Minds, Models and Markets: How Managerial Cognition Affects Pricing Strategies*

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Abstract

Traditional economic theory demonstrates how firms can sustain high prices and profits through repeated game strategies, but abstracts away from the bounded rationality of human managers. Behavioral models suggest that bounded rationality leads to biased mental models of competitor behavior, particularly underestimating competitor sophistication. We study a firm with over 20,000 gas stations, where managers have significant discretion over strategic choices, including setting fuel prices. Managers with lower cognitive skills tend to underestimate competitor sophistication in a lab-in-the-field beauty-contest game. These cognitive skills explain divergent beliefs about optimal strategies: high-skill managers favor maintaining high prices at the market's price ceiling, while low-skill managers prefer cutting prices, overestimating the profitability of such actions. Lower-skill managers set lower prices and engage more in price wars, leading to lower profits. We find that bounded rationality may increase market efficiency by lowering prices in markets with significant power, impacting producer and consumer surplus. This also implies a bias in standard measures of market power due to the role of cognitive skills in price markups.

JEL classification: D22, D91, L1

Keywords: Level-k; endogenous depth of reasoning; cognitive hierarchy; mental models; narratives; price wars.

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1 introduction

Traditional economic theory of strategic competition assumes fully rational firms. This has provided powerful insights, such as showing how market participants could use punishment strategies to maintain high prices and profits in repeated interactions. It abstracts away, however, from the reality that managers who guide firms are boundedly rational. Ex ante, the impact of bounded rationality on strategic behaviors and market power is not clear. Bounded rationality might be beneficial for maintaining high prices, if it manifests as a commitment device to not condition actions on certain information, or it could be inconsequential, if it is corrected by high stakes, learning opportunities, or institutional guardrails within firms. If bounded rationality works against maintaining optimally high prices, this could reflect different mechanisms. One possibility is that firms might pursue high price regimes, but make some errors of implementation, resulting in prices that are sometimes too high or too low. Another possible mechanism, with the seeming potential for more radical departures from optimality, is that bounded rationality might systematically affect understanding of the strategic environment, e.g., leading to a view that aggressive price cuts rather than high prices are the way to maximize profits.

A conceptual basis for this last, more radical effect of bounded rationality is proposed in recent theoretical work in behavioral economics, including level-k and endogenous depth of reasoning (EDR) models (e.g., Nagel, 1995; Costa-Gomez et al., 2001; Camerer et al., 2004; Alaoui and Penta, 2016). These models posit that individuals have biased mental models of competitor behavior, with a tendency to underestimate others' sophistication.[1] Extending this intuition to the context of repeated price competition, managers who underestimate their competitors' sophistication may systematically charge lower prices, due to their failure to fully anticipate competitors' retaliatory price cuts.[2] There is confirmatory evidence from one-shot and repeated laboratory games, with the structure of Bertrand competition, in the sense that players with lower cognitive ability are less able to anticipate the behavior of competitors and defect more often (Gill and Prowse, 2020, Proto et al., 2020).[3] What is less clear is whether and how the

[1]This could reflect overconfident beliefs about relative sophistication, as in models of level-k reasoning (Nagel, 1995; Costa-Gomez et al., 2001; Camerer et al., 2004), or an individual consciously deciding to model competitor behavior with a simplified heuristic because it is too costly to reason through how competitors will behave, as in endogenous depth of reasoning models (Alaoui and Penta, 2016). Models of cognitive uncertainty are similar in spirit to the latter, as they assume that boundedly rational individuals recognize their limitations and rely on heuristics (e.g., Enke and Graeber, 2023). Our paper is not focused on making fine distinctions between these mechanisms, and our findings are consistent with a potential role for all of these.

[2]Aoyagi et al. (2024) model level-k players in an indefinitely repeated PD game, and show that bounded rationality leads to pessimism about the possibility of sustaining cooperation.

[3]See also Bernham et al., 2009; Carpenter et al., 2013.

intuitions from this literature extend to real world competitions.

