Long-Term Relationships in the US Truckload Freight Industry

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Abstract

This paper provides evidence on relational contracting in the US truckload freight industry. In this setting, shippers and carriers engage in repeated interactions under contracts that fix prices but leave scope for inefficient opportunism. We describe empirically the strategies of shippers and the responses of carriers. We show that shippers use the threat of relationship termination to deter carriers from short-term opportunism. Carriers respond to the resultant dynamic incentives, behaving more cooperatively when their potential future rents are higher. While shippers and carriers often interact on multiple lanes, we show that separate relational contracts appear to govern transactions on each lane.

JEL Classification: L14, D86, D22, L92.

The importance and ubiquity of informal interfirm relationships is widely recognized. As the economics, management, and sociology literatures have documented, where contracts do not exist or are incomplete, interfirm relationships are governed by nebulous notions of goodwill, trust, and reciprocity.[1] A wide range of theoretical work has elucidated various reasons why such informal arrangements might exist, what form they might take, and how they might be sustained.[2] A budding empirical literature studies these relationships. This paper contributes to that empirical literature by

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[1]Early examples include Macaulay (1963).

[2]For an overview, see Malcomson (2010).

studying long-term relationships in the US truckload freight industry. The central role of informal long-term relationships in this setting, along with the existence of detailed microdata, makes this setting particularly well-suited for studying these relationships.[3] Exploiting this microdata, we find strong evidence that shippers create dynamic incentives for carriers by employing punishment strategies that condition relationship continuation on past cooperation.

Our analysis makes use of transaction-level data from a transportation management system (TMS) used by shippers to manage their relationships with carriers. The data records every interaction within these relationships. Moreover, it provides explicit rankings of the carriers entered into the TMS by the shipper. These rankings summarize both the status of the relationship and the shipper's intended play. As these are defining elements of the dynamics within shipper-carrier relationships, meaningful description of the form of relationships in this industry would not be possible without this kind of information. We complement this data set on long-term relationships between shippers and carriers with spot rate data. We use the combined TMS and spot rate data sets for two purposes: The first is to establish qualitative features of the setting that motivate our theoretical model, and the second is to draw quantitative conclusions using analysis guided by the theoretical model.

We first use this data to establish three key facts that, together, suggest that a shipper-carrier relationship can be thought of as a principal-agent game in which a relational contract deters carrier opportunism. *First*, we note that differences between the spot and contract rates create temptation for carriers to engage in short-term opportunism, which may be inefficient. As carrier costs are unobservable, the shipper cannot distinguish between efficient rejections and opportunistic ones. This indicates the existence of a potential moral hazard problem. *Second*, we note that shippers control relationship termination. Thinking of the shipper as a principal and the carrier as an agent, we can model their interactions as a principal-agent game, in which the shipper can use the threat of relationship termination to induce efficient cooperation by the carrier. *Third*, we note that this threat does indeed induce carrier cooperation. We find that when the promise of relationship continuation exists, it induces a strong cooperative response in carriers. This establishes that carriers' cooperative incentives are generated by the prospect of future relationship rents, a defining feature of relational contracts. Together, these three facts highlight the existence of a moral hazard problem and suggest that relational contracts govern shipper-carrier relationships, alleviating this problem. These findings motivate our modeling and empirical analysis of the setting.

We develop a theoretical model that reflects these three facts and captures key features of institutions in the truckload setting. This model of repeated interactions within a shipper-carrier relationship shares some elements with standard models from the theoretical literature on relational

[3] About 90% of total industry volume is arranged through long-term shipper-carrier relationships, which, as we will describe in Section 1, are largely informal.

contracting, but is specialized to capture the non-standard features of the truckload setting. For instance, our model features commitment strategies, rather than self-enforcing strategies, on the shipper's side, a feature consistent with industry experts' descriptions of shippers' approach to relationships. The model generates testable predictions on both shippers' strategies and carriers' responses.

Guided by the predictions of the model, we use our shipper-carrier microdata and our spot market data to estimate regressions motivated by *shippers'* strategies and find strong evidence that shippers punish carrier rejections by increasing the probability of relationship termination. Our estimates suggest that punishment strategies are soft, in the sense that a rejection is punished with low probability. Nevertheless, we show that the degree of punishment is economically and statistically significant. In addition, we show that shippers condition on long histories, which gives the carrier opportunities to recover from unfavorable events. On the other hand, we find that shippers take a cruder approach to managing relationships across lanes, i.e. origin-destination pairs. Our estimates suggest that a shipper does not, as might have been expected, pool incentives across the various lanes on which she interacts with a carrier.[4] In other words, a shipper and carrier act as if they have separate relational contracts for each of the lanes on which they interact. Furthermore, our estimates describe how shippers' strategies vary with relationship characteristics. These results not only verify predictions of the model, but also resolve key questions about shippers' strategies for which the model does not offer strong predictions.

Having shown that shippers create dynamic incentives by conditioning relationship termination decisions on past rejections, we next study *carriers'* responses and find strong evidence that carriers respond to dynamic incentives. To reach this conclusion, we estimate the effects of relationship characteristics—including volume, consistency of loads, contract rate—and the spot rate on carriers' acceptance decisions. The estimated coefficients strongly support the notion that carriers respond to dynamic incentives and have signs that are largely consistent with predictions from the model.

Finally, having presented empirical evidence consistent with a relational contracting model, we discuss switching costs and learning as two alternative models that might describe the interactions between shippers and carriers. While each of these theories can explain some general dynamic patterns in the data, we present evidence that neither is the driving force behind the existence of and dynamics within long-term relationships in this industry. The evidence reinforces our argument that shippers use commitment strategies to create dynamic incentives for their preferred carriers to accept more loads.

Our paper relates to the empirical literature on relational contracting. While this literature is

[4]To avoid confusion, we will, throughout the paper, refer to the shipper using she/her pronouns and the carrier using he/him pronouns.

relatively recent, the last two decades have seen the development of a rich body of empirical evidence. Recent papers have explored different aspects of relational contracts in a variety of settings. Macchiavello and Morjaria (2015) exploit an unanticipated supply shock to study the role of reputation in relationships between Kenyan rose growers and foreign buyers. Barron et al. (2020) study relational adaptations in the form of renegotiations over formal revenue-sharing contracts in the context of the movie industry. Gil et al. (2021) explore outsourcing decisions of airlines to regional carriers and show that, following a large permanent shock to the value of relationships, relational contracts may restructure, rather than terminate. Macchiavello and Morjaria (2021) show that in the Rwandan coffee industry, competition leads to worse outcomes by undermining relational contracts between mills and farmers. Gil and Marion (2013) study procurement auctions and describe how the prospect of future interactions influences firms' pricing and entry decision.

Our approach to studying relational contracts between shippers and carriers builds upon approaches used in this prior work. First, like Macchiavello and Morjaria (2015), we make use of exogenous variation in spot rates. While Macchiavello and Morjaria (2015) use spot rates to construct lower bounds on the value of relationships, we exploit exogenous variation in spot rates to estimate shippers' strategies and carriers' responses, giving a detailed description of the incentive contracts governing shipper-carrier relationships. Second, we construct a measure of expected volume similar to the measures of future contract volume used by Gil and Marion (2013). As in their paper, our volume measure serves as a proxy for the frequency of future interactions while being orthogonal to the parties' match-specific gains. However, the richness of our data allows us to take the approach a step further. While Gil and Marion (2013) use the stock of prior interactions as a proxy for match-specific gains, features of the truckload freight setting and our detailed data set allow us to directly measure a component of such gains: the consistency of load timing. Consistent timing of loads helps carriers plan their network of truck movement to reduce empty miles, thus contributing to carriers' value from transactions.[5]

Though some aspects of our empirical approach share commonalities with this prior work, there are several ways in which the incentive contracts in our setting differ from those studied in the relational contracting literature. This literature has focused on optimal stationary relational contracts in the tradition of MacLeod and Malcomson (1989), Baker et al. (2002) and Levin (2003). The relational contracts these papers have studied rely on relational bonuses and do not feature relationship termination on-path. In contrast, relationships in the truckload freight setting feature both *fixed contract rates* and potential *on-path termination*. Moreover, while reward-punishment cycles have been shown to be optimal in some environments with imperfect monitoring (Green

[5]Expected volume and consistency of loads are acknowledged by the trucking literature as important factors for carriers' acceptances. See, for example, Scott et al. (2017), which establishes a correlation between these factors and carrier acceptance, but does not establish causality or study the underlying incentive contracts that give rise to this correlation.

and Porter, 1984; Li and Matouschek, 2013), we do not document such cycles; on the contrary, we observe *permanent punishments*. A plausible explanation for why reward-punishment cycles do not occur in this setting is that both shippers and carriers value stability. For shippers, stability of rates help with budgeting, forecasting, and reducing haggling costs. For carriers, stability in load arrivals helps with network planning. This means that frequent changes in primary carriers, those carriers that are prioritized to receive the first offers, would induce costly adjustments.[6]

Relative to the empirical literature on relational contracting, we make three contributions. *First*, we study relational contracting in an important yet understudied industry, the US truckload freight industry.[7] Revenue in this industry was $700 billion in 2015, equivalent to about 4% of US GDP. Moreover, several aspects of this industry differentiate it from other settings in which relational contracts have been studied. For example, in this industry it is reasonable to assume that one side of the market, the shippers, employ commitment strategies rather than self-enforcing strategies. While previous papers have largely studied settings where the transactions governed by relational contracts represent both parties' primary business, shipping accounts for a small fraction of a shipper's business. It is therefore plausible that a shipper would commit to a strategy rather than devoting managerial attention to micro-managing each interaction within the relationship. *Second*, the fact that our TMS and spot market data together give reliable measures of all aspects of the relationship—its status, the agent's performance, the agent's outside option, and the firms' play—presents a unique data opportunity for studying relational contracting. One particularly important question that such detailed data allows us to explore is the "scope" of relationships. We find that although shippers and carriers interact on multiple lanes, relationships across these lanes are treated separately. This is in stark contrast to the assumption common in the relational contracting literature that relationships exist at the firm-to-firm level.[8] To our knowledge, our paper is the first to test the assumption of relationship scope. Since the relational contracts studied previously do not feature on-path termination, it would not be possible to test whether incentive power is pooled across all relationship sub-divisions (e.g. routes or lanes). The fact that relationship termination occurs in our setting and that we observe key measures of carrier performance at the level of the relationship sub-division (in our case, the lane) permits us to perform such a test. *Third*, our empirical analysis studies nonstationary contracts. We allow for an exogenously evolving state, the spot rate, as well as an endogenously evolving state, a rejection rate index that summarizes the carrier's past cooperation (or lack thereof). It is important to allow for autocorrelation in spot rates because movements in the trucking industry is closely tied to movements in the goods economy,

[6]Rationalizing these unique features of the truckload freight setting is beyond the scope of our paper. We will instead take these features as given, allowing us to focus on other aspects of the incentive contracts.

[7]The term "truckload" refers to the transportation of a shipment that fills all or nearly all of a standard-sized trailer.

[8]For example, Gil et al. (2021) assume that following a deviation by either the major or the regional airline, the outsourcing relationships would terminate on all routes.

which exhibit autocorrelation. Our empirical results also highlight the importance of allowing for a flexibly and endogenously evolving state variable summarizing past cooperation. Our results show that actions in the distant past matter a great deal in shipper-carrier relationships, a fact that would not be captured by an approach that assumed stationarity.

Our paper also contributes to the literature on the trucking industry. Among papers in this literature are Rose (1985, 1987), Hubbard (2001), Baker and Hubbard (2003, 2004), and Masten (2009). To the best of our knowledge, our paper is the first to study relational contracts between shippers and carriers in this industry.

The paper proceeds as follows. In Section 1, we describe the US for-hire truckload freight industry, its market institutions, and the structures and norms within which long-term shipper-carrier relationships operate. In Section 2, we describe our data, which includes both microdata on shipper-carrier relationships and data on spot market rates. In Section 3, we establish three key facts that motivate our modeling of a shipper-carrier relationship as a repeated principal-agent game in which a relational contract deters carrier opportunism. In Section 4, we present a theoretical model of shipper-carrier relationships and characterize optimal shipper and carrier strategies. In Section 5, motivated by the theoretical framework in the previous section, we estimate shippers' strategies, showing that shippers condition relationship continuation on past cooperation. Our estimates also speak to the harshness of the punishment scheme, the scope of the relational contract, and the way that shippers' strategies vary with relationship characteristics. In Section 6, we estimate how carriers' acceptance varies with relationships characteristics. The results strongly support the idea that carriers respond to the dynamic incentives generated by shippers' punishment strategies. In Section 7, we discuss two competing theories: switching costs and learning. Section 8 offers conclusions about our findings, their implications, and future related research.

1 Setting

We begin by describing our setting: the US for-hire truckload freight industry. This is an economically important industry in which informal interfirm relationships play a central role. We describe the distinguishing features of this subsegment of the trucking industry, as well as the market institutions that are relevant to our analysis.

1.1 The US for-hire truckload freight industry

The freight trucking industry plays a uniquely important role in the US goods economy. In 2015, trucks carried 66% of domestic shipments by weight and 72% of domestic shipments by value.[9] US

[9]See Bureau of Transportation Statistics Freight Facts and Figures 2017.

trucking firms had revenues of more than \$700 billion in 2015, with about \$350 billion accounted for by the for-hire truckload subsegment.[10] These figures are equivalent to nearly 4% and 2%, respectively, of US GDP in 2015.

Within the freight trucking industry, services are differentiated by the contractural relationships between shippers and carriers, by the size of shipments, and by the equipment required. In this paper, we focus on for-hire truckload carriers supplying dry-van services. We will explain each of these terms in turn: First, a *for-hire* carrier is one who sells his services to various different shippers. This is in contrast to a private-fleet carrier, who is vertically integrated with a single shipper. Second, a *truckload* carrier accepts only large shipments that fill all or nearly all of a trailer. Truckload service is "point-to-point": A truckload shipment has a single origin and a single destination. While a truckload carrier must plan his network of truck movements efficiently to minimize empty miles, his problem is far simpler than the optimization problem faced by a less-than-truckload carrier. The latter kind of carrier accepts smaller shipments from various different shippers and aggregates them together to fill the trailer. Finally, a freight truck consists of a tractor unit, which contains a heavy-duty towing engine and a driver cab, and a cargo trailer, which holds goods being hauled by the tractor. Some common trailer classes include refrigerated, flatbed and tanker. By far the most common trailer type is the *dry van*, used for hauling boxes or pallets of dry goods not requiring refrigeration. We will focus exclusively on dry van truckload services supplied by for-hire carriers. This is the largest subsegment of the trucking industry and one in which carriers' business model and logistical challenges are easy to understand.

1.2 Market institutions

In the US for-hire truckload freight market, shippers and carriers arrange loads through two primary market institutions: a spot market and (largely informal) long-term relationships.

Typically, about 10% of loads are arranged through the spot market. The dominant spot market platform is a single online "load board," organized by DAT Solutions. The load board is a marketplace that facilitates matches between shippers with loads and carriers with trucks. In exchange for a fee, shippers and carriers can access the load board and can either post or search existing postings to try to find a match.

The remaining 90% of US truckload volume is arranged through long-term relationships between shippers and carriers. While these relationships are typically formalized by contracts, the contracts are highly incomplete. In this setting, a *contract* is a bilateral agreement between a shipper and a carrier on a particular *lane*, i.e. an origin-destination pair.[11] The primary purposes of the contract are to (1) define liability for goods lost or damaged in transit and (2) establish the rate that

[10] *American Trucking Trends*, American Trucking Association, 2015.

[11] The origin-destination pair specified in a contract is typically a city-city pair.

the shipper will pay the carrier for each load on the lane. However, the contract imposes few other restrictions on the parties and does not obligate the shipper and carrier to behave cooperatively toward one another.[12] The contract may state an estimated number of loads per week, but this volume is just an estimate, not a guarantee. If the realized number of loads offered to the carrier is less than the estimated volume (or even if there are no realized loads), the contract does not give the carrier any legal recourse. Similarly, the contract does not obligate the carrier to accept any loads offered by the shipper under the terms of the contract. The carrier may reject some or all of the loads offered. If the carrier rejects loads, the contract does not give the shipper any legal recourse.

The dominance of long-term relationships in this industry suggests that they offer benefits not enjoyed in spot arrangements. Such benefits could take several forms: First, arranging loads through a long-term relationship might save shippers and/or carriers the costs associated with searching and haggling in the spot market. Such costs are likely non-negligible because the demand for transportation services is dispersed through space and time. Moreover, the spot market is thin.[13] Given that spot-market demand on a particular lane at a particular time might be scarce, carriers may prefer the more consistent demand from contracted shippers, which facilitates a stable, cost-effective network of truck movements for the carrier. Second, shippers and carriers who form and maintain long-term relationships may have high match-specific values from transacting with each other. This seems especially likely if such relationships arise as the outcome of a search process. Finally, if a shipper and a carrier interact repeatedly and enjoy direct benefits from such interactions, then the promise of future interactions could be used to deter inefficient short-term opportunism. While our analysis will allow for the first two kinds of benefits, our paper focuses on this last channel. We study dynamic incentives in long-term relationships and the level of cooperation they enable shippers and carriers to achieve.

1.3 Managing relationships: The routing guide

A shipper frequently has relationships with several different carriers on a particular lane. These various carriers, are not, however, equal in status. The shipper explicitly ranks the carriers in a catalog called the *routing guide*. This ranking specifies the order in which carriers are sequentially offered each load that the shipper has on this lane.[14]

[12] The fact that these agreements are informal and not legally binding is widely understood in the industry. For instance, Melton Truck Lines Senior Vice President Dan Taylor wrote "The 'rate agreements' and 'load commitments' for the most part have no contractual obligation or penalties on either party." (See Taylor (2011).)

