.90 [0.301]	
Observations	8,130		8,130	
Number of drivers	552		552	

** p<0.01, * p<0.05, # p<0.1. Feedback variables and the associated interaction terms are lagged by one week.
Source: Authors' own elaboration.

Table 8. Feasible Generalized Least Squared Regression Results (DV: MPG)

	(1)		(2)	
	Coef.	Robust std. error	Coef.	Robust std. error
StdRank	1.532**	(0.013)	1.201**	(0.022)
RankImprovement	-0.960**	(0.027)	-0.575**	(0.041)
RankDeterioration	0.500**	(0.029)	0.451**	(0.035)
StdRank*RankImprovement			-0.211	(0.144)
StdRank*RankDeterioration			-0.342*	(0.153)
LogDistance	0.109**	(0.009)	0.039**	(0.006)
Week dummies				
Constant	7.784**	(0.005)	7.734**	(0.005)
Observations	8,116		8,116	
Number of drivers	538		538	

** p<0.01, * p<0.05, # p<0.1. Feedback variables and the associated interaction terms are lagged by one week.
Source: Authors' own elaboration.

Table 9. Fixed Effects Regression Results (DV: MPG) – Additional Lags

	(1)		(2)	
	Coef.	Robust std. error	Coef.	Robust std. error
StdRank	0.235**	(0.036)	0.218**	(0.038)
L2.StdRank	0.128**	(0.033)	0.113**	(0.033)
L3.StdRank			-0.007	(0.033)
LogDistance	0.034	(0.024)	0.025	(0.026)
Week dummies				
Constant	7.788**	(0.041)	7.769**	(0.039)
Observations	7,344		6,614	
Number of drivers	536		513	
R-squared	0.138		0.142	

** p<0.01, * p<0.05, # p<0.1. *StdRank, L2.StdRank, and L3.StdRank* are standardized rank lagged by one, two, and three weeks, respectively.
Source: Authors' own elaboration.

Table 10. Fixed Effects Regression Results (DV: *ScaledMPG*) – Alternative RPF Measures

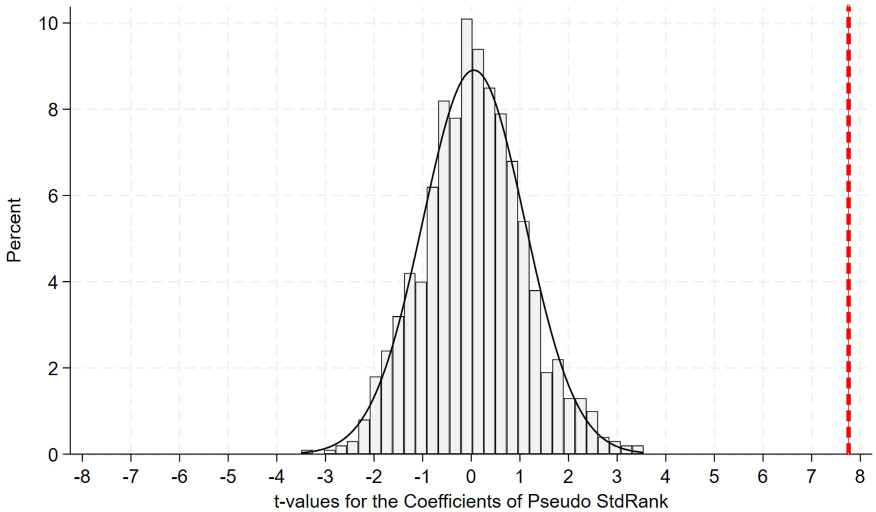
	(1)		(2)	
	Coef.	Robust std. error	Coef.	Robust std. error
Rank	20.105**	(2.730)	19.383**	(2.618)
AltRankImprovement	-6.482**	(2.436)	-2.421	(3.082)
AltRankDeterioration	6.417**	(2.337)	4.400	(2.709)
Rank*AltRankImprovement			-0.091*	(0.043)
Rank*AltRankDeterioration			-0.106*	(0.053)
LogDistance	390.878#	(227.564)	385.009#	(227.781)
PeerGroupSize	-20.731*	(8.695)	-20.112*	(8.714)
Week dummies				
Constant	77,819.6**	(468.798)	77,833.5**	(467.909)
Observations	8,130		8,130	
Number of drivers	552		552	
R-squared (within)	0.131		0.132	

** p<0.01, * p<0.05, # p<0.1. Feedback variables and the associated interaction terms are lagged by one week. *Rank* is the unstandardized rank. *AltRankImprovement* and *AltRankDeterioration* are constructed using rank instead of standardized rank (and *PeerGroupSize* is controlled for in a separate variable). Source: Authors' own elaboration.