This paper explores the largely uncharted territory of bounded rationality in real-world strategic firm competition, contributing to the nascent literature on behavioral firms (for a survey see, e.g., Heidheus and Koszegi, 2018). We aim to provide field evidence on several open questions. First, does bounded rationality among firm managers lead to biased mental models of competitors, with differences that persist in the face of experience, and if so, does this translate into systematically different beliefs about optimal pricing strategies? Second, do such differences in beliefs result in observable differences in actual pricing behavior, and engagement in price wars? Third, how do differences impact firm profits, producer surplus, and consumer surplus? Does bounded rationality potentially enhance market efficiency, because boundedly rational managers charge lower prices and fail to fully exploit market power? What are the implications of these findings for measuring market power and for competition policy?

Answering these questions requires a dataset with a rare combination of features. First, it is necessary to have access to a large sample of managers making high-stakes strategic choices repeatedly, with feedback and ample time to gain experience. Second, individual-level measures of the cognitive skills of these managers are needed to study bounded rationality. Third, there should be controls for other manager traits, ranging from economic preferences, such as risk and time preferences, to personality facets like conscientiousness, which may influence decisions and correlate with cognitive skills. Fourth, there need to be measures of managers' mental models regarding competitor behavior, and measures of their beliefs about optimal strategies to achieve success. Fifth, the data should measure key strategic decisions of the managers, such as pricing or engaging in price wars, as well as metrics of firm success like profits.

Our study leverages a collaboration with a firm managing over 20,000 gas stations to obtain a dataset encompassing all these features. The gas station managers make strategic choices such as setting prices for oil products (gas and diesel), and we measure their traits, mental models, pricing decisions, and profits.

We present four main sets of findings. (1) *Mental models:* The modal choice of managers in a beauty-contest type game indicates underappreciation of the sophistication of other managers, but this is associated with low cognitive skills; high cognitive skill managers are significantly better at anticipating competitor behavior. Ability in the game in turn helps explain *qualitatively* different ideas about how to obtain high oil profits: High skill managers favor maintaining high prices, while low-skill managers favor charging low prices and having high sales volume, consistent with overestimating the profitibility of deviating from high prices. (2) *Pricing:* Managers with lower cognitive skills in fact set lower prices for gas and diesel on average, with mental models of competitors mediating this link. The relationship of price to cognitive skills strengthens with an increasing number of competitors, consistent with a mechanism related to understanding competitors. An event-study design adds weight to a causal interpretation, by showing that pricing changes depending on the cognitive skills of newly arriving managers, holding the station and market constant. Low-skill managers are also about twice as likely to become engaged in price wars as the highest-skill managers. (3) *Profits:* Based on an IV analysis of how price affects profits, we estimate that the lower prices charged by low-ability managers translate into 6 percent lower profits per month. Although upper-level managers express concerns about excessive price cuts, they note several factors, including manager local knowledge, that prevent adopting more centralized pricing decisions, and we provide empirical evidence from a simple, estimated structural model that optimal price does indeed vary with local market conditions. (4) *Welfare and market power:* We calculate that the reduction in price due to bounded rationality increases consumer surplus and reduces deadweight loss in the presence of market power. Implications for competition policy include a prediction that bounded rationality can increase competition, that replacing human with algorithmic pricing may tend to increase prices, and that standard measures of market power may be biased because of how manager cognitive skills affect price markups.

Section 2 of the paper describes the work setting of the gas station managers, and explains the main datasets and measures used in the analysis. The analysis relies on four key datasets. (1) Survey of approximately 350 district-level managers to gather information about the discretion given to station managers, their views on potential mistakes made by station managers, and the reasons for allowing such autonomy despite these mistakes. (2) Two survey waves with the 20,000 station managers, achieving roughly 14,000 responses each time. These surveys collected data on manager traits, including cognitive ability measured using Raven's Progressive Matrices, a wide range of noncognitive skills such as preferences and personality, and measures of strategic sophistication and mental models. The repeated measures for some managers allow us to assess and correct for measurement error. (3) Four years of monthly panel data on the performance of nearly all the company's gas stations (approximately 17,500 stations), including profits and average prices. These data are matched to the surveys of manager traits and the district manager survey information. (4) For one region, we have higher frequency (daily) pricing data for all stations from our partner company, separately for each grade of gas and diesel, as well as prices of all competitor stations. This dataset allows for analysis of price wars, and calibration of a stylized model used to analyze optimal pricing and welfare.