[13] The role of transaction costs in driving the tendency towards contractual arrangements is a well established idea. For related studies in the context of the trucking industry, see Hubbard (2001) and Masten (2009).

[14] For a more detailed discussion of the routing guide and related features of truckload operations, see Section 4 of Caplice (2007).

Table 1: Example routing guide: Shipper Z, lane City X - City Y (on June 1, 2018)

Order	Carrier	Rate	Type
1	A	$1230	Primary carrier
2	B	$1327	Backup carriers
3	C	$1095	
4	D	$1450	

To illustrate this sequential offering process (sometimes called a *waterfall*), Table 1 gives an example of an (anonymized) routing guide for a shipper Z on the lane from City X to City Y.[15] When Z has a load at City X that she wants to ship to City Y on a particular date, she first offers the load to the *primary carrier*, in this case, A. If A accepts, then A carries the load and receives $1230. If A rejects, then the load is offered to B. If B rejects, the load is offered to C, and so on. If the routing guide is exhausted without a carrier accepting, the shipper will typically turn to the spot market to try to find a carrier to accept the load.

The rationale for the shipper maintaining a routing guide with multiple carriers who have the right to reject loads, rather than a single carrier for whom acceptance is obligatory, is that 100% acceptance by a single carrier is unlikely to be efficient. The demand of a shipper over time is random and, therefore, cannot be perfectly predicted by a carrier.[16] This means that when the shipper offers a load on a particular date, the carrier's trucks may be poorly positioned for carrying this load; doing so may be very costly or infeasible.[17]

There are several features of the routing guide that play an important role in the dynamics of the shipper-carrier relationship.

First, the process of sequentially offering loads is automated by software called a transportation management system (TMS) that allows each carrier only a short amount of time to respond to an

[15]This mechanism is similar to the waterfall mechanism that was once widely used to assign digital advertising space.

[16]While the timing of loads is random, the demand of a shipper is typically more consistent than the demand of a single consumer in some other transportation industries, e.g. the taxi or ride-hail industry.

[17]One might think that the GPS-equipped devices now installed on most trucks would seem to offer an opportunity for contracts that obligate carriers to accept unless some verifiable conditions are met, e.g. unless all of the carrier's trucks are more than 100 miles from the load pickup location. However, any such simple criterion on current truck locations is unlikely to be satisfactory. First, a load is typically offered and accepted several days before the load's pickup time. At the time the acceptance decision is made, only current truck locations are verifiable, but what is relevant to the carrier's ability to pick up a load is of course the location of his trucks at the pickup time. Second, any such simple condition on truck locations would fail to account for both network-related issues and the carrier's obligations to other shippers. A carrier may have a truck near the load pickup location, but that truck may be needed to fulfill an obligation to another shipper.

offer.[18] This rapidity suggests that the shipper does not have a strategic incentive to rank a carrier higher just because that carrier is in high demand by other shippers; so little time passes between offers that a lower-ranked carrier is unlikely to be "snatched up" by another shipper while higher-ranked carriers are responding to their offers. This means that a shipper's static best response is to rank the carriers according to her preference over the carriers. Thus, rejections by top-ranked carriers are generally undesirable for the shipper. In Table 1, for instance, the fact that the shipper chose to rank A above B indicates that she prefers paying $1230 for service from A to paying $1327 for service from B. Furthermore, the fact that she ranked B above C, despite the fact that C has markedly lower contract rate, suggests that B provides the shipper with superior service in some dimension other than rate (e.g. quality, reliability). More generally, differences in non-rate characteristics may also be important to the shipper.

Second, the shipper has discretion to alter the ranking of carriers in the routing guide at any time. Indeed, though Table 1 gives the ordering of carriers on June 1, 2018, the routing guide for the same lane two weeks later is substantially different, with these four carriers ordered C, A, B, D. Why might such a change occur? The shipper might, for instance, make a change to the routing guide if new information were revealed about the quality of service of one of the carriers. But, the power of reordering the routing guide can also be used strategically to incentivize carier cooperation. If a carrier were behaving opportunistically, rejecting many contract loads in favor of taking higher-paying loads in the spot market, the shipper could punish the carrier by downgrading him to a lower position in the routing guide. Being downgraded diminishes the carrier's future rents from the relationship, as he will now receive fewer offers on this lane. This possibility of punishment via reorganization of the routing guide is an essential feature of this setting and one that will be at the center of our model and empirical analysis.

Third, at the end of a contract period, the shipper holds a request for proposals (RFP) to determine the set of carriers, their rates, and their initial positions in the new routing guide. In an RFP, a shipper need not award the primary position to the lowest-bidding carrier; non-rate characteristics can be taken into account. While this is intuitively similar to a scoring auction, the ways these RFPs are carried out in practice is far more complicated than the formal auctions that have been studied theoretically and empirically in a wide range of economic settings. After a shipper receives carriers' initial bids, multiple rounds of negotiation between the shipper and the various carriers jointly determine carriers' final routing guide positions and rates.

[18] A typical response window might be fifteen minutes.

2 Data

We use transaction-level data from the transportation management system software used by shippers to manage their relationships with carriers. The data records every interaction within these relationships. To proxy for carriers' outside option in our analysis, we use a measure of the going rate for freight services in the spot market from DAT, the gold-standard provider of such spot market data.

2.1 Shipper-carrier microdata

Our analysis is made possible by the fact that shippers use the TMS to manage their relationships with carriers and to automate the waterfall of tenders.[19] The shipper enters carriers' rates and ranks into the TMS, and then, for each load, prompts the TMS to sequentially send electronic offers to the carriers. For each load sent through the TMS, the software records the details of the load, all offers that are made, and whether each is accepted or rejected. These records for one particular TMS software provider, called TMC, are the source of our microdata.[20]

The microdata covers the period from September 2015 through August 2019. In all, the data set includes 1,074,172 loads and 2,130,125 tenders (i.e. offers). 71% of loads are accepted by the first carrier to which they are offered. For all loads included in the data set, the haul distance is at least 250 miles.[21] The mean distance is 692 miles with a standard deviation of 440 miles. The average per-mile contract rate is \$1.85 with a standard deviation of \$0.51. This data set is fairly representative of the geographic distribution of contract truckload freight activity in the continental US, though activity in the Midwest is somewhat overrepresented, while activity on the West Coast is somewhat underrepresented.

Shipper-carrier relationships and networks The microdata includes 40 shippers with at least 500 loads. The median shipper has 8094 loads with, on average, 192 active lanes and 53 active carriers each year.

On many lanes, shippers and carriers interact frequently, though there is large variation in the frequency of interactions across shippers and across different lanes of the same shipper. For example, the median lane of the median shipper has only one load per month, but among the top 10% of lanes for the median shipper, each has, on average, a load for every four days. Such variation in frequency of interactions is important for our test of the effect of dynamic incentives on carriers' acceptance.

[19] In this industry, an offer of a load to a carrier is commonly referred to as a *tender*.

[20] TMC is a division of CH Robinson, a third-party logistics firm.

[21] For shorter-distance hauls, the prevailing market institutions are somewhat different. These loads are therefore excluded from our analysis.

Multilane interactions between a shipper and a carrier are also common. The top five and top ten carriers of the median shipper deliver, respectively, 58% and 73% of her loads. Relatedly, it is common for a carrier to serve as a shipper's primary carrier on multiple lanes. For example, the top five carriers of the median shipper hold primary status on an average of 21 lanes each. This means that there is significant potential for strategic exploitation of multilane interactions: a shipper might condition a carrier's primary position on one lane on his behavior on another lane. Our empirical analysis will address the question of whether shippers exploit the prevalence of multilane interactions in this setting for the purpose of creating cooperative incentives.

2.2 Spot rate data

We will use data on the average rate for truckload services in the spot market to capture the relevant outside option—the alternative opportunities available to shippers and carriers outside of their long-term relationships. This data comes from DAT Solutions, the leading provider of data on truckload spot markets. For our sample period, the data set gives us seven-day trailing average spot rates for a set of narrowly-defined lanes that cover the continental United States.[22]

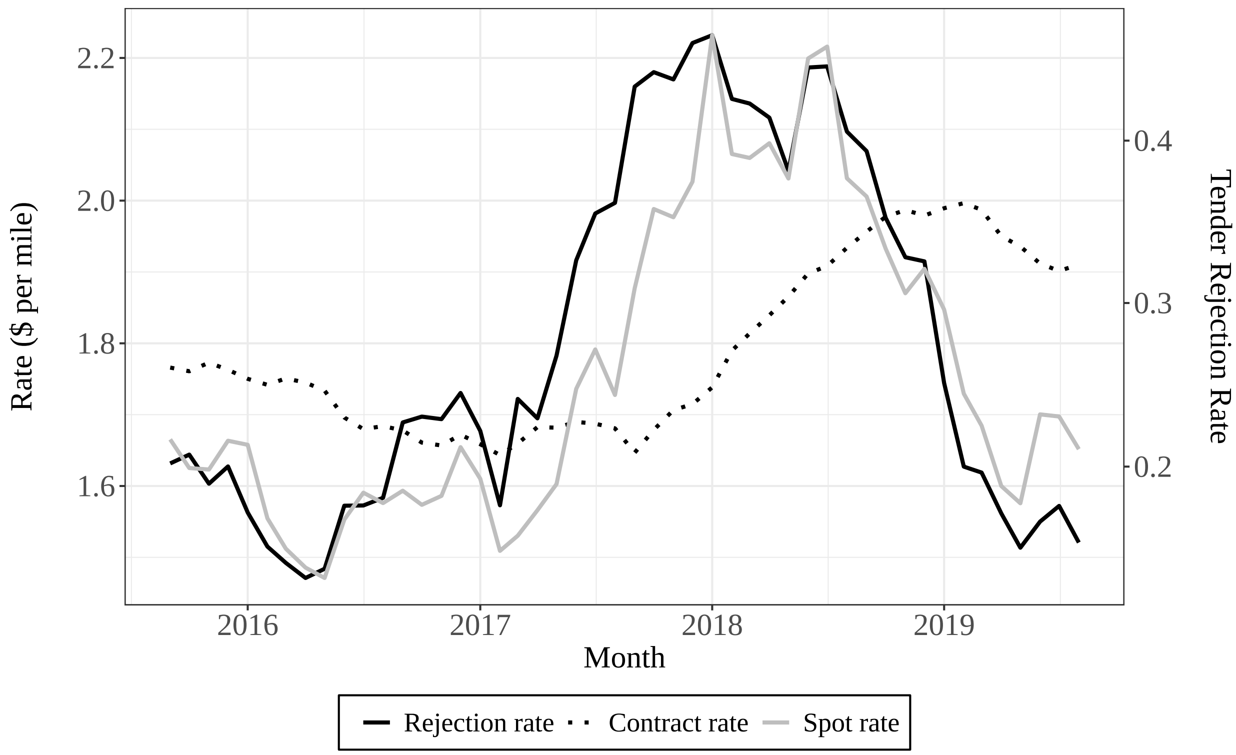
Across all lanes and dates, the overall mean spot rate per mile is \$1.68 with a standard deviation of \$0.60. The first quartile, the median, and the third quartile are \$1.26, \$1.53, and \$1.93, respectively. A notable feature of the data is persistent differences in rates across lanes; a regression of spot rates on a set of lane fixed effects has an R^2 of 0.78, indicating that across-lane differences are large relative to within-lane variation. In later empirical analysis, we pool observations across lanes for the purpose of estimating the strategies of shippers and carriers. To make for appropriate comparisons across lanes, we will use residualized, rather than raw, spot rates, partialling out lane fixed effects. For the time series of average monthly spot rates over our sample period, see Figure 1 in the next section.

3 Three Key Facts

In this section, we use our shipper-carrier microdata, together with the data on spot rates, to establish three key facts. Collectively, these facts motivate a particular model of the shipper-carrier relationship: this relationship can be thought of as a repeated principal-agent game in which a relational contract deters carrier opportunism.

[22]Each lane is defined by a pair of key market areas (or KMAs). The continental US is partitioned into 135 KMAs, so there are 135^2 KMA-to-KMA lanes.

Figure 1: Aggregate trends: National averages of rejection, contract, and spot rates



Notes: The monthly rejection rate is constructed from the TMS microdata as the fraction of loads rejected by the first carrier in the routing guide. The average monthly contract rate is constructed from the TMS microdata. The average monthly spot rate is constructed from the DAT data, on the same set of lanes covered by the TMS microdata. The rejection rate, contract rate, and spot rate are all volume-weighted averages.

3.1 Fact 1: Temporary spot-contract rate differences create temptation for carriers

We begin by using our DAT data on prevailing rates in the spot market, together with the average contract rate and a measure of carrier cooperation from our microdata, to argue that when spot rates are higher than contract rates, carriers are tempted by short-term opportunism. As such opportunism is detrimental to the shipper, a moral hazard problem exists within the shipper-carrier relationship.

Figure 1 illustrates the potential for carrier opportunism by depicting two key aggregate trends. First, there are periods in which spot rates are significantly higher than contract rates. Second, these periods coincide with a high proportion of rejections by carriers.

Figure 1 shows that there is considerably more intertemporal variation in spot rates than in contract rates. While spot rates were generally lower than contract rates in the first two years of our sample, an aggregate demand shock in late 2017 and early 2018 resulted in a sharp increase in spot rates.[23] At the peak in January 2018, the average spot rate is about 20% higher than the

[23]Contemporary articles from various trade publications (including Transportation Topics and FreightWaves.com)

average contract rate.

These spot market premia create the potential for short-term opportunism. Recall that a carrier in a long-term relationship always has the right to reject loads offered to him by the shipper. Thus, when the spot rate exceeds the contract rate, the carrier may choose to reject contract loads and instead opt to provide service in the spot market. Figure 1 shows evidence consistent with this hypothesis: The period of high relative spot rates coincides with a large increase in the proportion of tenders rejected by primary carriers. This observation strongly suggests that the spot market represents a key outside option for the carrier.

Such opportunism by the carrier presents a moral hazard problem. The fact that long-term relationships exist in the first place—rather than all transactions being arranged through the spot market–suggests that there is relationship surplus that would be foregone were the carrier to opportunistically choose to service the spot market.[24] Furthermore, the shipper has imperfect monitoring: the shipper cannot distinguish between an inefficient opportunistic rejection and an efficient rejection resulting from the carrier's current cost of service being high.

Yet Figure 1 also gives us reason to believe that some mechanism exists to alleviate the moral hazard problem. When spot rates reach their peak in January 2018, they are on average 20% higher than contract rates. Despite this seemingly strong incentive for the carriers to reject loads, the majority of loads are still accepted by primary carriers in this month. That many carriers are willing to forgo significant short-term profits suggests that their opportunistic tendencies are restrained by some other force.

One such force could be relational contracting, an incentive scheme in which the promise of future rents helps alleviate carrier's short-term opportunism. Necessary conditions for such an incentive scheme to be effective are that (i) the shipper has the power to deny the carrier future rents if he behaves opportunistically and (ii) the carriers' future rents from the relationship are sufficiently large. The next two subsections present preliminary evidence suggesting that these conditions hold.

Before addressing the role of shippers in the next subsection, we point out an asymmetry between shippers and carriers: While carriers might be tempted to short-term opportunism by high spot rates, industry experts tell us that it is "very rare" for a shipper to go directly to the spot market before the routing guide when spot rates are low. Perhaps because shipping represents only a small component of the operations of shippers, who are usually non-transportation firms (e.g. manufacturers or retailers), taking advantage of short-term opportunities to reduce shipping costs is not a priority. Shippers allow day-to-day shipping decisions to be automated by the TMS and

describe the high spot rates of the 2017-2018 period as being driven by increased spending on e-commerce, booming US industrial production, and the December 2017 corporate tax cut. See, for instance, www.freightwaves.com/news/market-insight/forecasting-2019.

[24] Such surplus may result from match-specific gains, a reduction of search or haggling costs, etc.