Table 11. Random Effects Regression Results (DV: MPG) – Expanded Sample

	(1)		**(2)**		**(3)**	
	Coef.	Robust std. error	Coef.	Robust std. error	Coef.	Robust std. error
StdRank	0.582**	(0.043)	0.559**	(0.042)	0.582**	(0.043)
RankImprovement	-0.227**	(0.046)	-0.139*	(0.059)	-0.227**	(0.046)
RankDeterioration	0.207**	(0.042)	0.151**	(0.055)	0.207**	(0.042)
StdRank*RankImprovement			-0.463*	(0.185)		
StdRank*RankDeterioration			-0.431*	(0.197)		
Switch					-0.095	(0.118)
LogDistance	0.052*	(0.021)	0.052*	(0.021)	0.052*	(0.021)
Week dummies	Yes		Yes			
Constant	7.709**	(0.043)	7.713**	(0.044)	7.710**	(0.044)
Observations	9,448		9,448		9,448	
Number of truck-drivers	979		979		979	
R-squared (within)	0.110		0.110		0.110	
R-squared (between)	0.314		0.324		0.316	

** p<0.01, * p<0.05, # p<0.1. Feedback variables and the associated interaction terms are lagged by one week. Switch is a dummy variable indicating when drivers first switch trucks. Source: Authors' own elaboration.



Note: The red vertical line represents the actual t-value of StdRank estimated from Table 2.
Source: Authors' own elaboration.

Figure 3. Distribution of t-values for coefficient estimates of *pseudo StdRank*

7. Discussion

7.1. Summary

In the motor carrier industry, people (drivers) play a crucial role in the pursuit of greater operational performance (Joglekar 2016). Trucking companies commonly employ relative performance feedback and associated awards or bonus payments to incentivize greater fuel efficiency. Contributing to the people-centric operations literature and prior RPF research, we examine the impact of RPF on drivers' fuel efficiency in trucking operations. The results of our empirical analysis provide evidence of RPF's effectiveness:

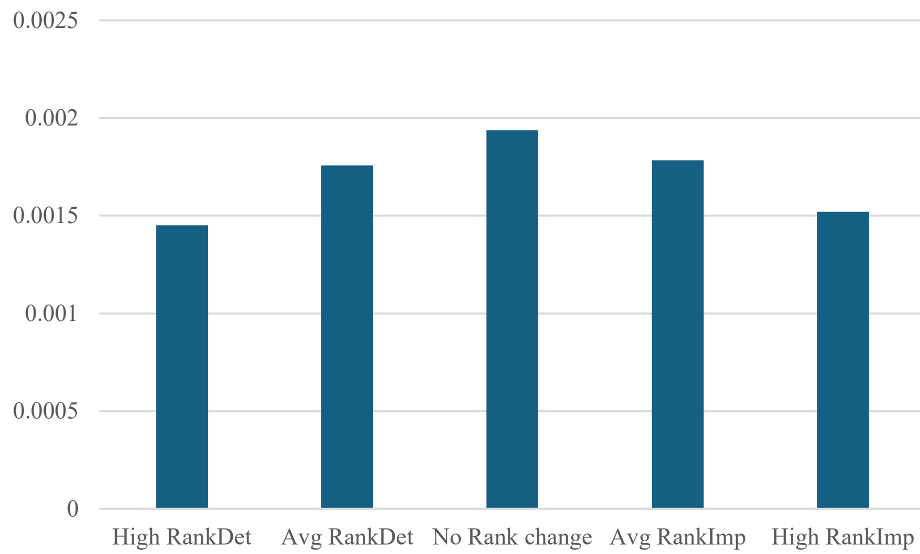
First, RPF conveying a higher rank is associated with greater subsequent fuel efficiency performance. Specifically, in periods where a given driver's rank is ten positions higher than in other periods, the driver's MPG will increase in the subsequent period by about .26% (evaluated at mean MPG levels). Conversely, in periods where a driver receives RPF indicating a lower rank, the driver's fuel efficiency performance will decrease, all else equal.

Second, our analyses reveal that the effect of rank information (RPF) is not uniform across all drivers along the performance spectrum (i.e., top-, middle-, and bottom-ranked drivers). Specifically, we observe positive rank-MPG relationships for top- and bottom-ranked drivers. For middle-ranked drivers, ranking conveyed through RPF appears to have less pronounced effects. This finding underscores the importance of studying differences across subgroups of individuals (Turkoglu and Tucker, 2022).