Section 3 of the paper presents our analysis on how cognitive skills shape the mental models of managers. Motivated by the level-k and endogenous depth of reasoning literature, we first investigate how cognitive skills relate to ability to model behavior of competitors. One measure we use is a variation on the beauty-contest game known as the money request game (see Arad and Rubenstein, 2012; Fe et al., 2022). In our survey, managers were asked to imagine that they were playing against another station manager. The modal choice in the game is consistent with thinking that other managers are unsophisticated (level-zero) types. High cognitive skills, however, strongly predict deviating from this choice to the expected-payoff maximizing choice in the game. This shows that, in this abstract game, cognitive skills matter for mental models of the relevant population of competitors. Some additional, more naturalistic survey questions also indicate that cognitive skills matter, for how managers think about competitors in their real strategic environment. Specifically, managers with lower cognitive skills think managers are more able to influence oil sales, consistent with believing they can successfully undercut competitors. Another measure shows that low skill managers are more likely to report adopting a simple heuristic of matching competitor prices, consistent with under-appreciating how this may affect competitors' pricing decisions.

To understand whether and how these differences in mental models of competitors translate into different beliefs about optimal strategies, we turn to a measure of what gas station managers think can cause high profits. We use a "narratives" approach (see Andre et al., 2023), which is an open-ended question to managers, asking them what they think would be the most important factor explaining why a manager would consistently achieve high oil (gas and diesel) profits. We categorize the responses into a set of distinct views on determinants, using a range of robustness checks on the categorization. A consistent message emerges from the data. Managers with high cognitive skills think maintaining high prices is the path to high profits (e.g., "Do not blindly engage in price wars"). Managers with low skills, however, think that low prices and high sales volume are optimal, consistent with being overconfident about the profitability of price cuts (e.g., "Increase sales through price cuts."). To directly test whether this difference in views about optimal strategies is explained by differences in mental models of competitors, we use regression analysis. We find that the probability of viewing high prices as optimal is significantly related to cognitive skills, and this relationship is at least partly mediated by choosing optimally in the money request game and the other measures of mental models of competitor behavior.

Section 4 analyzes how pricing decisions relate to managers' cognitive skills and mental models of competitors. The pricing environment in our study is characterized by two important features. First, there is a government-imposed price ceiling on the price of oil products, indexed to the world price of oil. This potentially serves as a natural focal point for charging high prices. Second, there are two large companies in the market, our partner company and another company, and the default pricing policies of these two companies is to charge at the price ceiling. There are also many smaller companies, however, which tend to price well below the price ceiling. In a set of survey questions on the desired pricing strategies, lower cognitive ability managers report wanting to cut prices more frequently. This indicates that low ability managers want to put their beliefs that low prices are optimal into practice. We also find that our measures of mental models of competitors help explain differences in self-reported pricing behavior.

We then turn to actual pricing decisions, using the ratio of price to the price ceiling as a measure of how much a manager exploits the possibility to cut prices. While managers with high cognitive skills have average prices close to the price ceiling, managers with lower cognitive skills charge significantly lower prices, e.g., a 2 s.d. reduction in cognitive skills is associated with 0.05 s.d. reduction in the average monthly price ratio, or about 0.08 s.d. reduction if we account for measurement error in cognitive skills.[4] These results hold controlling for many observable characteristics of the station and location, including local market conditions (number of competitors). We also show evidence that the link between cognitive skills and pricing is due to the underlying mechanism of different mental models of how competitors behave. If we add measures of mental models as explanatory variables (e.g. choosing optimally in the money request game), the coefficient on cognitive skills is smaller, and the types of mental models of competitor behavior possessed by low ability managers significantly predict charging lower prices. We also find that the relationship of cognitive skills to prices is larger as the number of competitors increases, again indicating a mechanism relating to understanding competitors. Using our dataset from one region with daily prices of all stations, we show that lower cognitive skills are also associated with being involved more frequently in price wars, defined as periods when there are substantial mutual price cuts by our partner manager and one or more competitors in the local market. The frequency of price wars for the lower ability managers is about double that of the higher ability managers, which could indicate that about half of the wars are strategic mistakes.