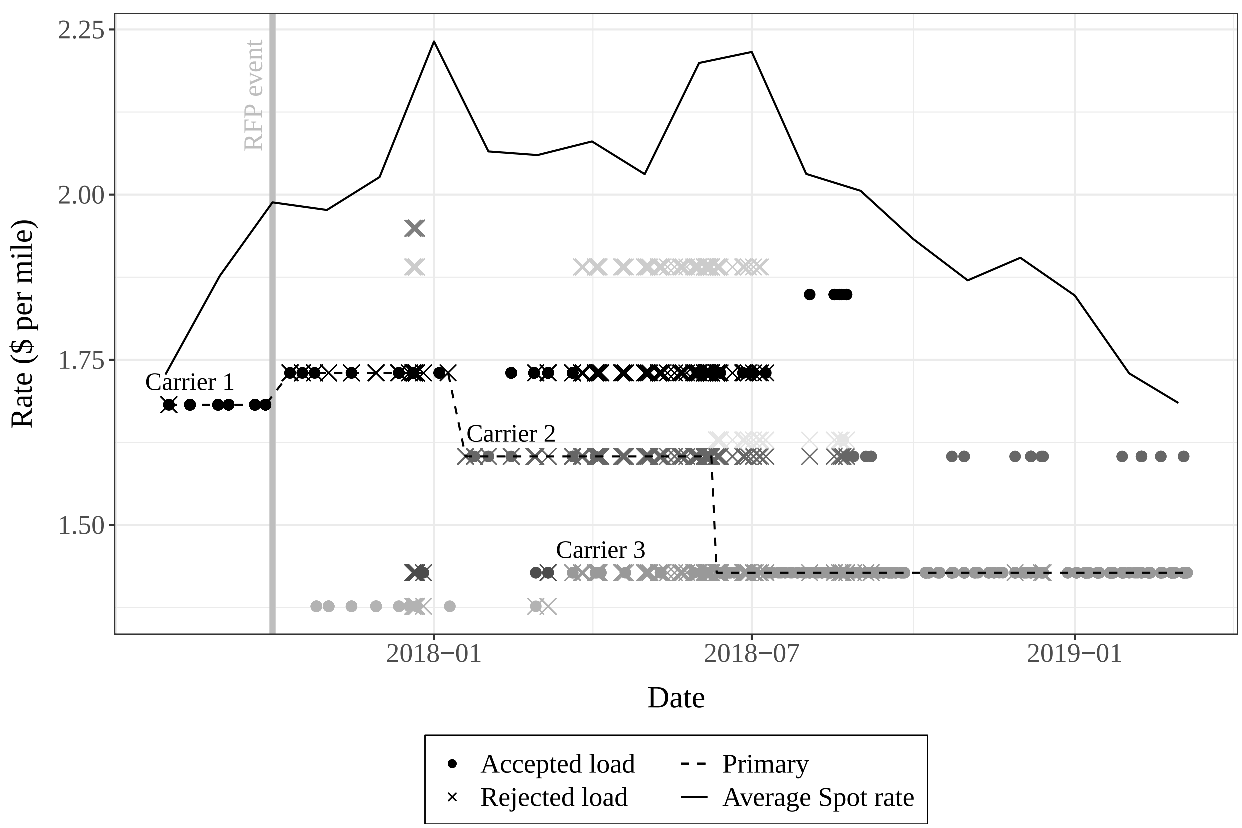
make strategic decisions only on a medium-term basis.

3.2 Fact 2: Shippers control relationship termination

We next use our shipper-carrier microdata to show that shippers control relationship termination and provide suggestive evidence on the form of shippers' termination strategies.

Figure 2 presents an example of a lane history that illustrates patterns we see in the data and motivates the way we think about the shipper's decisions. Recall that the chief decision faced by the shipper is that of when and how to change the routing guide. Such changes can be made at any time. Some are the result of RFPs, while others take place within the contract period, i.e. in the time between RFPs. Our analysis will focus on the latter and, in particular, on those changes that replace one primary carrier with another. We refer to such a change as a *demotion* of the current primary carrier.

Figure 2: An example: Tenders for Shipper X, City Y - City Z



Notes: Each point represents a tender: circles represent tenders that are accepted while crosses represent tenders that are rejected. Each carrier is indicated by a different color. The dotted black line indicates the rate of the primary carrier at each point in time. Carrier 1, Carrier 2 and Carrier 3 each serve as primary carrier for this shipper and lane for some subset of the period from October 2017 to May 2019. The tender data comes from the TMS microdata. The average monthly spot rate on the same lane is constructed from the DAT data set.

In the example in Figure 2, Carrier 1 initially holds primary status and accepts most of the tenders that are offered to him. Around early October 2017, the shipper holds an RFP for this lane in which Carrier 1 retains his primary status and gets a rate increase of about 5 cents per mile. However, over the next three months, a period of high spot rates, this carrier rejects many of the loads that are offered to him. In January 2018, Carrier 1 is demoted from primary status and replaced by Carrier 2. Over the next five months, Carrier 2 rejects most of the loads offered to him. Ultimately, he too is demoted in favor of Carrier 3, who maintains primary status for the remainder of the sample period.

This figure, which illustrates patterns that are common to many lanes, motivates two key conclusions about shipper-carrier relationships:

First, while shippers have almost unlimited discretion in what kind of routing guide changes they make, in practice, they do not switch primary carriers frequently; rather, a shipper maintains a primary carrier for a time before ultimately—and usually permanently—demoting that primary carrier.[25] From this observation, it seems appropriate to think of the shipper-carrier relationship in terms of the following kind of principal-agent model: the shipper controls relationship termination and, at each point in time, decides between continuation and (permanent) termination.

Second, a clear pattern on this lane, as well as many others, is that a series of rejections by the primary carrier often is followed by a demotion. This evidence is consistent with a relational contract in which the shipper generates dynamic incentives for the carrier by conditioning relationship continuation on acceptance.

The evidence in this subsection indicates that shippers have the power to terminate the relationships. This suggests that a shipper can—and, indeed, we have shown suggestive evidence that she does—use the threat of relationship termination to potentially deter carrier rejection. Whether such a threat is effective in deterring carrier opportunism will depend on whether the carrier's future relationship rents are sufficient to outweigh his short-term profit from deviating to the spot market. The next subsection will address this question.

3.3 Fact 3: Relationships create surplus, generating dynamic incentives

This subsection presents suggestive evidence that (i) carriers enjoy significant relationship surplus, and, relatedly, (ii) carriers' future relationship surplus induces a significant cooperative response.

[25] We find that in about 98% of instances where a carrier is demoted from primary status, he never regains primary status on the lane in our sample period (2015-2019). While there is a truncation issue here (a demoted carrier may regain primary status after the end of our sample period), it nevertheless seems clear that demotions are typically permanent. While it is possible that shippers are actually employing reward-punishment cycles like those described by Green and Porter (1984) or Li and Matouschek (2013), the cycles would have to be very long. We observe four years of data—quite a long period of time when one considers that the typical time between consecutive loads on a lane is one or two days—, and yet we almost never observe a demoted carrier regaining primary status. Hereafter, we assume that demotion is permanent and use the terms demotion and termination interchangeably.

If a carrier values future relationship rents and these future relationship rents create dynamic incentives, we might expect these dynamic incentives to be reflected in changes in carriers' behavior around RFPs. Future rents can only be enjoyed if the relationship continues, so the strength of dynamic incentives depends on the carrier's expectation about the likelihood of relationship continuation. While we have established that a relationship sometimes ends because the shipper demotes the carrier, it may also end because the shipper holds a new RFP and selects a different primary carrier. Suppose an RFP is held and the primary carrier learns that he has "lost" the RFP, so he will soon lose his primary position. This changes his expectations regarding relationship continuation and, therefore, alters his dynamic incentives. Typically, about four or five weeks pass between the announcement of the RFP outcome and the enactment of the new routing guide that results from that RFP. This means that the carrier experiences a one-month "lame duck" period.

During this lame duck period, we might expect to observe *endgame effects*. If the carrier values future relationship surplus and the shipper's strategy punishes rejections with demotion, then the carrier faces dynamic incentives that push him to accept more tenders. Once the carrier learns that he has lost the RFP, he knows that the relationship will terminate soon; his expected future relationship rents—and therefore his dynamic incentives—are eliminated (or at least greatly lessened). This could result in a decreased tendency to accept tenders after the RFP outcome is announced. Observing such endgame effects would strongly support the notions that (i) carriers enjoy significant relationship surplus, and (ii) prior to the last few weeks of the contract period, carriers' future relationship surplus induces a significant cooperative response.

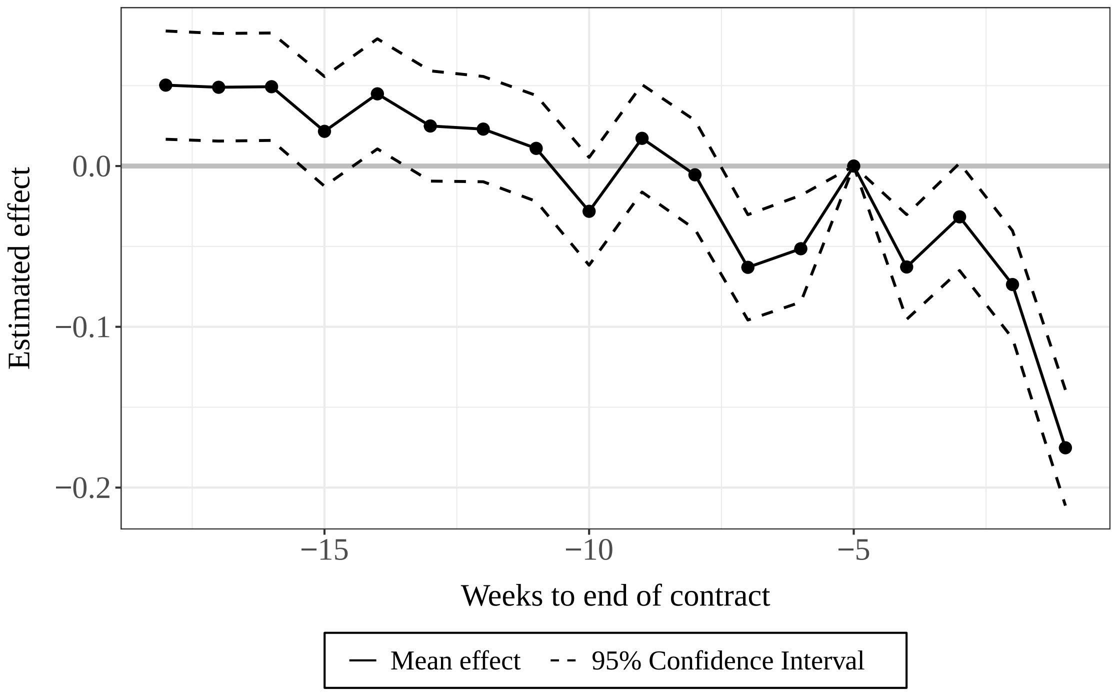
To study these hypothesized endgame effects, we estimate a linear probability model

$$\text{Accepted}_{sct}^{\ell} = \beta_0 + \beta_1 \left(\text{spot rate}_t^{\ell} - \text{contract rate}_{sct}^{\ell}\right) + \sum_{k=1}^{18} \alpha_k \mathbb{1}\{k \text{ weeks until end of contract}\} + \epsilon_{sct}^{\ell} \tag{1}$$

regressing an indicator for the primary carrier's acceptance of a tender on a set of dummies for the number of weeks until the end of the contract period (when new rates are enacted), along with the deviation profit (the difference between the spot and contract rates), which captures the carriers' short-run incentives.[26] The pattern of week fixed effects $\{\alpha_k\}$ over time will provide insight into the proposed end-of-contract effects. As we want to study whether we see evidence of endgame effects for lame duck carriers, we will estimate this regression on a sample of carriers who lose RFPs, i.e. will no longer be primary carriers once the new routing guide is enacted. To address possible selection issues related to the timing of RFPs, we further limit the subsample to *mass RFP events*. These are events where the shipper holds RFPs simultaneously on at least 30 lanes. We

[26]Notation: s indexes shippers, c indexes carriers, t indexes tenders, and ℓ indexes lanes.

Figure 3: End-of-contract effects on tender acceptance for losing carriers



think it is unlikely that declining carrier performance on one lane will affect the shipper's decision of when to hold an RFP on such a large set of lanes.[27]

The estimated coefficients $\{\hat{\alpha}_k\}$ on the weeks-to-end-of-contract dummies, along with 95% confidence intervals, are plotted in Figure 3.[28] The results show that the primary carrier becomes *ceteris paribus* much less likely to accept tenders in the final month of the contract period. The estimated magnitudes of these effects are both statistically and economically significant. The results indicate that in the last week before the end of the contract period, the carrier is 17 percentage points less likely to accept a tender relative to the baseline level. For reference, 71% of all tenders to primary carriers are accepted.

The gradual decline in acceptance in the weeks preceding the announcement of the RFP outcome is likely explained by a different sort of endgame effects. Primary carriers may anticipate an upcoming RFP, which decreases their expected probability of relationship continuation.[29] This gradual anticipatory decline, combined with the sharper decrease in the propensity to accept after the RFP outcome has been announced, strengthens the argument that future rents and dynamic incentives play an important role in carrier decision-making.[30]

[27] This approach is intuitively similar to the "mass layoff" approach used to address worker selection issues in the labor literature.

[28] The omitted level is $k = 5$, i.e. we normalize $\hat{\alpha}_5 = 0$.

[29] A primary carrier only wins the subsequent RFP only about one-third of the time.

[30] For further analysis of the incentives carriers face before the RFP is held, see Appendix B, where we also study the effects of RFP events for "winning" carriers, i.e. those that retain primary status after the RFP. The pattern of acceptance in the five weeks prior to the end of the contract period are broadly similar for winning carriers.

We take this result as strong evidence of endgame effects. For such endgame effects to exist, it must be the case that carriers value future relationships rents and that—prior to the carrier learning the RFP outcome—he believes that relationship continuation is conditional on cooperation. Therefore, our finding of endgame effects supports the notion that carriers value future rents and that shippers' punishment of rejections generates dynamic incentives. In short, this finding supports the hypothesis that relational contracts govern shipper-carrier relationships. Moreover, that the magnitude of these endgame effects is so economically significant seems to indicate that either (i) carriers' relationship rents are very large or (ii) shippers punish rejections very harshly.

In this section, we began by establishing that, to carriers, the spot market presents a temptation for short-term opportunism, creating a moral hazard problem. Next, we showed that shippers control relationship termination and potentially use that power to punish uncooperative carriers. Third, we presented suggestive evidence that carriers value future relationship rents and that they respond cooperatively to dynamic incentives. These features motivate our theoretical model in the next section.

4 A model of the incentive contract

We develop a theoretical model of repeated interactions within the relationship between a shipper and a primary carrier. While this model shares some elements with standard models from the theoretical literature on relational contracting, it is specialized to capture key features of institutions in the truckload setting. The model generates testable predictions on both shippers' strategies and carriers' acceptances that will guide our empirical analysis of these objects in the data.

4.1 Model setup

We begin by describing a model that focuses on the repeated interactions between a shipper and a primary carrier on a single lane. Two key features of the setting are taken as given: first, contract rates are fixed; second, relationship termination can occur on-path. To promote tractability, we abstract away from the existence of backup carriers, treating the spot market as the outside option for both the shipper and the carrier. Furthermore, we abstract away from RFP events.[31]

The model is specialized to capture the three facts established in Section 3:

Fact 1. Temporary spot-contract rate differences create temptation for carriers.

Fact 2. Shippers control relationship termination.

Fact 3. Relationships create surplus, generating dynamic incentives.

[31] In fact, incorporating RFPs would not affect our model qualitatively if (i) the histories of interactions between shippers and carriers are reset at new RFP events and (ii) the timing of RFP events is random and independent of the relationship history.

A tuple $(\psi, \eta, p, \delta, F, G)$ summarizes the key characteristics of a relationship. Here, ψ is the match-specific gain to the shipper from transacting with the carrier; η is the match-specific gain to the carrier from transacting with the shipper; p is the contract rate; δ is the discount factor, measuring the frequency of interactions between the shipper and the carrier; F is the distribution of the carrier's cost of servicing a load; and G is the distribution of the spot rate.

Let $\tilde{\psi}$ denote the shipper's gain from a transaction in the spot market. Moreover, let $\tilde{p}_t$ and c_t denote, respectively, the spot rate and the carrier's cost draw in period t. The shipper's period-t payoff is $u_t = \psi - p$ if she is served by the contracted carrier and $u_t = \tilde{\psi} - \tilde{p}_t$ if she is served by the spot market. The carrier receives period-t payoff of $v_t = \eta + p - c_t$ when delivering a load for the contracted shipper and period-t payoff of $v_t = \tilde{p}_t - c_t$ when serving the spot market. If the carrier chooses to remain idle, he gets zero payoff in that period. To reflect the fact that relationships create surplus, assume $\psi > \tilde{\psi}$ and $\eta > 0$. Assume that cost draws are independently and identically distributed over time with distribution F and spot rates are independently and identically distributed over time with distribution G. Let F and G permit densities f and g respectively.

The stage game is summarized in Figure 4. In each period t, a spot rate $\tilde{p}_t$ is drawn from G and publicly observed, and a cost draw c_t is drawn from F and privately observed by the carrier.[32] The shipper decides whether to "keep" the carrier as the primary carrier or "end" their relationship. If the relationship is maintained, the carrier chooses whether to accept (A) or reject (R) the shipper's load in that period. If he rejects, then he can either serve the spot market or remain idle. Otherwise, if the relationship is ended, both sides resort to the spot market for future transactions; the shipper gets expected payoff of $\underline{U}$ and the carrier gets expected payoff of $\underline{V}$.