Third, we examine how temporal changes in relative performance influence the impact of current rank signals. Simply put, the valence of being ranked, say, 20th among a group of peers may differ depending on whether this rank constitutes an improvement or a deterioration relative to the individual's rank in the prior period. Indeed, we find that a week-over-week decline in rank diminishes the positive effect of current rank on future fuel efficiency. Hence, a recent *deterioration* in relative performance has a demotivating effect that weakens the rank-MPG relationship. This aligns with theories showing that negative feedback such as decreased ranking reduces confidence (Bandura et al., 1999) and makes the positive signal of a high current rank less effective in sustaining high performance (Vroom, 1964; Barankay, 2012). For example, a driver seeing their rank decline may feel less confident in their ability to maintain or improve, causing them to disengage or give up on exerting effort even if their current rank remains relatively good.

Contrary to expectations, we find evidence of a significant negative moderating effect of rank *improvements* such that the positive effect of a higher rank on subsequent fuel efficiency is weakened when the driver's rank has recently improved. One possible explanation is that rising ranks may lead to overconfidence, causing drivers to overestimate their performance abilities relative to peers and reduce the effort to maintain or enhance performance (Moores and Chang, 2009). Overconfidence may also lead to optimism bias (Krueger and Dickson, 1994), which could encourage behaviors like idling or speeding that put the driver's relative performance at risk (Sharot, 2011). Additionally, after putting in significant effort to raise their rank, drivers might perceive further gains as increasingly challenging or less rewarding, thus lowering the perceived value of additional effort (Awaysheh et al., 2023). This lower perceived return on incremental effort then weakens the positive influence of a high current rank on subsequent fuel efficiency. Figure 4 illustrates the marginal effects of *Rank* for varying degrees of *AltRankDeterioration* and *AltRankImprovement*[4] and documents the potentially significant reduction in the efficacy of RPF contingent on week-over-week changes in drivers' ranks.

[4] These estimates are derived from the results shown in Table 10.



High RankDet (RankImp) refers to a week-over-week deterioration (improvement) in a driver's rank by 46 positions [mean + 1 std. deviation]; Avg RankDet (RankImp) refers to a week-over-week deterioration (improvement) in a driver's rank by 17 positions [mean]. Source: Authors' own elaboration.

Figure 4. Marginal effects of *Rank* on MPG for varying levels of *AltRankDeterioration* and *AltRankImprovement*

7.2. Contributions to Theory

Our study makes several contributions to behavioral theories of social comparison RPF, as well as to research on people-centric operations and the trucking industry. First, our study contributes to social comparison theory and the RPF literature by moving beyond a static view of relative performance to incorporate temporal dynamics consistent with a real-world operational context. Prior studies have predominantly focused on individuals' current standing (e.g., Casas-Arce and Martínez-Jerez, 2009; Gill et al., 2019), with limited attention given to the role of dynamic performance changes inherent in RPF. We show that changes in rank over time can alter how individuals interpret and respond to RPF information. This insight helps reconcile previous inconsistent findings on the effects of RPF: A higher current rank may encourage effort, but its effect is weakened or even reversed in the presence of substantial historical performance changes. Unlike earlier studies that mostly rely on experiments or stylized tasks such as word-spotting or simulated decision-making (e.g., Gill et al., 2019; Hannan et al., 2008), our findings are based on analyses of real-world archival data, thereby addressing concerns about the lack of realism in prior RPF research. More importantly, we extend existing knowledge in the RPF literature by identifying and investigating moderating factors—such as temporal changes in rank—that influence the effectiveness of ranking feedback. Specifically, we demonstrate that significant declines or improvements in rank from the previous period weaken the positive effect of the current rank. Further, by demonstrating that feedback effects vary across feedback receivers—with middle-ranked performers less affected than top or bottom performers (Chen et al., 2017)—we refine behavioral theories of feedback reception. Together, these findings advance social comparison theory by presenting recipient reactions to RPF as a more dynamic and heterogeneous process, offering a theoretical basis for understanding when and for whom relative performance feedback is effective.