As an additional robustness check on causality and mechanisms, we present results of an event study analysis, which looks at pricing at a given station before and after the arrival of a manager with low or high cognitive skills. This helps address the main threat to identification, which would be if managers with certain cognitive skills and mental models happen to be assigned to environments where optimal prices differ for some

[4]Using our repeated measures of cognitive skills for a subsample of managers, we estimate attenuation bias to be around 35 percent.

reason that is not captured by observable, e.g., due to some aspect of market conditions that is not perfectly controlled for in our main regressions. We identify treated stations as ones that receive a new manager, for whom we have trait measures, and we compare prices of the station before and after the new manager arrives. To address potential time trends, we also difference with respect to a control station that does not have a change in manager but has parallel pre-trends.[5] We find that the arrival of a manager with relatively lower cognitive skills leads to a significantly lower prices over time. Likewise, the new manager's mental models of competitors matter for prices, e.g., managers who fail to choose optimally in the money request game charge lower prices. Taken together, our findings in Section 4 indicate that cognitive skills matter for pricing, and that this is at least partly because of how they shape the manager's mental models of competitors.

Section 5 provides evidence that the pricing strategies of low cognitive ability managers lead to significantly lower average profits. We first document that on average, profits are much lower when price ratios fall substantially below the price ceiling, and we note that lower cognitive ability managers are significantly more likely to make such deep price cuts. One concern is the endogeneity between profit and price, both mechanical and through a potential reverse causality, such that low ability managers might have low profits for some other reasons, and charge low prices in attempt to address this. In our survey of district managers, however, we find that they overwhelmingly predict that managers would tend to lower prices, if given full autonomy, and that the resulting prices would be lower than optimal. Also, in an open-ended question about whether it is a good idea to cut prices to match competitors, the majority of district managers respond in the negative, and cite a need to avoid price wars as a primary reason. We have also seen that the lower prices of low ability managers are at least partly explained by their general view and approach towards competition, as captured by survey measures of mental models of competitors, rather than by a response to low profits. Indeed, the mental model measures are strongly predictive of prices. If we use mental models as instruments for price, as a way to avoid reverse causality, we find that lower prices lead, on average, to significantly lower profits. The results imply that the lowest skill managers earn about 6% less profits per month on average than the highest skilled managers, due to charging lower prices.

Given the costs to the firm of the price cuts by low ability managers, an interesting question is why such pricing policies are allowed. Our survey with the district managers is illuminating in this regard. It indicates that local knowledge of station managers is

[5]Because it is difficult to find a single control station with parallel pre-trends, we use the method of Synthetic Difference in Difference (SDID), which searches for a weighted average of candidate control stations to construct the best fitting pre-trends for each treated station. We can regress the resulting SDID treatment effects on the traits of the new manager.

one reason why it is important to give managers some autonomy over pricing, and based on a simple structural model of optimal pricing, calibrated with a station-level estimate of elasticity of demand, we provide empirical evidence that the optimal price does vary with local market conditions. Another explanation provided by district managers is that an inflexible pricing policy would remove a credible threat of price cuts. This suggests an interesting trade-off between needing to allow sophisticated managers the ability to have credible threats, and allowing less sophisticated managers to cut prices even when this is not optimal.