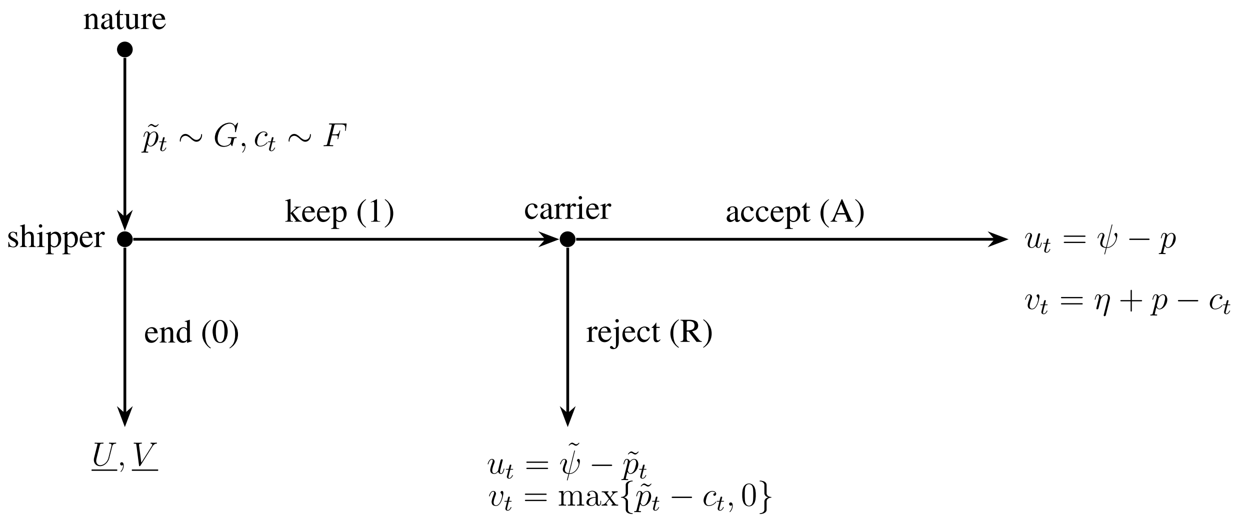
There is a *moral hazard* problem in the interactions between the shipper and the carrier. Under the assumption that $\psi > \tilde{\psi}$ and $\eta > 0$, it is never efficient for the carrier to reject the shipper's load to serve the spot market. However, requiring the carrier to always accept the shipper's load is also not efficient, since the carrier's cost in some periods might be very high.[33] The inability of the shipper to distinguish between rejections due to high cost draws and rejections due to high spot rates represents a source of inefficiency in this setting, one that the shipper may hope to alleviate using the threat of relationship termination.

Both the institutional details in Section 1 and the motivating facts in Section 3 suggest that the roles of the shipper and the carrier in the relationship are asymmetric: the shipper controls the relationship status while the carrier decides in each period whether to defect in the face of short-run temptations. Thus, we focus on *commitment strategies* for the shipper (the principal) but *self-enforcing strategies* for the carrier (the agent). That is, we require the carrier's play to be

[32] Carrier cost being drawn randomly each period reflects, among other things, the substantial day-to-day variation in the locations of the carrier's trucks. If the carrier's trucks are ill-positioned to pick up a load, doing so may require him to incur very large repositioning and opportunity costs.

[33] Specifically, when $c_t > \psi + \eta - (\tilde{\psi} - \tilde{p}_t)$, the efficient outcome is that the carrier remains idle.

Figure 4: The stage game



optimal at every history and evaluate the shipper's commitment strategy ex ante.

Furthermore, to generate clean predictions, we focus on the simplest class of shipper's commitment strategies, those that condition only on the carrier's decision in the last period. Denote such a strategy by $\sigma_0 : \{A, R\} \to [0,1]$, where $\sigma_0(d_{t-1})$ is the probability that the shipper maintains the relationship following decision d_{t-1} of the carrier in the last period. We interpret $\sigma_0(A)$ as the level of rewards following cooperation and $1 - \sigma_0(R)$ the level of punishment following noncooperation. Since the shipper conditions only on the last period's decision, we can focus on the carrier's stationary play. Denote a stationary strategy of the carrier by σ_1 : supp$(G) \times$ supp$(F) \to [0,1]$, where $\sigma_1(\tilde{p}_t, c_t)$ is the probability that the carrier accepts the offered load given spot rate $\tilde{p}_t$ and cost draw c_t.

4.2 Carrier acceptance

This subsection characterizes the carrier's optimal stationary strategy, generating predictions on how the carrier's play varies with relationship characteristics and with the incentive scheme implied by the shipper's strategy.

Denote by V the average discounted expected utility of the carrier from the relationship. Denote by $V(A)$ and $V(R)$ the average discounted expected utilities of the carrier at the beginning of period t following $d_{t-1} = A$ and $d_{t-1} = R$, respectively. We have

$$\begin{aligned} V &= \mathbf{E}_{\tilde{p}_t, c_t}\left[\max\left\{(1-\delta)(\eta + p - c_t) + \delta V(A), (1-\delta)(\tilde{p}_t - c_t) + \delta V(R), \delta V(R)\right\}\right] \\ &= \delta V(R) + (1-\delta)\mathbf{E}_{\tilde{p}_t, c_t}\left[\max\left\{\eta + p - c_t + \frac{\delta}{1-\delta}(V(A) - V(R)), \tilde{p}_t - c_t, 0\right\}\right], \end{aligned} \tag{2}$$

where

$$V(A) = \sigma_0(A)V + (1 - \sigma_0(A))\underline{V}, \tag{3}$$
$$V(R) = \sigma_0(R)V + (1 - \sigma_0(R))\underline{V}. \tag{4}$$

Let $\overline{p} = \eta + p + \frac{\delta}{1-\delta}(V(A) - V(R))$ and $h(\overline{p}) = \mathbf{E}_{\tilde{p}_t, c_t}[\max\{\overline{p} - c_t, \tilde{p}_t - c_t, 0\}]$. When $\tilde{p}_t < \overline{p}$, the carrier's optimal strategy is to accept whenever $c_t < \overline{p}$. When $\tilde{p}_t > \overline{p}$, the carrier optimally rejects regardless of the cost draw. Thus, the probability of acceptance at each level of spot rate is $\Pr(d_t = A|\tilde{p}_t) = \mathbf{1}(\tilde{p}_t < \overline{p})F(\overline{p})$, increasing in the acceptance threshold $\overline{p}$. Manipulating Equations (2), (3) and (4) yields the following fixed point equation of $\overline{p}$,

$$\frac{1 - \delta\sigma_0(R)}{\sigma_0(A) - \sigma_0(R)}(\overline{p} - \eta - p) = \delta(h(\overline{p}) - \underline{V}). \tag{5}$$

We exploit Equation (5) to generate predictions on how relationship characteristics and the reward-punishment scheme affect the likelihood of the carrier accepting, as captured by threshold $\overline{p}$.

Proposition 1. *For a fixed shipper's strategy with $\sigma_0(A) > \sigma_0(R)$, the acceptance threshold $\overline{p}$ varies with relationship characteristics in the following way:*

$$\frac{\partial \overline{p}}{\partial \delta} \geq 0, \quad \frac{\partial \overline{p}}{\partial \eta} \geq 1 \quad \textit{and} \quad \frac{\partial^2 \overline{p}}{\partial \delta \partial \eta} \geq 0. \tag{6}$$

Proof. See Appendix A.1.1. □

Intuitively, the larger is the discount factor, the higher is expected future surplus, which, under a fixed reward-punishment scheme, translates to a larger gain from cooperating today. Similarly, the acceptance threshold increases in the carrier's match-specific gain more than one-to-one because such gain contributes to both current and future payoffs. Finally, as the discount factor scales up such gains, we expect the same increase in match-specific gain to be more effective in inducing cooperation on lanes where the shipper and the carrier interact more frequently, i.e. when the discount factor is effectively higher.

The strength of the carrier's dynamic incentives also depends on the levels of rewards and punishments to which the shipper commits. Intuitively, the more generous are rewards or the harsher are punishments, the wider is the gap between the continuation value following an acceptance and the continuation value following a rejection. Thus, the probability of acceptance for a given level of short-run temptation should increase in the level of rewards and the level of punishments.

Proposition 2. *For fixed discount factor δ and carrier's match-specific gain η, it holds for every $\sigma_0(A) > \sigma_0(R)$ that the acceptance threshold $\overline{p}$ is increasing in the level of rewards and decreasing in the leniency of punishments*

$$\frac{\partial \bar{p}}{\partial \sigma_0(A)} \geq 0 \quad \textit{and} \quad \frac{\partial \bar{p}}{\partial \sigma_0(R)} \leq 0. \tag{7}$$

Proof. See Appendix A.1.2. □

4.3 Optimal shipper strategy

This subsection identifies key forces that shape the optimal commitment strategy of the shipper among the class of strategies that condition on only the carrier's last period decision. While simple, this set of strategies does allow for variation in incentive power. We analyze the intensity of the optimal punishment on a single lane, how it varies with relationship characteristics, and illustrate the potential gain from multi-lane punishment.

First, we derive the shipper's per-period payoff. Each period in a maintained relationship has three possible outcomes: either the carrier accepts the offered load, the carrier rejects because of a high cost draw, or the carrier rejects because of a high spot rate. Thus, the per-period expected utility of the shipper in the relationship equals

$$\begin{aligned} u &= \underbrace{G(\overline{p})F(\overline{p})(\psi - p)}_{\text{accepted}} + \underbrace{G(\overline{p})[1 - F(\overline{p})](\tilde{\psi} - \mathbf{E}[\tilde{p}_t | \tilde{p}_t \leq \overline{p}])}_{\text{rejected because of high cost}} + \underbrace{[1 - G(\overline{p})](\tilde{\psi} - \mathbf{E}[\tilde{p}_t | \tilde{p}_t > \overline{p}])}_{\text{rejected because of high spot rate}} \\ &= \tilde{\psi} - \mathbf{E}[\tilde{p}_t] + G(\overline{p})F(\overline{p})(\psi - p - \tilde{\psi} + \mathbf{E}[\tilde{p}_t | \tilde{p}_t \leq \overline{p}]). \end{aligned} \tag{8}$$

Notice that the term $\mathbf{E}[\tilde{p}_t | \tilde{p}_t \leq \overline{p}] \leq \mathbf{E}[\tilde{p}_t]$ is the shipper's expected payment were she to be served by the spot market conditional on the carrier being willing to accept the offered load. This term represents a selection effect: the carrier has the largest temptation to reject exactly when his acceptance is most valuable to the shipper.[34] This means that even when $\psi - p > \tilde{\psi} - \mathbf{E}[\tilde{p}_t]$, a relationship that cannot induce sufficiently high level of cooperation may not be worth sustaining for the shipper. The following is a sufficient condition for the relationship to be worth sustaining for any incentive scheme with $0 \leq \sigma_0(R) < \sigma_0(A) \leq 1$. We assume this condition throughout our analysis. The proof of its sufficiency is in Appendix A.2.1.

Condition 1. $\psi - p - \tilde{\psi} + \mathbf{E}[\tilde{p}_t | \tilde{p}_t \leq p] \geq 0.$

[34] Note that acceptances require both a low spot rate and a low cost draw. However, under the assumption that cost draws are independent of spot rates, as in our model, the hypothetical expected payment in the spot market of an accepted load does not depend on the cost draw being low.

We now derive the shipper's average discounted expected utility. Let

$$q = G(\overline{p})F(\overline{p})\sigma_0(A) + (1 - G(\overline{p})F(\overline{p}))\sigma_0(R) \tag{9}$$

denote the probability of maintaining the relationship next period calculated at the beginning of the current period's stage game. The average discounted expected utility U of the shipper in a maintained relationship is

$$U = (1-\delta)u + \delta(qU + (1-q)\underline{U}). \tag{10}$$

Without loss of generality, let $\tilde{\psi} = \mathbf{E}[\tilde{p}_t]$, so that $\underline{U} = 0$. Thus,

$$U = \frac{(1-\delta)u}{1-\delta q}. \tag{11}$$

For $x \in \{\sigma_0(A), \sigma_0(R)\}$,

$$\frac{dU}{dx} = \underbrace{\left(\frac{\partial U}{\partial u}\frac{\partial u}{\partial \overline{p}} + \frac{\partial U}{\partial q}\frac{\partial q}{\partial \overline{p}}\right)\frac{\partial \overline{p}}{\partial x}}_{\text{incentive-inducing effect}} + \underbrace{\frac{\partial U}{\partial q}\frac{\partial q}{\partial x}}_{\text{regime-switching effect}}, \tag{12}$$

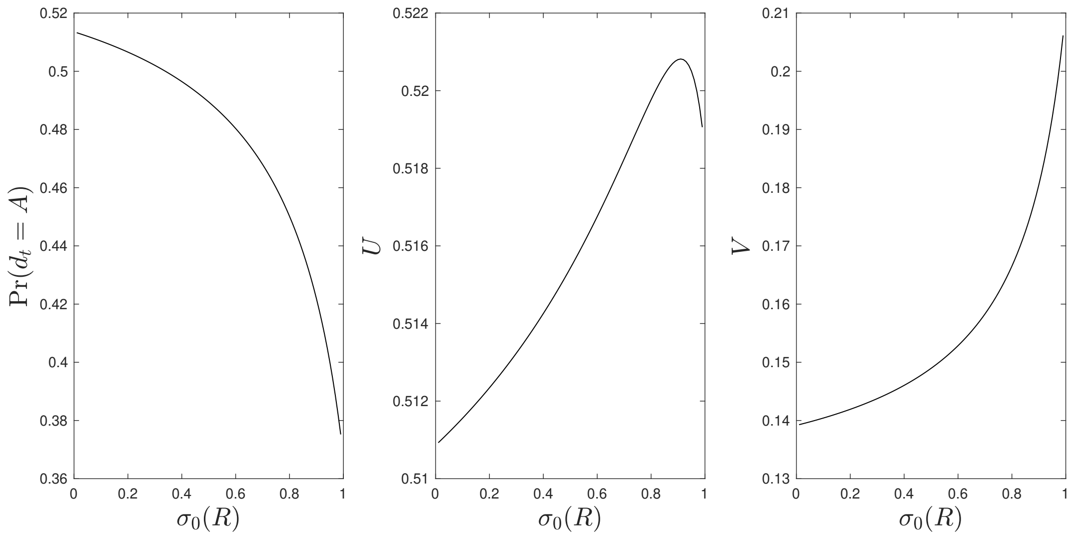
where $\partial U/\partial u, \partial U/\partial q, \partial u/\partial \overline{p}$ and $\partial q/\overline{p}$ are all positive.

Harsh versus soft punishment Equation (12) summarizes the two channels through which the levels of reward and punishment affect the shipper's payoff: the effect on carrier's acceptance probability (the incentive-inducing effect) and the direct effect on the probability of ending the relationship (the regime-switching effect). Since both $\overline{p}$ and q are increasing in $\sigma_0(A)$, the shipper faces no tradeoff when deciding on the level of reward. The highest level of reward is thus optimal. However, for the optimal level of punishment, there is a tradeoff between the two effects. On one hand, increasing the level of punishment, $1 - \sigma_0(R)$, increases the carrier's acceptance probability and thus the shipper's per-period gain. On the other hand, this also increases the probability of forever resorting to the spot market conditional on a rejection, an outcome undesirable for the shipper. It is possible that this tradeoff is not resolved by extreme punishment, but rather by soft punishment.[35] The following proposition formalizes our intuition.

Proposition 3. *For a relationship characterized by $(\psi, \eta, p, \delta, F, G)$, let σ_0^* be the optimal shipper's strategy. If σ_0^* gives expected utility higher than the shipper's outside option, then the following hold:*

[35]Note that the sense in which we mean that punishment may be "soft" is that rejections are punished with low probability, in contrast to the trigger strategies considered in other relational contracting papers. When punishment occurs, however, it is assumed to be permanent.

Figure 5: Soft punishment can be optimal



1. *For any parameter values of* $(\psi, \eta, p, \delta, F, G)$*,* $\sigma_0^*(A) = 1$.

2. *There exist parameters* $(\psi, \eta, p, \delta, F, G)$ *such that* $\sigma_0^*(R) \in (0, 1)$.

Proof. Part 1 follows from Equation (12), that $\partial \overline{p}/\partial \sigma_0(A) \geq 0$, and that $\partial q/\partial \sigma_0(A) \geq 0$. Part 2 is proved by Example 1. □

Example 1. *Let* $F \sim \alpha U(0, 1) + (1 - \alpha)\delta_K$ *for some large* K*. That is, a cost draw is with probability* α *distributed as a standard uniform random variable and with probability* $(1 - \alpha)$ *equal to some* $K \gg 1$*. Let* $G \sim U(0, 1), \psi = 1.3, \eta = 0.1, p = 0.6, \tilde{\psi} = 1, \delta = 0.9$ *and* $\alpha = 0.75$*. Then* $\sigma_0^*(R) \approx 0.9$*, i.e., soft punishment is optimal.*

Figure 5 plots the probability of the carrier's acceptance, the average discounted expected utility of the shipper, and the average discounted expected utility of the carrier from the relationship as the level of punishment varies. The intuition for the optimality of soft punishment in this relationship is as follows: On the one hand, the direct effect of punishments on the relationship status is strong. On the other hand, as suggested by the concavity of acceptance probability in $\sigma_0(R)$, there are diminishing returns in incentive power to punishments. Since the marginal return in incentive power to punishments is high at $\sigma_0(R) = 1$, some non-zero level of punishment is optimal.

The role of relationship characteristics Each relationship characteristic in (ψ, η, p, δ) influences how the shipper optimally resolves the tradeoff between the incentive-inducing effect and the regime-switching effect. Some characteristics do so by directly affecting the shipper's payoff while others do so by changing the effectiveness of punishment in inducing the carrier's acceptance. The shipper's match-specific gain only has the former effect and carrier's match-specific gain only has the latter effect. As the contract rate represents a transfer from the shipper to the carrier, the effect of an increase in contract rate is the same as the combined effect of an increase in the carrier's match-specific gain and a decrease by the same amount in the shipper's match-specific gain. Finally, the discount factor has both kinds of effects. To separate the two effects of the discount factor, we will consider potentially different discount factors for the shipper and the carrier, denoted by δ_s and δ_c respectively.

The following proposition shows that when the carrier's surplus from the relationship increases, the same increase in the level of punishment can induce more acceptances. This result, however, does not necessarily mean that the shipper wants to exploit the complementarities between her punishment strategy and the carrier's gain from the relationship by further increasing punishment. If a high level of acceptance probability can already be sustained, the shipper may not need to resort to a strong incentive scheme.