Second, our work contributes to the burgeoning research on people-centric operations and the trucking industry literature. While previous people-centric operations research has primarily examined operational contexts with close monitoring and supervision, such as healthcare and warehouse operations (e.g., Song et al., 2018; Zhang et al., 2022), this study focuses on the fuel efficiency performance of truck drivers, a group of individuals who have substantial autonomy in their roles (Mello & Shane Hunt, 2009), distinct demographic characteristics (Schulz et al., 2014), and exceptionally high turnover rates (LeMay and Keller, 2019; Miller et al., 2021). Designing effective performance feedback mechanisms that promote operational performance—i.e., fuel efficiency—thus, is of particular importance in the motor carrier sector. Our insights add to the ongoing conversation about how feedback strategies can promote behavioral changes that lead to greater operational efficiency in operational settings characterized by high individual autonomy and idiosyncratic workforces, thereby advancing both people-centric operations research and the trucking literature

7.3. Contributions to Practice

Our findings offer valuable insights for trucking managers seeking to enhance fuel efficiency and optimize driver performance through more effective feedback mechanisms. First, our research highlights the importance of tailoring feedback strategies to different segments of the driver population based on their current performance tier. In particular, we find that RPF is effective in motivating highly ranked drivers, rendering RPF a powerful tool for trucking companies to maintain and enhance these drivers' superior performance. Sharing consistent RPF with these drivers helps reinforce their status and encourage continued high performance. Conversely, lower-ranked drivers may be demotivated upon learning of their relatively lower performance. Therefore, carriers should exercise caution when it comes to sharing RPF with lower-ranked drivers. It is conceivable that providing constructive feedback with specific guidance on how to improve their ranking may alleviate the potential adverse effects of RPF. Furthermore, managers could offer low-ranked drivers educational programs, including detailed performance metrics for review (e.g., harsh braking, idling, and cruise control) and targeted training or mentorship from top-ranked drivers. Seeing that middle-ranked drivers are less influenced by their specific rank as conveyed through RPF, trucking companies might consider alternative feedback approaches for middle-ranked drivers, such as individual performance feedback (Choudhary et al., 2021).

Furthermore, our analysis reveals that temporal rank changes affect how drivers react to RPF. Notably, week-over-week improvements and deteriorations in drivers' ranks tend to reduce the positive impact of current rank on future performance. This finding carries implications for feedback strategies in trucking companies as frequent feedback may inadvertently emphasize these rank shifts, potentially undermining RPF's effectiveness. As such, trucking companies might consider less frequent feedback to mitigate this attenuating effect and reduce the focus on recent performance fluctuations. This conclusion aligns with previous research highlighting the drawbacks of high-frequency feedback on performance outcomes (Lam et al., 2011). Alternatively, firms might add messages that motivate drivers to increase or keep up their efforts in light of recent negative or positive changes in their rank. Table 12 outlines recommendations for trucking companies to implement performance feedback more effectively.

Table 12. Recommended feedback strategy for trucking companies

Driver tier	Effect of RPF	Recommended feedback strategy
Top-ranked drivers	RPF motivates and reinforces superior performance.	Share RPF to sustain high performance; emphasize recognition and status.
Middle-ranked drivers	Less influenced by rank information.	Use alternative feedback (e.g., individualized performance feedback) rather than rank-based RPF.
Bottom-ranked drivers	RPF demotivates low-ranked drivers.	Provide detailed behavioral performance feedback (e.g., harsh braking, idling), targeted training, and mentorship from top performers.
Drivers experiencing rank fluctuations	Rank fluctuations reduce RPF's effectiveness.	Provide less frequent RPF; frame messages to encourage persistence after rank drops and sustained effort after rank gains.

Source: Authors' own elaboration.

7.4. Limitations and Future Research

Of course, our study is not without limitations. First, our secondary data does not provide demographic information or detail on specific route or operating conditions. Truck-driver fixed effects offer some level of control for such characteristics and conditions. Yet, it would be interesting to study if age, gender, and education affect the effectiveness of RPF in the trucking context. Second, whereas we show that truck drivers increase their performance upon receiving RPF that conveys a higher rank, our research setting does not allow us to assess how the provision of RPF affects performance compared to scenarios where no RPF is given. Future research might address this issue and also explore, perhaps via field experiments, how different RPF characteristics such as feedback frequency (Lam et al., 2011) and the type of feedback (i.e., private versus public; Song et al., 2018) can affect operational performance outcomes. Studies that help design optimal feedback policies and incentive schemes for motor carriers —including items such as peer group size and incentive values (Gross, 2017)—might also be of great interest. Finally, further research is needed to understand how RPF works in different operational settings such as manufacturing (Kwasnitschka et al., 2024) and technology development (Kagan et al., 2018).

References

Albert, S. (1977). Temporal comparison theory. *Psychological Review*, 84(6), p.485.

Anderson, C., John, O. P., Keltner, D., & Kring, A. M. (2001). Who attains social status? Effects of personality and physical attractiveness in social groups. *Journal of personality and social psychology*, *81*(1), p.116.

Arellano, M. and Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, 68(1), pp.29–51.

Ashraf, N., Bandiera, O. and Lee, S.S. (2014). Awards unbundled: Evidence from a natural field experiment. *Journal of Economic Behavior and Organization*, 100, pp.44–63.