Section 6 provides quantitative estimates on the implications of bounded rationality for producer surplus, consumer surplus, market efficiency, and measured market power. We calculate that stations with the lowest skilled managers produce as much as $5,211 less producer surplus per year, due to lower prices, compared to the highest skilled managers. This is associated, however, with about $6,199 more consumer surplus per year, and a reduction in dead weight loss of about 7 percent. Thus, in the setting we consider, bounded rationality of firm managers may actually improve the efficiency of markets, because they do not fully exploit market power. Turning to a standard measure of market power, the price markup, we find that the average price markup is about 4 percent lower comparing the lowest ability managers to the highest. This impact on price is sizeable, equivalent to one tenth of the impact of having an additional competitor enter the local market (Hastings, 2004). Neglecting cognitive skills of managers can thus substantially bias measures of market power used to guide competition policy. Our quantitative estimates are a lower bound, in the sense that measurement error in cognitive skills attenuates the estimates. While these calculations of magnitudes involve some strong assumptions, they provide indications that bounded rationality of managers has a consequential impact on market outcomes.

Our study is complementary to previous literature on bounded rationality, mental models, and strategic competition. We show that intuitions from a largely theoretical and lab-experiment-based literature on level-k and EDR models have purchase for real strategic competitions. Our findings also suggest generalizability of the result observed in the lab, that implementing repeated game strategies can be cognitively costly (Oprea, 2020; Proto et al., 2020). Our results also contribute to a recent empirical literature on the role of mis-specified mental models and narratives in economic decision making (e.g., Kendall and Charles, 2022; Andre et al., 2023a; Andre et al., 2023b; Esponda et al., 2024), providing some of the first evidence on how mental models vary with cognitive skills, and how differences can persist and influence real economic decisions and market outcomes. The findings also add to a literature on behavioral firms (Hortascu and Puller, 2008; Goldfarb and Xiao, 2011 and 2019; DellaVigna and Gentzkow, 2019;

Strulov-Shlain, 2023; Tadelis et al., 2023), by providing direct measures of cognitive ability for decision makers in firms and linking these to beliefs, systematic influences on pricing strategies, and firm performance. Our findings complement a lab-based literature identifying heterogeneity in strategies used in repeated games (e.g., Dal Bo and Frechette, 2019) by showing heterogeneity in real strategic competition and how this relates to cognitive skills.

Our findings are relevant for a traditional literature on strategic competition, and the related literature on relational contracting. Our findings add nuance to the idea that price wars are a sign of maintaining collusion (e.g., Green and Porter, 1984 ; Slade, 1992), by suggesting that some price wars may instead reflect cognitive mistakes. By identifying bounded rationality as a novel factor that can matter for price markups, our results also contribute to a large literature studying determinants of measured market power (for a survey see Berry et al., 2019). Our study adds to evidence that price ceilings can be a focal point for pricing (e.g., Knittel and Stango, 2003), but shows that this can depend on cognitive skills of market participants. Our study also adds new insights to a literature that has focused specifically on understanding retail gas markets (e.g., Hastings, 2004; Noel, 2007; Barron et al., 2008; Houde, 2012; Luco, 2019, and many others). For example, Assad et al. (2023) show that introducing algorithmic pricing increased gas prices in Germany; our findings provide a potential explanation, by showing that human pricing may not fully exploit market power. The relational contracting literature has shown how repeated game incentives can potentially sustain mutually beneficial cooperation (for a survey see Malcomson, 1999) but has hypothesized that complexity may be a barrier (Macleod, 1996); our findings are consistent with heterogeneity in how participants approach such interactions, determined by cognitive skills.

The findings in our paper also add to a literature in economics showing that managers matter for performance (e.g., Ichniowski et al., 1997; Bloom and Van Reenen, 2007; Bloom et al., 2013; Bloom et al., 2019; Bandiera et al., 2020; Hoffman et al., 2021; Fenizia, 2022; Adhvaryu et al., 2023; Metcalf et al., 2023; Minni et al., 2023). While most studies have looked at managers who are involved primarily in supervising workers, our paper is different by studying managers who make strategic decisions, and by showing the importance of cognitive ability and how this shapes mental models, pricing, and firm profits. Previous work has shown that overconfidence matters for the investment behavior of CEOs (e.g., Malmendier and Tate, 2015) and that overconfidence about future performance is persistent among managers despite feedback (Huffman et al., 2023). Our work implicates a role for cognitive skills, and mental models that underestimate competitor sophistication, in fostering managerial overconfidence about certain strategies, and shows how this influences pricing decisions.[6]

2 Market setting and Data

2.1 Details on the market setting and manager descriptives

Our partner company operates more than 20,000 gas stations across a country. Stations essentially always have a convenience store, and typically sell both gas and diesel oil products. The stations are primarily company owned, rather than franchises, and are controlled by company managers. Each station has a station manager, who has substantial influence over station operations, including pricing decisions. Station operation is also governed, however, by the policies of district level managers. There are about 350 districts, each with a district level manager who sets policies about precisely what type and degree of discretion is given to station managers operating in their district.