Proposition 4. *For every $(\psi, \eta, p, \delta_s, \delta_c)$ and shipper's strategy with $0 \leq \sigma_0(R) \leq \sigma_0(A) \leq 1$, punishment is more effective in increasing the acceptance threshold $\overline{p}$ when δ_c or η is higher:*

$$\frac{\partial^2 \overline{p}}{\partial \delta_c \partial \sigma_0(R)} \leq 0 \quad \textit{and} \quad \frac{\partial^2 \overline{p}}{\partial \eta \partial \sigma_0(R)} \leq 0. \tag{13}$$

Proof. See Appendix A.2.2. □

While changes in relationship characteristics that affect the carrier's surplus have ambiguous effects on the optimal shipper's strategy, we have clear predictions on the role of relationship characteristics that affect the shipper's surplus, δ_s and ψ. When either of these parameters increases, the regime-switching effect dominates and the shipper tends to choose softer punishment.[36]

Proposition 5. *For every $(\psi, \eta, p, \delta_s, \delta_c)$, if the shipper's optimal punishment strategy is not extreme, $\sigma_0^*(R) \in (0, 1)$, then it becomes softer when δ_s or ψ is higher*

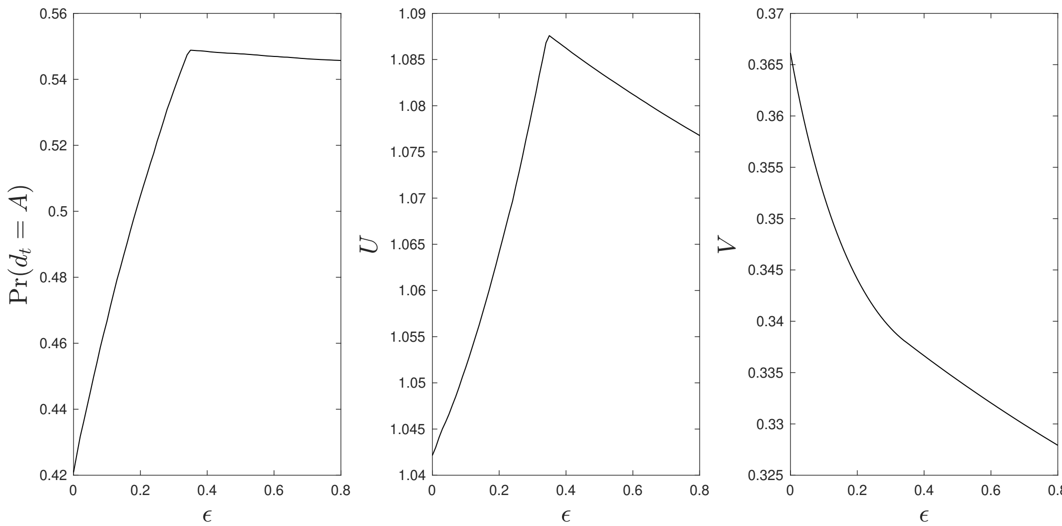
$$\frac{\partial \sigma_0^*(R)}{\partial \delta_s} \geq 0 \quad \textit{and} \quad \frac{\partial \sigma_0^*(R)}{\partial \psi} \geq 0. \tag{14}$$

Proof. See Appendix A.2.3. □

Notice that for $\delta = \delta_s = \delta_c$, $\frac{dU}{d\delta} = \frac{dU}{d\delta_s} + \frac{dU}{d\delta_c}$, the discount factor affects the shipper's incentive both directly through how much she values future payoffs and indirectly through how much the carrier values future payoffs. When the discount factor is higher, the former effect pushes towards more lenient punishment but the second effect is ambiguous. For the role of contract rate, we have that $\frac{dU}{dp} = -\frac{dU}{d\psi} + \frac{dU}{d\eta}$. The first channel is that a higher price lowers the shipper's value, pushing

[36]The conclusions are the same if we treat the shipper's objective as her discounted expected utility rather than her average discounted expected utility; the discount factor only scales the objective function.

Figure 6: Some level of joint punishment increases shipper's expected utility



towards harsher punishment. However, a higher price also increases the carrier's value and thus the effectiveness of a punishment scheme. If we later find that the shipper tends to choose a harsher scheme following an increase in the carrier's match-specific gain, then we expect her to do so following an increase in contract rate.

Multi-lane punishment Finally, shippers and carriers in our setting often interact on multiple lanes, a feature that provides opportunities for combining incentives across lanes. The following example illustrates one way of combining incentives that makes the shipper strictly better off.

Example 2. *Suppose the shipper and the carrier interact on two lanes that are both characterized by $(\psi, \eta, p, \delta, F, G)$ as in Example 1. Consider a strategy that maps the carrier's decisions on both lanes last period to probabilities of maintaining the relationship on both lanes, maintaining the relationship only on the first lane, maintaining the relationship only on the second lane, and ending the relationship on both lanes. Compared to the single-lane strategy described in Example 1, let this multi-lane strategy increase the probability of ending the relationship on both lanes following joint rejections, i.e. rejections on both lanes, by an amount $\epsilon > 0$. Then for some $\epsilon > 0$, the multi-lane strategy outperforms the (optimal) single-lane strategy applied to the two lanes separately.*[37]

Figure 6 plots the probability of acceptance on each lane when relationships on both lanes are maintained, the average discounted expected utility of the shipper, and the average discounted expected utility of the carrier, as ϵ varies. In this example, harsher punishments on joint rejections benefit the shipper significantly; at $\epsilon \approx 0.4$, the gain to the shipper compared to $\epsilon = 0$ is more than compensating the loss to the carrier.

[37]See Appendix A.3 for a detailed description of this multi-lane strategy.

The intuition for why harsher punishments on joint rejections may be optimal is that a joint rejection is a very informative signal of non-cooperation (since high cost draws on both lanes are unlikely). A carrier facing a scheme that punishes joint rejections harshly will, despite sometimes having short-term temptations on both lanes, try to serve at least the lane with the weaker temptation. While our theoretical analysis does not explore incentive schemes that condition on longer histories, this intuition can also apply to rejections across time. Multiple rejections (whether across time or across lanes) are informative of non-cooperation, and should be punished more harshly.

4.4 From theory to empirics

To test the model's theoretical predictions, our empirical exercises exploit variation across relationships. A relationship is defined for a shipper (s) and a primary carrier (c) on a lane (ℓ), with the potential for interactions on other lanes ($-\ell$) of the same shipper. This section defines variables that will be key to our empirical analysis and takes stock of observable versus unobservable sources of relationship-specific heterogeneity in the data.

Key variables The first key variable is the *log of average monthly volume*, which is a proxy for the frequency of interactions between the shipper and the primary carrier on a lane (δ). We measure monthly volume as the number of loads tendered by the shipper on that lane in an active month. By not conditioning on the identity of the accepting carrier, this measure avoids potential endogeneity issues. Moreover, since the primary carrier is the first carrier to receive an offer for each load, this measure approximates the expected number of offers the primary carrier receives per month during the relationship.

The second key variable is *inconsistency of loads*, which we measure as the coefficient of variation of weekly volume within a month, averaged across all active months for the shipper-lane. We treat consistency of loads as a component of the carrier's match-specific gain (η_1). Conceptually, if the timing of loads is more consistent, it is easier for the primary carrier to plan his network of truck movements around the expected timing of offers. As discussed in Section 1.2, in the context of the trucking industry, such network planning is important for reducing wasteful expenditures on fuel and labor.[38]

Extensions from the model While our model prioritizes parsimony, describing the simplest model of this setting that captures the dynamic incentives faced by the carriers, our empirical analysis prioritizes realism, seeking to capture potentially richer patterns of behavior than the model allows. We depart from the simplifying assumptions of the model in two ways:

[38]This network-planning explanation for carriers valuing consistent timing of load offers is one we have heard from multiple experts familiar with the operations of truckload carriers.

First, our empirical analysis allows shippers to have memories longer than one period. We adopt a functional form that allows the shipper's strategy to condition on a rejection rate index that summarizes the entire history of rejections in the relationship, though potentially giving greater weight to more recent rejections than less recent ones. For a shipper s, lane ℓ, and carrier c, this index takes the following form:

$$\text{Rejection rate}^{\ell}_{sct} = \frac{\sum_{k=0}^{t-1} \alpha^{\text{days}(t-k,t)} \text{Rejection}^{\ell}_{sct-k}}{\sum_{k=0}^{t-1} \alpha^{\text{days}(t-k,t)}} \tag{15}$$

where $\text{Rejection}^{\ell}_{sct}$ is an indicator for carrier c rejecting a load t from shipper s on lane ℓ, days $(t-k,t)$ indicates the number of days that pass between load $t-k$ and load t, and $\alpha \in [0,1]$ is a daily decay rate. Note that the special case $\alpha \downarrow 0$ corresponds to the single-load memory restriction imposed in the model.

Second, our empirical analysis allows the spot process to be AR(1), in recognition of the fact that real-world spot rates do exhibit serial correlation. Since a high spot rate today implies in expectation a better outside option for the carrier and a worse outside option for the shipper in the future, the current spot rate $\tilde{p}^{\ell}_t$ could affect both the incentive-inducing effect and the regime-switching effect of a given demotion strategy, and thus, how the shipper resolves such tradeoff.[39] We continue to assume, however, that shippers' strategies do not condition on past spot rates, $\{\tilde{p}^{l}_{t-k}\}_{k>0}$.

In summary, our empirical analysis allows the state of a relationship to be a Markov state consisting of the current rejection rate and the current spot rate, rather than just the decision of the carrier in the last period (as in the model).

Informational assumptions Table 2 summarizes the mapping from parameters of the model to their analogs in our setting and clarifies our empirical assumptions on the information type of each variable. Relationship characteristics that are public information include average monthly volume (δ), contract rate (p), consistency of loads (η_1), and the process of spot rates (G). Unobservable heterogeneity includes the shipper's match-specific gain (ψ), which is private to the shipper, as well as the carrier's residual match-specific gain (η_2) and his cost distribution (F), which are private to the carrier. The unobservable component of the carrier's match-specific gain might include, for instance, the degree of compatibility of a lane ℓ with the rest of a carrier's network of truck movements. Finally, both the shipper and the carrier know the shipper's commitment strategy (σ_0). Together with the observable characteristics of the lane and the private costs and gains of the

[39] Note that this argument relies on the shipper being attentive to medium-run changes in spot rates rather than short-run changes. As noted earlier, we have learned from industry experts that shippers do not pay close attention to daily changes in spot rates and that they are unlikely to opportunistically choose the spot market over the routing guide.

Table 2: Interpretation of model parameters

Parameters	Interpretation	Information type
δ	shipper-lane average monthly volume	public
p	contract rate	public
G	process of spot rates	public
σ_0	demotion probability	known to shipper and carrier
η_1	consistency of loads	public
η_2	other match-specific gains to the carrier	private to carrier
F	distribution of operational costs	private to carrier
ψ	shipper's match-specific gains	private to shipper

carrier, this commitment strategy induces a self-enforceable level of carrier's acceptance ($\bar{p}$).

In the next two sections, we estimate shippers' strategies and carriers' acceptances using an empirical approach that addresses potential endogeneity issues resulting from the above sources of unobservable heterogeneity.

5 Empirical Evidence: Shippers' Strategies

Guided by the predictions of the model developed in the previous section, we empirically estimate shippers' strategies. The results constitute strong evidence that shippers punish carrier rejections by increasing the probability of demotion. Our estimates also resolve key questions about shippers' strategies for which the model did not offer strong predictions. The estimated strategies exhibit soft punishment, though the degree of punishment is economically and statistically significant. Our estimates also—perhaps surprisingly—show evidence that shippers use single-lane, rather than multi-lane, punishment schemes. This supports the conclusion that relational contracts are lane-specific, rather than a single relational contract governing the entire relationship between a shipper and a carrier. Our results also describe how shippers' strategies vary with relationship characteristics and spot rates.

We estimate shippers' strategies as functions of the rejection rate, the current spot rate and a number of time-invariant relationship characteristics: the average monthly volume (δ), a measure of the inconsistency of load arrival ($-\eta_1$), and the contract rate (p).[40] While the model does not give us strong predictions for how the optimal shipper's strategy varies with these time-invariant characteristics, the fact that all three affect the expected future payoffs of shippers and/or carriers suggests that they likely play a role in determining the optimal shipper's strategy.

In addition, recall that Example 2 showed that, in a shipper-carrier relationship that spans multiple lanes, a punishment strategy that combines incentives across different lanes may be optimal. We hope that our empirical results can shed light on this question of multi-lane punishment,

[40] See Section 5.4 for the definitions of these variables.

thereby helping us better understand the scope of the relational contracts governing relationships. To that end, we define a measure Rejection rate$_{sct}^{-\ell}$ analogous to (15) that captures the (weighted) proportion of rejected tenders to carrier c on all lanes other than ℓ on which s and c interact.

With this in mind, we seek to estimate a shipper's strategy that takes the form of the following linear probability model:

$$\begin{aligned}\text{Demotion}_{sct}^{\ell} = \gamma_0 &+ \gamma_1 \text{Rejection rate}_{sct}^{\ell} + \gamma_2 \text{Rejection rate}_{sct}^{-\ell} \\ &+ \gamma_3 \text{Rejection rate}_{sct}^{\ell} \times \text{Rejection rate}_{sct}^{-\ell} \\ &+ \gamma_4 X_{sct}^{\ell} + \gamma_5 \text{Rejection rate}_{sct}^{\ell} \times X_{sct}^{\ell} + \epsilon_{sct}^{\ell}\end{aligned} \tag{16}$$

where Demotion$_{sct}^{\ell}$ is an indicator for primary carrier c being demoted from primary status on lane ℓ between load t and load $t+1$, and X_{sct}^{ℓ} is a vector that includes the time-invariant relationship characteristics described above, along with the spot rate at the time of load t.[41]

For ease of interpretation, we will denote the elements of γ_4 and γ_5 in accordance with the representation of their respective regressors in the model: $\gamma_4 = (\gamma_p, \gamma_\delta, \gamma_{-\eta_1}, \gamma_{\tilde{p}_t})$ and $\gamma_5 = (\gamma_{R_t p}, \gamma_{R_t \delta}, \gamma_{-R_t \eta_1}, \gamma_{R_t \tilde{p}_t})$.

Identification strategy In estimating the parameters $\gamma = (\gamma_0, \gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5)$, we face a potential identification challenge stemming from the fact that the shipper's match-specific value (ψ) shapes the shipper's optimal strategy (see Section 4.3), but is unobserved and therefore omitted. Several variables on the right-hand side of (16) are endogenous and are likely correlated with ψ. One such variable is the rejection rate. By Proposition 5, a shipper with higher match-specific value tends to choose a softer punishment strategy. Under softer punishment, the carrier will reject more often (Proposition 2). This potentially creates a negative bias on the estimated strength of shipper's punishment strategy. The second endogenous variable is the contract rate, p_{sc}^{ℓ}, which is among the relationship characteristics included in the vector X_{sct}^{ℓ}. As it is an outcome of the RFP process, p_{sc}^{ℓ} is likely to be positively correlated with ψ. This would tend to induce a negative bias in the coefficient of the contract rate.

To address these endogeneity concerns, we use an instrumental variables approach that exploits exogenous variation in spot rates. First, we instrument for past acceptance/rejection decisions using the spot rates at the time at which each acceptance/rejection decision was made. To that end, we construct an index of past spot rates analogous to the construction of the rejection rate index:

[41] Recall that by demotion, we mean a change to the lane-ℓ routing guide within a contract period that results in carrier c losing his primary position and being replaced by a new primary carrier. Since this definition is limited to changes within contract periods, any change in primary carrier that coincides with a change in rates (i.e. an RFP) on lane ℓ is not considered a demotion in our analysis.

$$\text{Past spot index}_{sct}^{\ell} = \frac{\sum_{k=0}^{t-1} \alpha^{\text{days}(t-k,t)} \tilde{p}_{t-k}^{\ell}}{\sum_{k=0}^{t-1} \alpha^{\text{days}(t-k,t)}} \tag{17}$$

This index serves as an instrument for the rejection rate. We likewise construct Past spot index$_{sct}^{-\ell}$, an index of past spot rates on other lanes on which shipper s and carrier c interact. This serves as an instrument for the other-lanes rejection rate. Second, we instrument for the contract rate using the spot rate at the time of the RFP in which the contract rate was established. The idea is that at the RFP stage, the current spot rate serves as a competitive pressure on proposed contract rates.[42]

This strategy of using past spot rates as instruments is attractive in that variation in spot rates is, for our purposes, plausibly exogenous. While spot rates are of course determined endogenously by changes in supply and demand, the industry is sufficiently competitive that no one shipper or carrier is likely to have the power to meaningfully alter these rates. Yet, for the exclusion restriction to be satisfied, past spot rates cannot enter directly into the shipper's strategy; an identifying assumption is that only the period-t spot rate directly affects the shipper's period-t demotion decision. This assumption is consistent with industry experts' descriptions of the typical shipper's process for making demotion decisions. In talking with industry experts, we have learned that shippers track carrier performance using a scorecard which records various aspects of carrier performance (including rejection history), but does not include the history of spot rates at the time those decisions were made.

We jointly estimate the parameters (α, γ) by GMM. The parameters γ are identified by the standard 2SLS moments. To identify α, we include a set of additional instruments: the prevailing spot rate on lane ℓ at the time each of the last five loads tendered by shipper s to carrier c on lane ℓ.[43] For computational efficiency, we implement this GMM estimation via a nested algorithm. For a given value of α, the inner step uses 2SLS to obtain estimates of γ, while the outer loop searches for the value of α that minimizes the GMM objective function.