Awaysheh, A., Bonet, R. and Ortega, J. (2023). Performance feedback and productivity: Evidence from a field experiment. *Production and Operations Management*, 32(1), pp.98–115.

Azmat, G., Bagues, M., Cabrales, A. and Iriberri, N. (2019). What you don't know...can't hurt you? A natural field experiment on relative performance feedback in higher education. *Management Science*, 65(8), pp.3714–3736.

Bandiera, O., Barankay, I. and Rasul, I. (2013). Team incentives: Evidence from a firm level experiment. *Journal of the European Economic Association*, 11(5), pp.1079–1114.

Bandura, A., Freeman, W.H. and Lightsey, R. (1999). Self-efficacy: The exercise of control. *Journal of Cognitive Psychotherapy*, 13(2), pp.0889–8391.

Barankay, I. (2012). Rank incentives: Evidence from a randomized workplace experiment. *Business Economics and Public Policy Papers University*, Working Paper, University of Pennsylvania.

Bendoly, E., Croson, R., Goncalves, P. and Schultz, K. (2010). Bodies of knowledge for research in behavioral operations. *Production and Operations Management*, 19(4), pp.434–452.

Berger, J., Rosenholtz, S. J., & Zelditch, M. (1980). Status organizing processes. *Annual review of sociology*, *6*, pp.479-508.

Blundell, R. and Bond, S. (2023). Reprint of: Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 234, pp.38–55.

Boudreau, J., Hopp, W., McClain, J.O. and Thomas, L.J. (2003). On the interface between operations and human resources management. *Manufacturing and Service Operations Management*, 5(3), pp.179–202.

Cantor, D. E., Corsi, T. M., & Grimm, C. M. (2006). Safety technology adoption patterns in the US motor carrier industry. *Transportation Journal*, *45*(3), pp.20–45.

Cantor, D. E., Corsi, T. M., Grimm, C. M., & Singh, P. (2016). Technology, firm size, and safety: Theory and empirical evidence from the US motor-carrier industry. *Transportation Journal*, *55*(2), pp.149–167.

Cantor, D. E., Macdonald, J. R., & Crum, M. R. (2011). The influence of workplace justice perceptions on commercial driver turnover intentions. *Journal of Business Logistics*, *32*(3), pp.274–286.

Casas-Arce, P. and Martínez-Jerez, F.A. (2009). Relative performance compensation, contests, and dynamic incentives. *Management Science*, 55(8), pp.1306–1320.

Certo, S.T., Withers, M.C. and Semadeni, M. (2017). A tale of two effects: Using longitudinal data to compare within- and between- firm effects. *Strategic Management Journal*, 38(7), pp.1536–1556.

Charness, G., Masclet, D. and Villeval, M.C. (2014). The dark side of competition for status. *Management Science*, 60(1), pp.38–55.

Chen, Y., Lu, F. and Zhang, J. (2017). Social comparisons, status and driving behavior. *Journal of Public Economics*, 155, pp.11–20.

Choudhary, V., Shunko, M. and Netessine, S. (2021). Does immediate feedback make you not try as hard? A study on automotive telematics. *Manufacturing and Service Operations Management*, 23(4), pp.835–853.

Choudhury, N.A., Kim, S. and Ramkumar, M. (2022). Effects of supply chain disruptions due to COVID-19 on shareholder value. *International Journal of Operations & Production Management*, 42(13), pp.482–505.

Davis-Sramek, B., Robinson, J. L., Darby, J. L., & Thomas, R. W. (2020). Exploring the differential roles of environmental and social sustainability in carrier selection decisions. *International Journal of Production Economics*, *227*, p.107660.

de Vries, J., de Koster, R. and Stam, D. (2016). Aligning order picking methods, incentive systems, and regulatory focus to increase performance. *Production and Operations Management*, 25(8), pp.1363–1376.

Delhomme, P. et al. (2009). *Manual for designing, implementing and evaluating road safety communication campaigns. Part I*. Brussels: Belgian Road Safety Institute.

Dohmen, T., Falk, A., Fliessbach, K., Sunde, U. and Weber, B. (2011). Relative versus absolute income, joy of winning, and gender: Brain imaging evidence. *Journal of Public Economics*, 95(3–4), pp.279–285.

Donohue, K., Özer, Ö. and Zheng, Y. (2020). Behavioral operations: Past, present, and future. *Manufacturing and Service Operations Management*, 22(1), pp.191–202.

Ebbes, P., Papies, D. and van Heerde, H.J. (2021). Dealing with endogeneity: A nontechnical guide for marketing researchers. In: *Handbook of Market Research*. Cham: Springer International Publishing, pp.181–217.