Our partner company is one of two large competitors in the market for retail gasoline, and then there are many smaller companies. One key difference between the large companies and small companies is that the former produce their own oil, while the latter must buy oil products on the market. Another difference is that the larger companies position themselves as offering a premium oil product, and for this reason typically charge more than the independent companies for the same grade of gas or diesel.

An important feature of the pricing environment is that there is a government-imposed price ceiling for oil products, indexed to the world price of oil. The price ceiling arguably serves as a natural focal point for coordinating pricing, and indeed, the two large competitors have a policy of generally pricing near the price ceiling, for gas. Independent companies, by contrast, typically price substantially lower for the same grades of gas. Diesel prices tend to be lower than the price ceiling, for both the large and small companies, and more volatile. This reflects the greater price sensitivity of buyers of diesel, who are mainly truck drivers.

Table 1 shows descriptive stations for station managers and their stations. The median age of a station manager is 39, and about 70 percent of managers are male. The modal level of education is a junior college degree. Managers stay in their jobs for a relatively long time, with median experience at the company being 7 years. Managers do switch gas stations periodically, with median tenure in a gas station of about 2.5 years. The median number of employees is 5, so managers have some people management

[6]Our findings also complement a literature in psychology, on how cognitive ability is positively related to workplace performance evaluations (for a survey see, e.g., Schmidt and Hunter, 2004), by showing a link to economic profits, and shedding light on how cognitive skills systematically affect strategic behavior.

Table 1: Descriptive statistics on managers and stations

Manager descriptives:	
Median age	39
Female	34%
Education level:	
High school	26%
Junior college	45%
College	28%
Graduate	1%
Median experience (years)	7
Med. tenure current station (years)	2.5
Station descriptives:	
Med. n. employees	5
Med. n. competitors in local mkt.	3
Med. mkt. share (of oil sales)	30%

duties, but not for very large groups of workers. The median number of competitors within 2km, the company's definition of a local market, is 3 competitor stations. The median market share for a station from our partner company, in terms of oils sales in the local market, is about 30 percent.

2.2 Datasets

We have obtained data through a collaboration with the research arm of the partner company. The research department has access to certain types of data, but not others. One type of data is performance data on the gas stations, including profits but also prices. Another type of data is survey data. The research department has an infrastructure for conducting surveys with station managers, and has allowed us to periodically design the survey. Because these surveys are internal, managers are supposed to fill them out, and thus response rates are quite high. At the same time, managers know the research arm is a separate entity from their senior management team, and the research department can credibly promise confidentiality of individual responses. One key type of data that is not available is data from the human resources side of the company. For this reason, our surveys were designed to collect key variables that describe some aspects of the work environment that would normally be collected by human resources, such as work history of the manager. We were not allowed to collect certain variables, however, such as manager earnings or work hours.

Our analysis is based on four types of datasets, the first of which is from a survey conducted with district level managers. Our survey was sent to all district level managers, and we have responses from 353, close to a 100 percent response rate. One purpose of this survey was to collect systematic information about the amount and types of discretion given to station managers in their jobs. Another purpose was to elicit manager views on potential mistakes by station managers, including regarding pricing.

A second type of dataset comes from surveys conducted with the station managers. We have conducted three survey waves so far, each time sending the survey to all 20,000 station managers. The response rate has been roughly 70 percent each time, yielding roughly 14,000 responses each time. There is substantial overlap in the managers filling out the different survey waves, e.g., more than 10,000 filled out both the first and second survey waves despite these occurring roughly one year apart. The main purpose of the surveys was to measure manager traits, such as cognitive ability and personality type, as well as assess how managers think about different aspects of their job. Specifically, our first survey, conducted in 2021, wave mainly collected information about the nature of the job, and manager views on various topics. The second survey wave in 2022 collected measures of a wide array of manager traits, as well as measures of managers' mental models of competition. The third survey, which was completed in 2023, collected measures of the same traits again, to assess and correct for measurement error in manager traits. The survey also included additional measures of mental models.