We estimate a daily decay rate of $\hat{\alpha} = 0.9966$. This means that the shipper puts 2% less weight on a rejection one week ago as compared with a rejection today and puts 10% less weight on a rejection one month ago as compared with a rejection today.[44] Our estimates of the linear parameters $\hat{\gamma}$ are reported in Table 3. The parameter estimates for our main specification are the GMM estimates in the second column. For contrast and to illustrate the endogeneity problem

[42]Figure 1 shows that the average contract rate tends to adjust with spot rates, though with some lag. This supports the idea that spot rates create competitive pressure on contract rates.

[43]These five lagged spot rates are instruments for the past five acceptance/rejection decisions. Under the functional form assumption in (15), however, individual rejection decisions enter into the shipper's strategy only through the rejection rate index. Thus, at the true α, these instruments for the individual acceptance/rejection decisions should be uncorrelated with the error term.

[44]$1 - 0.9966^7 \approx 0.02356$ and $1 - 0.9966^{30} \approx 0.09712$.

Table 3: Estimation of shipper's strategy

Demotion	(OLS)	(GMM)
Rejection rate	0.00726	0.0167
	(0.000474)	(0.00560)
Other lanes rejection rate	-0.00307	-0.00201
	(0.000774)	(0.00876)
Rejection rate × Other lanes rejection rate	0.0136	-0.00544
	(0.00130)	(0.0254)
Contract rate	0.00140	-0.0104
	(0.000376)	(0.00863)
Average monthly volume	-0.00530	-0.00337
	(0.000123)	(0.00120)
Inconsistency	0.0174	0.0694
	(0.000797)	(0.0217)
Spot rate	-0.00306	-0.00709
	(0.000535)	(0.00171)
Rejection rate × Contract rate	0.000859	0.0479
	(0.000821)	(0.0298)
Rejection rate × Average monthly volume	-0.00766	-0.0112
	(0.000269)	(0.00287)
Rejection rate × Inconsistency	-0.00998	-0.119
	(0.00127)	(0.0452)
Rejection rate × Spot rate	0.00600	0.0131
	(0.00108)	(0.00465)
Observations	667446	667446

Notes: Standard errors are in parentheses. For ease of interpretation, covariates that are interacted with rejection rate (other lanes rejection rate, contract rate, volume, inconsistency, and spot rate) are normalized to have mean zero. The GMM specification jointly estimates α and the linear coefficients presented in this table. An outer loop searches over values of α, while, for a given α, an inner step estimates the linear coefficients by 2SLS and computes the 2SLS objective function. We estimate $\hat{\alpha} = 0.9966$. The OLS specification takes this value of α as given and estimates the linear coefficients by OLS.

described above, we also report in the first column the OLS estimates of the parameters γ.[45] We discuss the GMM estimates and their interpretation below.

Harsh versus soft punishment The estimated coefficient $\hat{\gamma}_1$ on the own-lane rejection rate index strongly supports the notion that rejections are punished with demotions, but suggests that the punishment scheme is soft, not harsh. Our estimate $\hat{\gamma}_1$ is positive and very statistically significant, indicating that shippers punish rejections with an increased probability of demotion. At first glance, however, this coefficient may appear very small, as it indicates that an increase in the rejection rate

[45] These are the OLS estimates of γ with rejection rate measures constructed using the GMM estimate of the daily decay rate $\hat{\alpha} = 0.9966$.

from 0% to 100% increases the probability of demotion between load t and load $t+1$ by only 1.7 percentage points. However, this coefficient should be interpreted in light of the fact that Rejection rate$^{\ell}_{sct}$ is a persistent state variable; since $\hat{\alpha} \gg 0$, a rejection of one load results in a sustained increase in the probability of demotion for many periods to come.

To get a sense of the economic significance of the estimated degree of punishment, we run a simple simulation to illustrate the effect of a single rejection on the expected duration of a relationship. Using the estimated shipper's strategy and the mean tender acceptance probability, we simulate relationships under two scenarios. In the first scenario, the carrier accepts the first load; in the second, he rejects the first load.[46] The expected relationship duration for these two scenarios is 103.0 loads and 95.5 loads, respectively. This 7.5 load effect of a rejection is economically large and therefore likely to create meaningful incentives for carrier cooperation.[47] Nevertheless, we conclude that punishment is soft, not harsh. The estimated degree of punishment is far from the benchmark of trigger strategies (where a single rejection results in demotion with probability one) we had in mind when discussing harsh punishment strategies in our theoretical analysis. Proposition 5 offers one possible interpretation of this finding; this proposition tells us that the optimal degree of harshness of punishment is weakly decreasing in the shipper's match-specific value from the relationship. The soft punishment scheme we estimate would be consistent with shippers placing very high value on their relationships.

Multi-lane punishment In our GMM specifcation, we do not find either the coefficient $\hat{\gamma}_2$ on the other-lane rejection rate index or the coefficient $\hat{\gamma}_3$ on joint rejections to be significantly different from zero. This suggests that shippers do not exhibit the kind of multi-lane punishment proposed in our theoretical analysis. This is perhaps quite a surprising finding. In light of previous work on relational contracting (both theoretical and empirical), one might have expected shippers to take full advantage of their potential to create incentives by punishing rejections on one lane with an increased probability of demotion on other lanes. To that end, one might think the natural unit of analysis for relational contracts in this setting would be the shipper-carrier relationship. Our finding of an absence of multi-lane punishment suggests that, in fact, relational contracts exist at the narrower shipper-carrier-lane level. In instances where a shipper and carrier interact on several different lanes, they have several separate relational contracts. This result indicates that shippers do not fully exploit their power to create incentives for carrier acceptance, perhaps due to attention costs, organizational boundaries, or other frictions in this setting.

[46] Each load $t > 1$ is accepted with probability 0.71, the average primary carrier acceptance rate. Based on each acceptance/rejection, we update the rejection rate and compute the probability of demotion between each load t and $t+1$. For each scenario, we run 10 million simulations.

[47] Note that the form of the rejection rate means that the first acceptance/rejection decision has a larger effect on the rejection rate than later acceptance/rejection decisions.

Lane and relationship characteristics The estimated coefficients $\hat{\gamma}_5$ on the interaction between the rejection rate and the lane/relationship characteristics (namely the contract rate, the volume, and the consistency of loads) indicate how the degree of harshness or softness of punishment varies with these characteristics. In interpreting these estimates, it is useful to recall Proposition 5 and the subsequent discussion in the previous section. While this proposition does not offer strong predictions for the signs of these coefficients, it does give us a framework for thinking about the effect of each characteristic in terms of effects on the shipper's future surplus and effects on the carrier's future surplus.

We find $\hat{\gamma}_{-R_t\eta_1} < 0$, indicating that an increase in the inconsistency of loads on a lane is associated with softer punishment. Our theoretical analysis indicated that, when this is true, it will also be optimal for the shipper to employ harsher punishment when the contract rate is higher. This prediction is consistent with our positive—though statistically insignificant—estimate of $\hat{\gamma}_{R_tp}$. Finally, we estimate $\gamma_{R_t\delta} < 0$; while an increase in volume increases the future surplus of the relationship for both shipper and carrier, having potentially offsetting effects on the optimal harshness of punishment, this estimate indicates that the effect on the shipper's surplus dominates, resulting in softer punishment.

Spot rates and punishment We estimate a positive coefficient $\hat{\gamma}_{R_t\tilde{p}_t}$ on the interaction between the rejection rate and the spot rate, indicating that shippers tend to punish rejections more harshly when spot rates are higher. This coefficient is most easily interpreted in conjunction with $\hat{\gamma}_{\tilde{p}_t}$. We find $\hat{\gamma}_{\tilde{p}_t}$ to be positive, indicating that shippers are less likely to demote the current primary carrier when the spot rate is high. This is quite intuitive in that the spot market represents a key outside option for the shipper; all else equal, the shipper will be less likely to terminate the current relationship when spot market conditions are less favorable. But the fact that $\hat{\gamma}_{R_t\tilde{p}_t} > 0$ indicates that this effect is attenuated when the carrier has rejected more loads. Preserving the relationship does not allow the shipper to avoid paying high spot rates if the carrier is rejecting frequently.

6 Empirical Evidence: Carriers' Acceptance

Having shown that shippers condition demotion decisions on past rejections, we next argue that carriers respond to the resultant dynamic incentives. To do so, we estimate the effects of various relationship characteristics on carriers' acceptance decisions. Our key finding is that an increase in average monthly volume is associated with an increase in the carrier's acceptance probability; we further show that this effect is unlikely to be driven by selection. We argue that this, along with additional coefficient estimates, is consistent with carriers responding to the dynamic incentives created by shippers' punishment strategies. The estimated coefficients also empirically verify many of the predictions of our model.

As we did for shippers' strategies in the previous section, we estimate a linear probability model,

$$
\begin{aligned}
\text{Accepted}^{\ell}_{sct} = \beta_0 \text{ controls}^{\ell}_{s} + \ & \beta_{\delta}\text{volume}^{\ell}_{s} \\
& + \beta_{-\eta_1}\text{inconsistency}^{\ell}_{s} + \beta_{-\delta\eta_1}\text{volume}^{\ell}_{s} \times \text{inconsistency}^{\ell}_{s} \\
& + \beta_{p}\text{contract rate}^{\ell}_{sc} + \beta_{\delta p}\text{volume}^{\ell}_{s} \times \text{contract rate}^{\ell}_{sc} \\
& + \ \beta_{\tilde{p}_t} \text{ spot rate}^{\ell}_{t} + \beta_{\delta\tilde{p}_t}\text{volume}^{\ell}_{s} \times \text{spot rate}^{\ell}_{t} + \epsilon^{\ell}_{sct},
\end{aligned} \tag{18}
$$

regressing an indicator for carrier c accepting load t from shipper s on lane ℓ on controls, along with a set of lane and relationship characteristics. Our choice of functional form—in particular, the inclusion of interactions between volume and other characteristics—reflects insights from our theoretical analysis. In estimating this regression, we are taking the predictions of Proposition 1 to the data.[48]

Identification strategy In estimating (18), we face two potential identification challenges, both stemming from the fact that η_2, a component of the carrier's match-specific gain, is unobserved and thus omitted.

First, as in our estimation of shipper's strategies in the previous section, we must contend with the fact that the contract rate is an endogenous object likely correlated with η_2.[49] We address this issue by employing the same instrumental variables approach used in the previous section: we instrument for the contract rate using the spot rate at the time of the RFP in which the contract rate was established.

Second, while our use of average volume as a proxy for the frequency of future interactions (and thus for the discount factor δ) is in keeping with other empirical papers on relational contracting, such as Gil and Marion (2013), we face a potential selection issue. In our setting, it is possible that carriers with high match-specific gains are systematically more likely to be primary carriers on higher-volume lanes.[50] If this were the case, it would likely induce an upward-bias in our key parameter of interest, β_{δ}. To address this potential selection bias, we include two sets of fixed effects that absorb variation in the unobserved carrier's match-specific gain η_2: the first

[48] Consistent with our approach to estimating shippers' strategies, we restrict the sample to primary carriers in all specifications. The nature of dynamic incentives faced by backup carriers is likely to be meaningfully different from those faced by primary carriers.

[49] Since contract rates are established through an RFP process, a carrier with high η would tend to submit a lower bid, so we expect downward bias in the OLS estimates of β_p and $\beta_{\delta p}$.

[50] There are several ways this selection could arise. First, carriers with high η could be more likely to submit bids for RFPs on high-volume lanes. Second, in choosing winners of RFPs, shippers might be more likely to select high-η carriers from among the bidders on high-volume lanes.

are shipper-carrier fixed effects; the second are carrier-origin-destination fixed effects, where origin and destination are defined as Census regions. By including the shipper-carrier fixed effects, we absorb a variety of potential shipper-carrier specific components of η_2, including, for instance, relationship-specific knowledge and integration of payment or communication systems.[51] By including the carrier-origin-destination fixed effects, we absorb key geographic components of η_2, namely the compatability of a particular (broadly defined) route with the rest of the carrier's network.

The first column of Table 4 reports the OLS estimates of Equation (18) while the second column reports the IV estimates. The fifth column reports estimates for the main specification, IV with both sets of fixed effects included. For transparency, the third and fourth columns report IV estimates with each of the two sets of fixed effects included alone. Comparing estimates across these various specifications, it is notable that the main specification (IV-FE3) estimates are very similar to the (IV-FE2) estimates, but differ substantially from the (IV) and (IV-FE1) estimates. This suggests that, of the two sets of fixed effects, the carrier-geographic fixed effects absorb more of the variation in match-specific gains that is correlated with the endogenous covariates.

Direct versus mediating effects Before describing the coefficient estimates, it is necessary to make a brief econometric detour to clarify the economic effects these estimates capture. We are primarily interested in the *direct effects* of the relationship characteristics on the probability of acceptance. However, in the previous section, we showed that the harshness of shippers' punishment strategies varies with these characteristics. In particular, we allow shippers' strategies to vary with η_1, p and δ. This means that our coefficient estimates may also capture the *mediating effects* of shipper's strategies, i.e. the effects of the characteristics on acceptance through their effects on the incentive contract.

For η_1 and p, our (IV) estimates of the effects of load consistency and contract rate on acceptance probability satisfy

$$-\beta_{-\eta_1} = \frac{\partial \Pr(\text{Accept}^{\ell}_{sct}|X^{\ell}_{sct})}{\partial \eta_1} + \underbrace{\frac{\partial \Pr(\text{Accept}^{\ell}_{sct}|X^{\ell}_{sct})}{\partial [1-\sigma_0(R)]} \times \frac{\partial [1-\sigma_0(R)]}{\partial \eta_1}\bigg|_{X^{\ell}_{sct}}}_{(+)\text{ mediating effect of }\sigma_0} \tag{19}$$

[51] Note, however, that when these fixed effects are included, we estimate the parameters by exploiting variation in characteristics *across* different lanes of the same shipper-carrier pair. This approach would not produce meaningful estimates of the effects of these characteristics if shippers employed multilane punishment strategies; if that were the case, a carrier's acceptance/rejection decisions on lane ℓ might respond to characteristics of other lanes. However, our analysis in the previous section refutes this possibility; as we find no evidence of multilane punishment, we conclude that relationships exist at the shipper-carrier-lane level.

Table 4: Estimation of carriers' acceptance

	(OLS)	(IV)	(IV-FE1)	(IV-FE2)	(IV-FE3)
Average monthly volume	0.0354	0.0342	0.0459	0.0454	0.0429
	(0.0004)	(0.0013)	(0.0013)	(0.0009)	(0.0009)
Inconsistency	-0.0941	-0.0996	-0.0863	-0.0741	-0.0739
	(0.0025)	(0.0067)	(0.0032)	(0.0037)	(0.0038)
Contract rate	0.0390	0.141	0.0751	0.0540	0.0508
	(0.0006)	(0.0128)	(0.0134)	(0.0102)	(0.0106)
Spot rate	-0.315	-0.336	-0.304	-0.294	-0.289
	(0.0016)	(0.0050)	(0.0036)	(0.0024)	(0.0024)
Average monthly volume $\times$ Inconsistency	-0.0332	-0.0392	-0.0302	-0.0254	-0.0245
	(0.0014)	(0.0038)	(0.0032)	(0.0021)	(0.0021)
Average monthly volume $\times$ Contract rate	0.0303	-0.0401	-0.0375	-0.0166	-0.0184
	(0.0004)	(0.0103)	(0.0080)	(0.0056)	(0.0057)
Average monthly volume $\times$ Spot rate	0.0676	0.0809	0.0763	0.0864	0.0805
	(0.0014)	(0.0041)	(0.0030)	(0.0020)	(0.0020)
$<$ 7 days since promotion	-0.0773	-0.102	-0.0476	-0.0343	-0.0304
	(0.0017)	(0.0054)	(0.0041)	(0.0025)	(0.0025)
Fixed Effects:					
Shipper $\times$ Carrier			X		X
Carrier $\times$ Origin region $\times$ Dest. region				X	X
Observations	818750	818750	818687	818489	818476

Notes: Controls include distance and distance squared. Standard errors are in parentheses. For ease of interpretation, the covariates that are interacted with volume (inconsistency, contract rate, and spot rate) are normalized to have mean zero. Specifications IV-FE1 and IV-FE3 include shipper $\times$ carrier fixed effects; specifications IV-FE2 and IV-FE3 include carrier $\times$ origin region $\times$ destination region fixed effects. For the latter, regions are determined using US Census regions of loads' origin and destination locations. The small difference in sample size across the specifications with and without fixed effects reflects the fact that singleton observations are dropped in the specifications with fixed effects.

and

$$\beta_p = \frac{\partial \Pr(\text{Accept}^{\ell}_{sct}|X^{\ell}_{sct})}{\partial p} + \underbrace{\frac{\partial \Pr(\text{Accept}^{\ell}_{sct}|X^{\ell}_{sct})}{\partial[1-\sigma_0(R)]} \times \left.\frac{\partial[1-\sigma_0(R)]}{\partial p}\right|_{X^{\ell}_{sct}}}_{(+)\text{ mediating effect of } \sigma_0}. \tag{20}$$

Here, the notation $1-\sigma_0(R)$ is borrowed from the model to represent the strength of the dynamic incentives.[52] In view of Proposition 2, we expect that $\partial \Pr(\text{Accept}^{\ell}_{sct}|X^{\ell}_{sct})/\partial[1-\sigma_0(R)] \geq 0$. We can therefore use the coefficient estimates of the interaction terms in the shipper's strategy to

[52]But recall that while the model considers shippers' strategies that condition on a single period of history, our empirical analysis allows the shipper to condition on a longer history summarized by the index Rejection Rate$^{\ell}_{sct}$. The strength of the dynamic incentives faced by the carrier is then measured by how the probability of demotion varies with this index, $\gamma_1 + \gamma_{R_t\delta}\text{volume}^{\ell}_{sc} + \gamma_{-R_t\eta_1}\text{inconsistency}^{\ell}_{sc} + \gamma_{R_tp}\text{contract rate}^{\ell}_{sc} + \gamma_{R_t\tilde{p}_t}\text{spot rate}^{\ell}_{sct}$.

sign the mediating effect of the shipper's strategy. In particular, $\partial[1-\sigma_0(R)]/\partial\eta_1 = -\gamma_{-R_t\eta_1}$ has estimate $-\hat{\gamma}_{-R_t\eta_1} > 0$ and $\partial[1-\sigma_0(R)]/\partial p = \gamma_{R_tp}$ has estimate $\hat{\gamma}_{R_tp} > 0$. This means that the mediating effect of shipper's strategy contributes positively to our estimates of both $-\beta_{-\eta_1}$ and β_p.