Ellinger, A.E., Keller, S.B. and Baş, A.B.E. (2010). The empowerment of frontline service staff in 3PL companies. *Journal of Business Logistics*, 31(1), pp.79–98.

Eriksson, T., Poulsen, A. and Villeval, M.C. (2009). Feedback and incentives: Experimental evidence. *Labour Economics*, 16(6), pp.679–688.

Falk, A. and Ichino, A. (2021). Clean evidence on peer pressure. *SSRN Electronic Journal*. [online] Available at: https://doi.org/10.2139/ssrn.391701 [Accessed 15 Apr. 2025].

Feng, B. and Ye, Q. (2021). Operations management of smart logistics: A literature review and future research. *Frontiers of Engineering Management*, 8(3), pp.344–355.

Festinger, L. (1954). A theory of social comparison processes. *Human Relations*, 7(2), pp.117–140.

Fiske, A. P. (1991). *Structures of social life: The four elementary forms of human relations: Communal sharing, authority ranking, equality matching, market pricing*. Free Press.

Flannery, M.J. and Hankins, K.W. (2013). Estimating dynamic panel models in corporate finance. *Journal of Corporate Finance*, 19(1), pp.1–19.

Fors, C., Kircher, K. and Ahlström, C. (2015). Interface design of eco-driving support systems – Truck drivers' preferences and behavioural compliance. *Transportation Research Part C: Emerging Technologies*, 58, pp.706–720.

Genakos, C. and Pagliero, M. (2012). Interim rank, risk taking, and performance in dynamic tournaments. *Journal of Political Economy*, 120(4), pp.782–813.

Gill, D., Kissová, Z., Lee, J. and Prowse, V. (2019). First-place loving and last-place loathing: How rank in the distribution of performance affects effort provision. *Management Science*, 65(2), pp.494–507.

Gross, D.P. (2017). Performance feedback in competitive product development. *RAND Journal of Economics*, 48(2), pp.438–466.

Halaby, C.N. (2004). Panel models in sociological research: Theory into practice. *Annual Review of Sociology*, 30, pp.507–544.

Hannan, R.L., Krishnan, R. and Newman, A.H. (2008). The effects of disseminating relative performance feedback in tournament and individual performance compensation plans. *Accounting Review*, 83(4), pp.893–913.

Huang, Y. H., Roetting, M., McDevitt, J. R., Melton, D., & Smith, G. S. (2005). Feedback by technology: Attitudes and opinions of truck drivers. *Transportation Research Part F: Traffic Psychology and Behaviour*, *8*(4-5), pp.277–297.

Jazairy, A., Pohjosenperä, T., Sassali, J., Juga, J., & von Haartman, R. (2023). Driving the talk: examining professional truck drivers' motivations to engage in eco-driving. *International Journal of Physical Distribution & Logistics Management*, *53*(11), pp.98–124.

Joglekar, N. R., Davies, J., & Anderson, E. G. (2016). The role of industry studies and public policies in production and operations management. *Production and Operations Management*, *25*(12), 1977-2001.

Kagan, E., Leider, S. and Lovejoy, W.S. (2018). Ideation-execution transition in product development: An experimental analysis. *Management Science*, 64(5), pp.2238–2262.

Kandel, E. and Lazear, E.P. (1992). Peer pressure and partnerships. *Journal of Political Economy*, 100(4), pp.801–817.

Keller, S. B., & Ozment, J. (2009). Research on personnel issues published in leading logistics journals: What we know and don't know. *The International Journal of Logistics Management*, *20*(3), pp.378–407.

Kemp, E., Kopp, S.W. and Kemp, E.C. (2013). Take this job and shove it: Examining the influence of role stressors and emotional exhaustion on organizational commitment and identification in professional truck drivers. *Journal of Business Logistics*, 34(1), pp.33–45.

Kemper, T. D. (1991). Predicting emotions from social relations. *Social Psychology Quarterly*, pp.330-342.

Kluger, A.N. and DeNisi, A. (1996). The effects of feedback interventions on performance: A historical review, a meta-analysis, and a preliminary feedback intervention theory. *Psychological Bulletin*, 119(2), p.254.

Krueger, N. and Dickson, P.R. (1994). How believing in ourselves increases risk taking: Perceived self-efficacy and opportunity recognition. *Decision Sciences*, 25(3), pp.385–400.

Kuhnen, C.M. and Tymula, A. (2012). Feedback, self-esteem, and performance in organizations. *Management Science*, 58(1), pp.94–113.