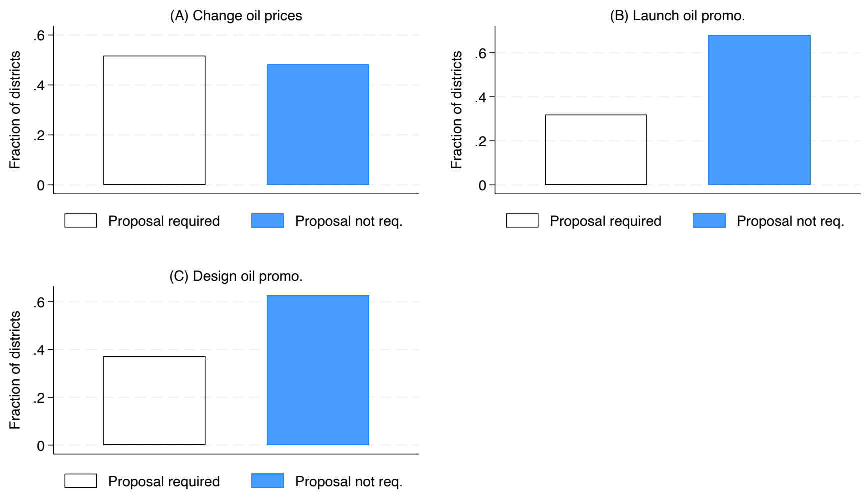
A third dataset is monthly performance data on the company's gas stations, for the period 2019 to 2022. These are panel data for each station, recording key outcomes such as oil and nonoil profits, sales volume in gallons, etc.. The data also record average monthly prices charged for gas and diesel products. We have access to the performance data in 26 regions out of the 31 regions the company operates (we do not use data from one region, where data was available only quarterly). The total data set has about 17,000 gas stations. We can match manager survey responses to the performance data. Since we have about a 70 percent response rate to the survey, we have data on manager traits and station performance for roughly 10,000 managers.

A fourth dataset includes daily price and sales data for one region, including prices of all competitors. The region has roughly 900 stations from our partner company. The data form a daily panel for each station, from 2018 to 2021. These data allow a more detailed analysis of pricing behavior than is possible with the monthly data. We use these data to understand how manager traits and mental models affect pricing decisions. Importantly, we can also identify price wars in this dataset, because we can see what is happening with competitor prices.

2.3 Degree and nature of managerial discretion over oil prices

We use our survey of the district managers to provide systematic evidence on whether station managers can influence key strategic decisions, with a focus on ability to adjust oil prices (prices for gas and diesel). We asked about ability to directly change the posted price of oil products, affecting all customers. We also ask about ability affect oil prices through launching and designing special promotions, which cut prices in more targeted and limited ways: At certain times or days of the week, or for subsets of customers like loyalty card holders. For these decisions, we asked about whether managers were required to make proposals to make changes, or whether they had the freedom to make changes without proposals (either in a pre-specified range, or without any restrictions).

Figure 1: Degree of manager discretion for oil pricing



We find that for these key strategic choices, managers do have influence, although higher-level management does exert some control. Panel (A) of Figure 1 shows discretion over direct oil price cuts. For this decision, arguably the most sensitive strategic choice from the perspective of upper level management, about 50 percent of district managers report that managers can change these without a proposal. In the case that managers make proposals, they are approved about 35 percent of the time, according to district level managers. Thus, even when they must make proposals, managers can still influence oil prices. In Panels (B) and (C) of Figure 1 we see relatively more discretion over changing oil prices through more targeted or limited promotions, with more than 60 percent of districts not requiring proposals to affect oil prices in these ways. In summary, the station managers clearly have a role to play in setting oil prices, opening up the possibility that cognitive skills of station managers may matter for pricing and performance.