In the case of β_δ, the coefficient on volume, we need to additionally consider the complementarity between volume and the unobservable component of carrier's match-specific gains (see Proposition 1)

$$\begin{aligned}\beta_\delta = \quad & \frac{\partial \Pr(\text{Accept}_{sct^\ell}|X^\ell_{sct},\eta_2)}{\partial\delta} + \underbrace{\frac{\partial^2 \Pr(\text{Accept}^\ell_{sct}|X^\ell_{sct})}{\partial\delta\partial\eta_2}\mathbf{E}[\eta_2|X^\ell_{sct}]}_{\text{omitted variable } \delta\eta_2} \\ & + \underbrace{\frac{\partial \Pr(\text{Accept}^\ell_{sct}|X^\ell_{sct})}{\partial[1-\sigma_0(R)]} \times \left.\frac{\partial[1-\sigma_0(R)]}{\delta}\right|_{X^\ell_{sct}}}_{(-)\text{ mediating effect of } \sigma_0}. \qquad (21)\end{aligned}$$

If selection is absent, $\mathbf{E}[\eta_2|X^\ell_{sct}] = \mathbf{E}[\eta_2]$, then the sum of the first two components represents the direct effect of volume at the mean levels of observable and unobservable relationship characteristics. That is, β captures only the direct and mediating effects. Furthermore, since $\partial[1-\sigma_0(R)]/\partial\delta = \gamma_{R_t\delta}$ has estimate $\hat{\gamma}_{R_t\delta} < 0$, the mediating effect contributes negatively to the estimate of β_δ.

Response to dynamic incentives We now test whether carriers respond to dynamic incentives using the estimated coefficients on average monthly volume and its interactions with inconsistency, contract rate and spot rate. If carriers respond to dynamic incentives, then acceptance should vary with average monthly volume, both because of the direct effect (volume determines how future rents are valued today) and because of the mediating effect of shipper's strategy. If carriers instead employed static best responses, acceptances would depend only on the current spot rate and threshold $\underline{p} = \eta_1 + \eta_2 + p$. In other words, there would be no channel through which average monthly volume affects acceptances. This means that under the null hypothesis that carriers use static best responses, $\beta_\delta = \beta_{-\delta\eta_1} = \beta_{\delta p} = \beta_{\delta\tilde{p}_t} = 0$. This hypothesis is strongly rejected by our estimates in all specifications; in the IV-FE3 specification, the Chi-square statistic for this joint test is 913.89.[53] We interpret this result as strong evidence that carriers respond to dynamic incentives.

As described above, the appropriateness of our average volume measure as a proxy for the discount factor δ is potentially threatened by a selection problem which, if present, would result in an upward bias in $\hat{\beta}_\delta$. However, comparing the estimates from the IV and IV-FE3 specifications, we see that the inclusion of fixed effects to address this selection concern actually results in an

[53] While a joint test is clearly appropriate here, Table 4 shows that even if we tested these hypotheses separately, rather than jointly, all would be rejected at the 0.001 level.

increase in $\hat{\beta}_\delta$. We take this result as an indication that the hypothesized selection issue is not present. Going forward, however, we still treat the IV-FE3 specification as our main specification.

Relationship characteristics Next, we interpret the coefficient estimates that speak to the effects of relationship characteristics on carriers' acceptance. In interpreting these estimates, we must consider how estimates of some coefficients capture both direct and mediating effects. Having now established that carriers respond to dynamic incentives, we have reason to believe that these mediating effects are non-zero.

For δ, the mediating effect of shipper's strategy on acceptance probability is negative. This means that $\hat{\beta}_\delta$ is a lower bound on the mean direct effect of average monthly volume on the probability of acceptance. The interpretation of this lower bound is that doubling the average monthly volume increases the average probability of acceptance by at least 3.0 percentage points (pp), confirming the model's prediction that δ has a positive direct effect on acceptance probability.[54]

For η_1 and p, the mediating effects of shipper's strategy on acceptance probability are positive. Thus, $-\beta_{-\eta_1}$ and β_p are upper bounds on the mean direct effects of consistency and contract rate, respectively. Since these direct effects are predicted to be positive by the model, our findings would be inconsistent with the theoretical predictions only if we estimated $-\hat{\beta}_{-\eta_1}, \hat{\beta}_p < 0$. This is not the case. Our IV estimate predicts that a one unit decrease in the coefficient of variation of weekly volume increases the average acceptance probability by 7.4 pp. Furthermore, the IV estimate predicts that when the contract rate increases by one within-lane standard deviation (\$0.34), the average acceptance probability increases by 1.7 pp. These estimates show that consistency of loads and the contract rate both have large effects on carriers' tendency to accept loads, though this is partly due to shippers employing harsher punishments on lanes with higher load consistency or a higher contract rate.

We now check if the estimated coefficients on the interacted terms are consistent with the predictions of our model. Proposition 1 predicts $\beta_{\delta\eta_1}, \beta_{\delta p} > 0$. Our estimates show that the former is statistically significant and positive, while the latter is negative. Economically, however, both of these coefficients are small.

We also estimate that acceptances respond strongly to spot rates, but less so on high volume lanes. An increase of one (within-lane) standard deviation (\$0.44) in spot rates decreases the probability of acceptance by 12.7 pp. Doubling the volume, however, would decrease this effect by 2.4 pp. The latter effect further supports the conclusion that higher volume supports dynamic incentives.

Finally, note that among the other included controls is an indicator for whether carrier j was promoted to primary carrier on lane ℓ within the last seven days. Given the central importance

[54]Recall that, on average, 71% of offers to primary carriers are accepted.

of network planning, the inclusion of this variable captures the idea that a newly-promoted carrier may need time to adjust his network of truck movements in response to an increase in offered loads on lane ℓ. Our estimate of the coefficient on this regressor confirms this idea—a load offered in the first seven days since promotion is on average 3.0 pp less likely to be accepted.

7 Competing theories

In this section we discuss two alternative models of the interactions between shippers and carriers. Unlike the model presented in Section 4, these models do not involve shippers committing to strategies that create dynamic incentives for carriers. While each of these theories can explain some general dynamic patterns in the data, we present evidence that neither is the driving force behind the existence of and dynamics within long-term relationships in this industry. The evidence reinforces our argument that shippers use commitment strategies to create dynamic incentives for their preferred carriers to accept more loads.

7.1 Switching costs

Consider a model in which a shipper incurs a random cost if the carrier providing service to her for load t is different from the carrier who provided her service for load $t-1$. With such switching costs, a carrier's desirability is determined not only by the direct benefit of his service to the shipper, but also by the likelihood of his future acceptances. The shipper's static best response then weighs carriers' desirability against switching costs, the randomness of which helps rationalize the probabilistic nature of decisions to change the routing guide. Such a model could account for some of the observations documented in Section 3: (i) reordering of the routing guide is infrequent, and (ii) demotion tends to follow a rejection by the primary carrier.[55] A richer model could also allow switching costs to be carrier-specific.

However, as long as switching costs are the sole dynamic linkage in shippers' strategies, only the primary carrier's most recent acceptance/rejection decision would enter the Markov state space. This notion is strongly rejected by our data. In Section 5, we found that shippers' strategies put lower but strictly positive weight on rejections in the distant past. For past rejections beyond the most recent one to affect routing guide decisions, some force beyond a single-period switching cost is required.

[55] Both patterns are illustrated by the example in Figure 3.

7.2 Learning

One candidate explanation for why a shipper conditions her demotion decision on the primary carrier's past rejections is learning. Suppose carriers have unobserved characteristics, such as idiosyncratic benefits from the relationship or an unobserved mean cost. In this case, past rejections would be indicative of future rejections, thereby affecting the shipper's expected value from maintaining the carrier's primary status. There are several possible reasons why a shipper might prefer a primary carrier with high acceptance probability. First, being ranked first on the routing guide ensures the primary carrier greater consistency in the timing of offered loads. This facilitates the carrier's network planning and eventually load fulfillment. This means that the opportunity cost of maintaining a primary carrier who is likely to reject the shipper's offers is the higher acceptance probability of the first backup carrier were he to be primary. Second, switching carriers from one load to the next might be costly, and frequent rejections by the primary carrier result in more switches.[56] From the perspective of a primary carrier, learning by the shipper that conditions on past rejections would materialize as a commitment strategy and would create similar dynamic incentives for him to accept more loads.

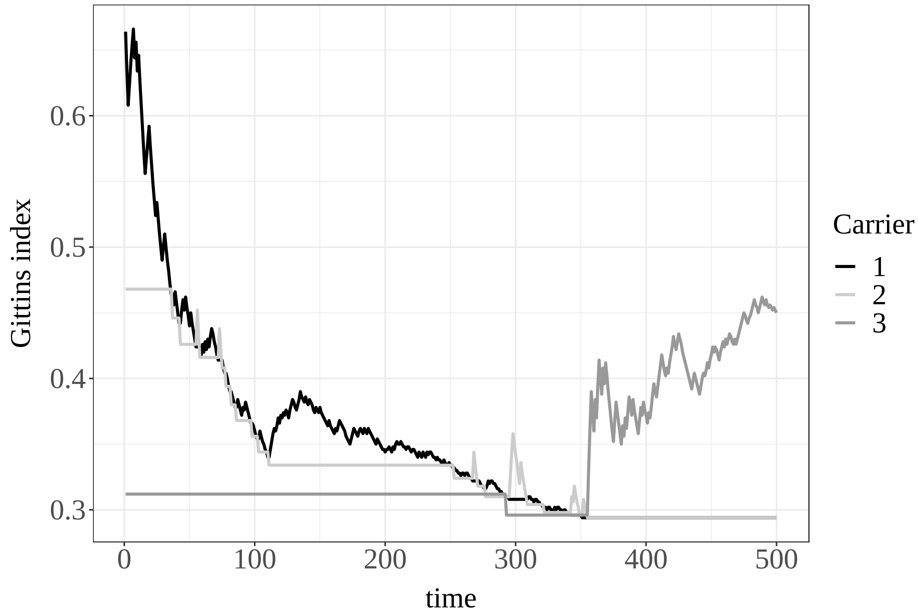
However, the learning story above has another implication that is rejected by our data. By imposing two natural assumptions, the potential learning described here can be simplified to a bandit problem with independent arms, a common model in the literature on learning. First, suppose each carrier has a permanent tendency to accept loads and that the shipper holds independent priors over carriers' acceptance tendencies. Second, suppose that each period the shipper chooses a carrier to be the primary carrier and receive the first offer. By doing so, she gradually learns the carrier's tendency to accept loads as a primary carrier. The solution of the shipper's dynamic optimization problem is as follows: each period she chooses the carrier with the highest Gittins index, an index that captures both the exploitation and exploration value of choosing a carrier over the outside option.[57] Given that the tendency to accept loads should be independent across carriers once conditioned on observed characteristics, a carrier's Gittins index evolves only when he is chosen as primary.

Figure 7 illustrates the evolution of Gittins indices in a learning problem with three carriers. Initially, Carrier 1 is primary. The shipper continues to choose Carrier 1 until her belief about this carrier's tendency to accept loads drops just below that of Carrier 2, at which point she switches to the latter carrier. While the shipper chooses Carrier 2, the Gittins index of Carrier 1 remains the same and well above that of Carrier 3. Thus, the next time the shipper needs to make a switch, she

[56] Note that the costs of rejections are unlikely due to waiting time, since the TMS requires speedy responses by carriers.

[57] The exploitation value of an option refers to the expected payoff of that option given the current beliefs. The exploration value refers to the informational value of an additional observation of that option. See Whittle (1980) and Weber et al. (1992) for details.

Figure 7: A simulated learning path



Notes: In this example, the shipper's prior is overly optimistic about Carriers 1 and 2, and overly pessimistic about Carrier 3. Thus, the Gittins indices of the former two carriers are generally decreasing, both because of the initial overoptimism and because the decrease in informational values as they are chosen. The shipper makes many switches between these two carriers before she starts to experiment with Carrier 3, at which time the Gittins index of Carrier 3 evolves.

switches back to Carrier 1 rather than switching to Carrier 3.

This intuition is general. When learning steps are small, we expect to see the shipper switching from Carrier 1 to Carrier 2 and then back to Carrier 1 ("switch-back pattern") much more often than we see her switching from Carrier 1 to Carrier 2 and then to Carrier 3 ("continue-sampling pattern"). This prediction holds even under relaxations of the assumptions of this standard bandit model. First, allowing for temporary cost shocks that affect the carrier's tendency to accept loads is unlikely to generate the continue-sampling pattern; with such shocks, the shipper may just switch back to Carrier 1 even earlier since she partially attributes the streak of rejections by Carrier 1 in the past to a temporary negative shock. Second, if there were switching costs, the shipper would switch primary carriers less frequently, but we should still expect switches to be mostly back and forth between two carriers.

While the learning story predicts the prevalence of the switch-back pattern, we observe the continue-sampling pattern far more often in our TMS microdata: There are 954 instances of the switch-back pattern, while there are 9,164 instances of the continue-sampling pattern. There is, however, one complication in our setting compared to a standard learning story: the set of available carriers may vary over time. To control for arrivals and exits of carriers, we focus on instances in which there are two changes in primary carrier on a lane, but (i) the last primary carrier is present prior to the first demotion (not an arrival), and (ii) the first primary carrier is present after the second demotion (not an exit). In this subset, we see 908 instances of the switch-back pattern, as compared with 5,306 instances of the continue-sampling pattern.

Based on this evidence, we reject models in which learning is the main mechanism underlying the shipper's choice of primary carrier. These findings speak against both models of learning about acceptance probability and models in which the shipper learns about other carrier dimensions, such as quality. On the contrary, this evidence, combined with the related fact that demotions are nearly always permanent, supports our theoretical and empirical assumption that shippers use termination strategies.

8 Conclusion

Interfirm relationships are always, to some degree, informal, and such relationships are a pervasive feature of the economy. In this paper, we study such relationships in an important setting: the US truckload freight industry. We use a novel transaction-level data set uniquely well-suited to studying relational contracting. We harness this data to provide a detailed description of the relational contracts that govern shipper-carrier relationships. Guided by the predictions of a theoretical model specialized to capture key features of this setting, we estimate shippers' strategies and carriers' responses to the dynamic incentives generated by these strategies.

On the *shippers'* side, we show that shippers employ punishment strategies that condition relationship continuation on carriers' past behavior. Punishment is soft, but nevertheless sufficient to generate economically meaningful incentives for carrier cooperation. We also find, consistent with the predictions of our theoretical model, that punishment tends to be softer when a relationship is more valuable to the shipper and harsher when a relationship is more valuable to the carrier. Finally, we show that, despite the prevalence of multi-lane contact between shippers and carriers, shippers do not combine incentives across lanes. In other words, the scope of the relational contract is not at the firm-to-firm level, as is commonly assumed in the relational contracting literature. In other settings where similarly rich data is available, it should also possible to test the scope of the relationship; our finding suggests that such tests might be worthwhile.

On the *carriers'* side, we find strong evidence that carriers respond to the dynamic incentives created by shippers' punishment strategies. Estimating how carriers' propensity to accept loads varies with relationship characteristics, we show that carriers are significantly more likely to accept loads on higher-volume lanes. Moreover, we show that an increase in the consistency of load timing—which contributes directly to carrier surplus—also makes carriers significantly more likely to accept loads. Both findings are consistent with the theoretical prediction that relationships with higher potential future rents can generate more cooperation from carriers. We also show that carriers' acceptance decisions are less sensitive to spot rates on higher volume lanes, further supporting the importance of dynamic incentives. These findings demonstrate that, in this setting, relational contracts alleviate the moral hazard problem created by the potential for inefficient carrier opportunism.

While the freight trucking industry plays a uniquely critical role in the US goods economy, it has been understudied by economists in recent decades. Our description of shipper-carrier relationships in this paper serves as a key stepping stone to studying other important questions about this industry and its future evolution. In light of the fact that technological advances have greatly reduced the cost of organizing efficient spot markets, will long-term relationships continue to be the dominant feature of the industry or will the market coalesce around a centralized spot platform, like Uber Freight or Convoy? Answering this question will require studying the tradeoff between the benefits of long-term relationships and the potential efficiency gains from a sophisticated spot platform. Understanding shipper-carrier relationships and the dynamics within those relationships is an important prerequisite to such an analysis.