Kwasnitschka, D., Franke, H. and Netland, T.H. (2024). Effects of feedback in manufacturing: A field experiment using smartwatch technology. *Journal of Operations Management*, 70(6), pp.933–956.

Lam, C.F., DeRue, D.S., Karam, E.P. and Hollenbeck, J.R. (2011). The impact of feedback frequency on learning and task performance: Challenging the “more is better” assumption. *Organizational Behavior and Human Decision Processes*, 116(2), pp.217–228.

Lam, C. K., Van der Vegt, G. S., Walter, F., & Huang, X. (2011). Harming high performers: A social comparison perspective on interpersonal harming in work teams. *Journal of Applied Psychology*, *96*(3), p.588.

Lambert, R.A., Larcker, D.F. and Weigelt, K. (1993). The structure of organizational incentives. *Administrative Science Quarterly*, 38(3), pp.438–461.

Lazear, E.P. and Rosen, S. (1981). Rank-order tournaments as optimum labor contracts. *Journal of Political Economy*, 89(5), pp.841–864.

LeMay, S. and Keller, S.B. (2019). Fifty years inside the minds of truck drivers. *International Journal of Physical Distribution and Logistics Management*, 49(6), pp.626–643.

Locke, E.A. and Latham, G.P. (1990). *A theory of goal setting & task performance*. Englewood Cliffs, NJ: Prentice-Hall, Inc.

Lourenço, S.M., Greenberg, J.O., Littlefield, M., Bates, D.W. and Narayanan, V.G. (2018). The performance effect of feedback in a context of negative incentives: Evidence from a field experiment. *Management Accounting Research*, 40, pp.1–14.

Lu, G., Ding, X. (David), Peng, D.X. and Chuang, H.-C. (2018). Addressing endogeneity in operations management research: Recent developments, common problems, and directions for future research. *Journal of Operations Management*, 64, pp.53–64.

Mackelprang, A.W., Habermann, M. and Swink, M. (2015). How firm innovativeness and unexpected product reliability failures affect profitability. *Journal of Operations Management*, 38, pp.71–86.

Mane, A., Djordjevic, B. and Ghosh, B. (2021). A data-driven framework for incentivising fuel-efficient driving behaviour in heavy-duty vehicles. *Transportation Research Part D: Transport and Environment*, 95, p.102845.

Marr, J. C., & Thau, S. (2014). Falling from great (and not-so-great) heights: How initial status position influences performance after status loss. *Academy of Management Journal*, *57*(1), pp.223-248.

Mello, J.E. and Shane Hunt, C. (2009). Developing a theoretical framework for research into driver control practices in the trucking industry. *Transportation Journal*, 48(4), pp.20–39.

Miller, J.W., Bolumole, Y. and Muir, W.A. (2021). Exploring longitudinal industry-level large truckload driver turnover. *Journal of Business Logistics*, 42(4), pp.428–450.

Miller, J. W., Saldanha, J. P., Hunt, C. S., & Mello, J. E. (2013). Combining formal controls to improve firm performance. *Journal of Business Logistics*, *34*(4), pp.301–318.

Miller, J. W., Saldanha, J. P., Rungtusanatham, M., & Knemeyer, M. (2017). How does driver turnover affect motor carrier safety performance and what can managers do about it?. *Journal of Business Logistics*, *38*(3), pp.197–216.

Miotti, M., Needell, Z.A., Ramakrishnan, S., Heywood, J. and Trancik, J.E. (2021). Quantifying the impact of driving style changes on light-duty vehicle fuel consumption. *Transportation Research Part D: Transport and Environment*, 98, p.102918.

Modi, S.B. and Cantor, D.E. (2021). How coopetition influences environmental performance: Role of financial slack, leverage, and leanness. *Production and Operations Management*, 30(7), pp.2046–2068.

Moores, T.T. and Chang, J.C.J. (2009). Self-efficacy, overconfidence, and the negative effect on subsequent performance: A field study. *Information and Management*, 46(2), pp.69–76.

Phares, J. and Balthrop, A. (2022). Investigating the role of competing wage opportunities in truck driver occupational choice. *Journal of Business Logistics*, 43(2), pp.265–289.

Redersdorff, S. and Guimond, S. (2005). Comparing oneself over time: The temporal dimension in social comparison. In: Guimond, S., ed. *Social comparison and social psychology: Understanding cognition, intergroup relations, and culture*. Cambridge: Cambridge University Press, pp.76–96.

Reh, S., Tröster, C. and Van Quaquebeke, N. (2018). Keeping (future) rivals down: Temporal social comparison predicts coworker social undermining via future status threat and envy. *Journal of Applied Psychology*, 103(4), p.399.