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A Proofs

A.1 Carriers' acceptance

Lemma 1. *$h' \in [0,1]$ and $h'' \geq 0$.*

Proof. By the independence of spot rates and cost draws,

$$h(\overline{p}) = G(\overline{p}) \int_0^{\overline{p}} (\overline{p} - c) f(c) dc + \int_{\overline{p}}^{\infty} \int_0^{\tilde{p}} (\tilde{p} - c) f(c) g(\tilde{p}) dc d\tilde{p}.$$

Thus $h'(\overline{p}) = G(\overline{p}) F(\overline{p}) \in [0,1]$ and $h''(\overline{p}) = g(\overline{p}) F(\overline{p}) + G(\overline{p}) f(\overline{p}) \geq 0$. $\square$

A.1.1 Proof of Proposition 1

Recall Equation (5)

$$LHS = \frac{1 - \delta\sigma_0(R)}{\sigma_0(A) - \sigma_0(R)} (\overline{p} - \eta - p) = \delta(h(\overline{p}) - \underline{V}) = RHS.$$

We have

$$\frac{\partial(LHS - RHS)}{\partial \overline{p}} = \frac{1 - \delta\sigma_0(R)}{\sigma_0(A) - \sigma_0(R)} - \delta h'(\overline{p}) > 1 - h'(\overline{p}) \geq 0,$$

where the last inequality follows from Lemma 1. Also,

$$\frac{\partial(LHS - RHS)}{\partial \delta} = \frac{-\sigma_0(R)}{\sigma_0(A) - \sigma_0(R)} (\overline{p} - \eta - p) - (h(\overline{p}) - \underline{V})) < 0.$$

and

$$\frac{\partial(LHS - RHS)}{\partial \eta} = -\frac{1 - \delta\sigma_0(R)}{\sigma_0(A) - \sigma_0(R)} < 0.$$

Thus it follows from the implicit function theorem that $\frac{\partial \overline{p}}{\partial \delta} > 0$ and

$$\frac{\partial \overline{p}}{\partial \eta} = \left[1 - \frac{\delta(\sigma_0(A) - \sigma_0(R)) h'(\overline{p})}{1 - \delta\sigma_0(R)}\right]^{-1} \geq 1.$$

Furthermore, notice that $\frac{\partial h'(\overline{p})}{\partial \delta} = h''(\overline{p}) \frac{\partial \overline{p}}{\partial \delta} \geq 0$. It follows that $\frac{\partial^2 \overline{p}}{\partial \delta \partial \eta} \geq 0$.

Remark 1. *Since $\frac{\partial(LHS - RHS)}{\partial \overline{p}} > 0$ for all $\overline{p}$, Equation (5) has a unique solution $\overline{p}$.*

A.1.2 Proof of Proposition 2

Rewrite Equation (5) as following

$$(1-\delta\sigma_0(R))(\overline{p}-\eta-p)-\delta(\sigma_0(A)-\sigma_0(R))(h(\overline{p})-\underline{V})=0.$$

Applying the implicit function theorem to the above equation yields

$$\frac{\partial\overline{p}}{\partial\sigma_0(A)}=-\frac{-\delta(h(\overline{p})-\underline{V})}{1-\delta\sigma_0(R)-\delta(\sigma_0(A)-\sigma_0(R))h'(\overline{p})}>0,$$

and

$$\frac{\partial\overline{p}}{\partial\sigma_0(R)}=-\frac{-\delta(\overline{p}-\eta-p-h(\overline{p})+\underline{V})}{1-\delta\sigma_0(R)-\delta(\sigma_0(A)-\sigma_0(R))h'(\overline{p})}<0.$$

The first inequality follows because $h'(\overline{p})\leq 1$. For the second inequality notice in addition that from Equation (5), $\frac{\overline{p}-\eta-p}{h(\overline{p})-\underline{V}}=\frac{\delta(\sigma_0(A)-\sigma_0(R))}{1-\delta\sigma_0(R)}<1$.

A.2 Shipper's strategies

A.2.1 Proof of Condition 1

Recall that

$$u=\tilde{\psi}-\mathbf{E}[\tilde{p}_t]+G(\overline{p})F(\overline{p})(\psi-p-\tilde{\psi}+\mathbf{E}[\tilde{p}_t|\tilde{p}_t\leq\overline{p}]),$$

where $\mathbf{E}[\tilde{p}_t|\tilde{p}_t\leq\overline{p}]$ represents a selection effect. Define

$$\hat{p}=\inf\{p'\in\text{supp }G:\psi-p-\tilde{\psi}+\mathbf{E}[\tilde{p}_t|\tilde{p}_t\leq p']\geq 0\}.$$

Then $u>\underline{U}$ and $\frac{\partial u}{\partial\overline{p}}>0$ for all $\overline{p}>\hat{p}$. The shipper should opt out of the relationship if and only if the sustained level of cooperation satisfies that $\overline{p}<\hat{p}$.

Under Condition 1 that $\psi-p-\tilde{\psi}+\mathbf{E}[\tilde{p}|\tilde{p}\leq p]\geq 0$, we have $\hat{p}\leq p\leq\overline{p}$, so the relationship is worth sustaining.

A.2.2 Proof of Proposition 4

From Equation 5, we can rewrite

$$\frac{\partial\overline{p}}{\partial\sigma_0(R)}=-\delta\left(\frac{1-\delta\sigma_0(A)}{1-\delta\sigma_0(R)}\right)\left(\frac{h(\overline{p})-\underline{V}}{1-\delta\sigma_0(R)-\delta(\sigma_0(A)-\sigma_0(R))h'(\overline{p})}\right),$$

where the last multiplicative term is increasingn in $\overline{p}$ because $h'(\overline{p}) \geq 0$ and $h''(\overline{p}) \geq 0$. Then, it follows from $\partial \overline{p}/\partial \eta \geq 0$ that

$$\frac{\partial^2 \overline{p}}{\partial \eta \partial \sigma_0(R)} = -\delta \left(\frac{1 - \delta \sigma_0(A)}{1 - \delta \sigma_0(R)} \right) \left[\frac{\partial}{\partial \overline{p}} \left(\frac{h(\overline{p}) - \underline{V}}{1 - \delta \sigma_0(R) - \delta(\sigma_0(A) - \sigma_0(R))h'(\overline{p})} \right) \right] \frac{\partial \overline{p}}{\partial \eta} \leq 0.$$

Moreover,

$$\begin{aligned} \frac{\partial^2 \overline{p}}{\partial \delta \partial \sigma_0(R)} = & \left[\frac{\partial}{\partial \delta} \left(\frac{-\delta}{1 - \delta \sigma_0(A) - \delta(\sigma_0(A) - \sigma_0(R))h'(\overline{p})} \right) \right] \left(\frac{1 - \delta \sigma_0(A)}{1 - \delta \sigma_0(R)} \right) (h(\overline{p}) - \underline{V}) \\ & + \left[- \left(\frac{1 - \delta \sigma_0(A)}{1 - \delta \sigma_0(R)} \right) \right] \left[\frac{\partial}{\partial \overline{p}} \left(\frac{h(\overline{p}) - \underline{V}}{1 - \delta \sigma_0(R) - \delta(\sigma_0(A) - \sigma_0(R))h'(\overline{p})} \right) \right] \frac{\partial \overline{p}}{\partial \delta} \leq 0. \end{aligned}$$

The first term is negative because $h(\overline{p}) \geq \underline{V}$, and the second term is negative because $h'(\overline{p}) \geq 0, h''(\overline{p}) \geq 0$ and $\partial \overline{p}/\partial \delta \geq 0$.

A.2.3 Proof of Proposition 5

Treating the discount factors for the shipper (δ_s) and the carrier (δ_c) as potentially different and with some algebra, we can rewrite Equation (12) as following

$$\frac{dU}{d\sigma_0(R)} = \frac{1 - \delta_s}{1 - \delta_s q} \frac{\partial u}{\partial \overline{p}} \frac{\partial \overline{p}}{\partial \sigma_0(R)} + \frac{\delta_s (1 - \delta_s) u}{(1 - \delta_s q)^2} \left(\frac{\partial q}{\partial \overline{p}} \frac{\partial \overline{p}}{\partial \sigma_0(R)} + \frac{\partial q}{\partial \sigma_0(R)} \right),$$

which is equal to 0 at $\sigma_0(R) = \sigma_0^*(R) \in (0, 1)$. Since $\partial \overline{p}/\partial \sigma_0(R) \leq 0$, it must hold that at $\sigma_0(R) = \sigma_0^*(R)$,

$$\frac{\partial q}{\partial \overline{p}} \frac{\partial \overline{p}}{\partial \sigma_0(R)} + \frac{\partial q}{\partial \sigma_0(R)} \geq 0.$$

We have

$$\frac{d^2 U}{d\psi d\sigma_0(R)} = \frac{1 - \delta_s}{1 - \delta_s q} h''(\overline{p}) \frac{\partial \overline{p}}{\partial \sigma_0(R)} + \frac{\delta_s (1 - \delta_s)}{(1 - \delta_s q)^2} h'(\overline{p}) \left(\frac{\partial q}{\partial \overline{p}} \frac{\partial \overline{p}}{\partial \sigma_0(R)} + \frac{\partial q}{\partial \sigma_0(R)} \right),$$

which uses the fact that $h'(\overline{p}) = G(\overline{p})F(\overline{p})$. Note that

$$\frac{\partial u / \partial \overline{p}}{u} = \frac{h''(\overline{p})(\psi - p - \tilde{\psi} + \mathbf{E}[\tilde{p}_t | \tilde{p}_t < \overline{p}]) + h'(\overline{p}) \frac{\partial \mathbf{E}[\tilde{p}_t | \tilde{p}_t < \overline{p}]}{\partial \overline{p}}}{h'(\overline{p})(\psi - p - \tilde{\psi} + \mathbf{E}[\tilde{p}_t | \tilde{p}_t < \overline{p}])} \geq \frac{h''(\overline{p})}{h'(\overline{p})}.$$

The inequality follows from that $\partial \mathbf{E}[\tilde{p}_t | \tilde{p}_t < \overline{p}]/\partial \overline{p} \geq 0$. It follows that at $\sigma_0(R) = \sigma_0^*(R)$,

$$\frac{d^2 U}{d\psi d\sigma_0(R)} \geq 0$$

This means that if $\sigma_0^*(R) \in (0,1)$ is the (unique) optimal punishment strategy, then

$$\frac{\partial \sigma_0^*(R)}{\partial \psi} \geq 0.$$

Notice that here a strict inequality is possible exactly because of the selection effect in the term $\mathbf{E}[\tilde{p}_t | \tilde{p}_t < \overline{p}]$.

This completes the proof that the optimal punishment strategy gets more lenient when the shipper's match-specific gain is higher. We now show the tendency towards leniency if the discount factor of the shipper is higher. We have

$$\frac{d^2 U}{d\delta_s d\sigma_0(R)} = \frac{-(1-q)}{(1-\delta_s q)^2} \frac{\partial u}{\partial \overline{p}} \frac{\partial \overline{p}}{\partial \sigma_0(R)} + \frac{1 - 2\delta_s + \delta_s q}{(1-\delta_s q)^3} \left(\frac{\partial q}{\partial \overline{p}} \frac{\partial \overline{p}}{\partial \sigma_0(R)} + \frac{\partial q}{\partial \sigma_0(R)} \right) u.$$

At $\sigma_0(R) = \sigma_0^*(R)$, the above equation can be rewritten as following

$$\begin{aligned} \frac{d^2 U}{d\delta_s d\sigma_0(R)} &= \frac{-(1-q)}{(1-\delta_s q)^2} \frac{\partial u}{\partial \overline{p}} \frac{\partial \overline{p}}{\partial \sigma_0(R)} - \frac{1 - 2\delta_s + \delta_s q}{(1-\delta_s q)^3} \frac{1 - \delta_s q}{\delta_s} \frac{\partial u}{\partial \overline{p}} \frac{\partial \overline{p}}{\partial \sigma_0(R)} \\ &= -\frac{1-\delta_s}{\delta_s (1-\delta_s q)^2} \underbrace{\frac{\partial u}{\partial \overline{p}}}_{(+)} \underbrace{\frac{\partial \overline{p}}{\partial \sigma_0(R)}}_{(-)} \geq 0. \end{aligned}$$

This means that if $\sigma_0^*(R) \in (0,1)$ is the (unique) optimal punishment strategy, then

$$\frac{\partial \sigma_0^*(R)}{\partial \delta_s} \geq 0.$$

A.3 Details of Example 2

Recall from Example 1 that the optimal shipper's strategy on a single lane (1 or 2) is to choose the highest level of reward and a soft punishment level $x_1^* = x_2^* \approx 0.9$. Consider extending the shipper's strategy to condition on the carrier's decisions on both lanes last period, $\sigma_0 : \{A, R\}^2 \to [0,1]^4$, where $\sigma_0(d_{t-1}^1, d_{t-1}^2)$ gives the probabilities of maintaining both relationships, maintaining only the first relationship, maintaining only the second relationship, and ending both relationships, following the carrier's decisions d_{t-1}^1 on lane 1 and d_{t-1}^2 on lane 2 in the last period. Assume that when the relationship on exactly one lane is ended, both sides resort to the spot market for that lane but play on the other lane proceeds under the single-lane strategy in Example 1.

Consider the multi-lane strategy σ_0 such that for some $\epsilon \in [0, x_1^* x_2^*]$,

$$
\begin{aligned}
\sigma_0(A, A) &= (1, 0, 0, 0) \\
\sigma_0(A, R) &= (x_2^*, 1 - x_2^*, 0, 0) \\
\sigma_0(R, A) &= (x_1^*, 0, 1 - x_1^*, 0) \\
\sigma_0(R, R) &= (x_1^* x_2^* - \epsilon, x_1^*(1 - x_2^*), (1 - x_1^*)x_2^*, (1 - x_1^*)(1 - x_2^*) + \epsilon).
\end{aligned}
$$

When $\epsilon = 0$, the two lanes are treated separately with the single-lane strategy in Example 1. When $\epsilon > 0$, there are harsher punishments following joint rejections.

The intuition for why harsher punishments on joint rejections, but not necessarily on single rejection, benefits the shipper is as following. When faced with short-term temptations on both lanes, the carrier would try to serve at least the lane with the weaker temptation so as to avoid the harsh multi-lane punishment. This selection effect means that joint rejections occur with low probability, in turn making such punishments relatively low cost to the shipper.

B Additional plots of end-of-contract effects

To complement our analysis in Section 4.3, we re-estimate the linear probability model in Equation (1) for "winning" carriers, i.e. those that will retain primary status after new RFP events. Figure 8 plots the estimated coefficients on the weeks-to-end-of-contract dummies and their 95% confidence intervals. For this group of winning carriers, we see evidence of *window-dressing effects*, that is, the tendency to improve performance in the weeks preceding the RFP in order to increase the chance of being selected as the RFP winner. In the six weeks preceding the announcement of the RFP outcome, when carriers have likely been informed that an RFP will be held, the average acceptance of the winning carriers increases slightly relative to previous weeks. After the announcement of the RFP outcomes, the average acceptance of these winning carriers declines, just like that of the losing carriers (though the magnitude of this effect is larger for the losing carriers). This happens despite the fact that the winning carriers now know they will continue to be primary carriers. This suggests that, to some extent, shippers "wipe the slate clean" at the start of the new contract period, i.e. shippers' demotion decisions put much less weight on carriers' rejections in previous contract periods. Once their primary status in the next contract period is secured, the carriers' incentive to perform well in the current contract period is much weakened.

In Figure 9, we plot the estimated coefficients of the weeks-to-end-of-contract dummies from a regression that pools winning and losing carriers.

Figure 8: End-of-contract effects on tender acceptance: Winning carriers

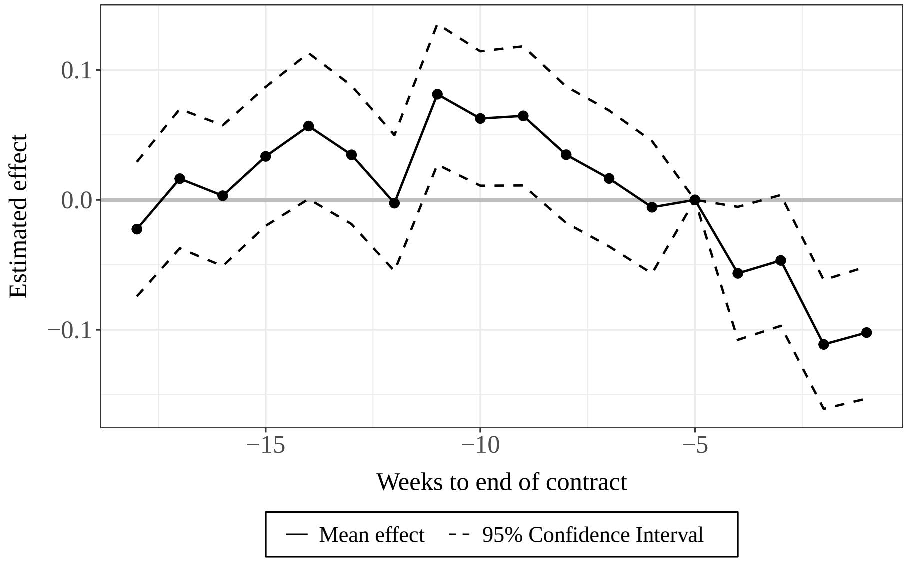

Figure 9: End-of-contract effects on tender acceptance: All carriers