Reh, S., Van Quaquebeke, N., Tröster, C., & Giessner, S. R. (2022). When and why does status threat at work bring out the best and the worst in us? A temporal social comparison theory. *Organizational Psychology Review*, *12*(3), pp.241–267.

Roels, G. and Staats, B.R. (2021). People-centric operations: Achievements and future research directions. *Manufacturing and Service Operations Management*, 23(4), pp.745–757.

Roels, G. and Su, X. (2014). Optimal design of social comparison effects: Setting reference groups and reference points. *Management Science*, 60(3), pp.606–627.

Rolim, C., Baptista, P., Duarte, G., Farias, T. and Pereira, J. (2016). Impacts of delayed feedback on eco-driving behavior and resulting environmental performance changes. *Transportation Research Part F: Traffic Psychology and Behaviour*, 43, pp.366–378.

Roodman, D. (2009). A note on the theme of too many instruments. *Oxford Bulletin of Economics and Statistics*, 71(1), pp.135–158.

Schulz, S.A., Luthans, K.W. and Messersmith, J.G. (2014). Psychological capital: A new tool for driver retention. *International Journal of Physical Distribution and Logistics Management*, 44, pp.621–634.

Scott, A., & Davis-Sramek, B. (2023). Driving in a man's world: examining gender disparity in the trucking industry. *International Journal of Physical Distribution & Logistics Management*, *53*(3), pp.330–353.

Sharot, T. (2011). The optimism bias. *Current Biology*, 21(23), pp.R941–R945.

Sheu, J.B. and Choi, T.M. (2023). Can we work more safely and healthily with robot partners? A human-friendly robot–human-coordinated order fulfillment scheme. *Production and Operations Management*, 32(3), pp.794–812.

Sigurjonsdottir, S.S., Elnes, A.K. and Couto, K.C. (2022). Turn off your engine: Reducing idling amongst professional truck drivers. *Transportation Research Interdisciplinary Perspectives*, 15, p.100654.

Song, H., Tucker, A.L., Murrell, K.L. and Vinsonc, D.R. (2018). Closing the productivity gap: Improving worker productivity through public relative performance feedback and validation of best practices. *Management Science*, 64(6), pp.2628–2649.

Suls, J., Martin, R. and Wheeler, L. (2002). Social comparison: Why, with whom, and with what effect? *Current Directions in Psychological Science*, 11(5), pp.159–163.

Szymanski, K. and Harkins, S.G. (1987). Social loafing and self-evaluation with a social standard. *Journal of Personality and Social Psychology*, 53(5), p.891.

Thijssen, R., Hofman, T. and Ham, J. (2014). Ecodriving acceptance: An experimental study on anticipation behavior of truck drivers. *Transportation Research Part F: Traffic Psychology and Behaviour*, 22, pp.249–260.

Thomas, S. P., Liao-Troth, S., & Williams, D. F. (2020). Inefficacy: the tipping point of driver burnout. *International Journal of Physical Distribution & Logistics Management*, *50*(4), pp.483–501.

Turkoglu, A. and Tucker, A. (2022). The demotivating effects of relative performance feedback on middle-ranked workers' performance. *SSRN Electronic Journal*. [online] Available at: https://doi.org/10.2139/ssrn.4242303 [Accessed 15 Apr. 2025].

Vidal, J.B.I. and Nossol, M. (2011). Tournaments without prizes: Evidence from personnel records. *Management Science*, 57(10), pp.1721–1736.

Vroom, V.H. (1964). *Work and motivation*. New York: John Wiley and Sons.

Walton, D. (1999). Examining the self-enhancement bias: Professional truck drivers' perceptions of speed, safety, skill and consideration. *Transportation Research Part F: Traffic Psychology and Behaviour*, 2(2), pp.91–113.

Winkelhaus, S. (2022). *The digital transformation of logistics from a human-centred perspective*. [PhD thesis] Technische Universität Darmstadt. Available at: https://tuprints.ulb.tu-darmstadt.de/id/eprint/19895 [Accessed 15 Apr. 2025].

Zhang, X.L., de Vries, J., de Koster, R. and Liu, C.G. (2022). Fast and faultless? Quantity and quality feedback in order picking. *Production and Operations Management*, 31(4), pp.1536–1559.

Zhou, Z. and Wan, X. (2022). Does the sharing economy technology disrupt incumbents? Exploring the influences of mobile digital freight matching platforms on road freight logistics firms. *Production and Operations Management*, 31(1), pp.117–137.

Zizzo, D.J. (2002). Between utility and cognition: The neurobiology of relative position. *Journal of Economic Behavior and Organization*, 48(1), pp.71–91.