2.4 Manager incentives

The station managers have a base salary, but also performance-based incentives. The incentive pay makes up about 50% of total earnings, so good performance is important for manager earnings. Incentive pay is based mainly on three KPIs: Oil profits, oil volume sold in gallons (sales volume), and nonoil profits. Performance on each of these is measured relative to a target, and these are multiplied by coefficients to determine overall bonus pay. We do not have data on manager earnings, as this is HR department data, and we do not have data on the targets. Thus, we cannot back out the earnings of managers. Knowing the structure of the performance incentives, however, makes clear that managers have a financial motive to care about improving station performance.

2.5 Measures of manager traits

Our second survey wave provides measures of a wide range of manager traits (so does our third wave). The survey was designed to measure aspects of manager cognitive skills, and also noncognitive skills such as preferences and personality traits. The survey was administered online, and managers were invited to participate, and reminded to respond, by the company's research department. We have roughly 13,500 respondents to the second survey wave.

Table 2: Measures of manager traits

Cognitive ability	IQ test involving 9 progressive Raven's matrices (+)
Numeracy	Question about understanding probabilities (+)
Economic preferences	Risk tol. (+), patience (+), altruism (+), pos. rec. (+), neg rec. (-)
Ambiguity aversion	Prefer urn with known distribution (-)
Personality type	Consc. (+), agree. (+), extra. (+), open. (+), neur. (-)
Locus of control	Inventory from psychology (+)
Competitiveness	On a scale from "not at all" to "very' (+)'
Confidence	On a scale from "not at all" to "very" (+)
Procrastination	Agreement on a scale about tendency to procrastinate (-)
Liking for authority	On a scale from "not at all" to "very much" (-)
Self control	Inventory from psychology (+)
Emotional intelligence	7 item test (+)
Gender	Female indicator
Age	In years
Experience	In months

Notes: Cognitive skills are measured by the first factor of items colored in red. Noncognitive skills are measured by the first factor of items colored blue. The signs of factor loadings are shown in parentheses.

Table 2 summarizes the traits we measured for the managers, starting with cognitive skills measure. Cognitive ability was measured using a 9 question Raven's progressive matrices test. While the standard test involves 60 questions, this length of test has been shown to serve as a reliable proxy for the full-length test (Bilker et al., 2012). We also asked a question designed to assess numeracy, which asks about the probability that a flipped coin will come up heads.

For the noncognitive traits, we drew on measures of traits that are viewed by economists as fundamentally important for economic decision making, and by psychologists as key facets of human nature. Economic preferences were measured using the survey module from the Global Preference Survey (Falk et al., 2018). These survey measures were developed based on ability to predict choices in incentivized experiments measuring the corresponding preferences (Dohmen et al., 2005). Personality type was measured by an inventory of the big five from psychology. Other items captured beliefs, in the form of locus of control and self-reported confidence, taste for competition and authority, and biases such as procrastination and ambiguity aversion. The measure of emotional intelligence was a seven question test, showing respondents photographs of a person's eyes, and asking the respondent to guess the person's facial expression.

We used factor analysis to reduce dimensionality and combine the various items into cognitive and noncognitive skills measures. We use the entire sample of respondents to the second wave for the factor analysis. Our measure of cognitive skills is the first factor of the responses to the Raven's questions and the numeracy question. The measure of noncognitive skills is the first factor from the set of noncognitive traits. The signs of the factor loadings are shown in parentheses in Table 2. For each individual we predict these two factors based on their traits, and use these as the measures of their cognitive and noncognitive skills.

The construction of our measures is supported by additional factor analysis. Pooling all measures, cognitive and noncognitive, we see that the cognitive traits load on a separate factor from noncognitive traits. This supports separation into two sets of traits. The factor analysis on the Raven's questions and the numeracy question yields a single factor with eigenvalue greater than 1. The factor analysis of the noncognitive traits also yields a single important factor, with eigenvalue well above 1. This factor loads positively on plausibly "positive traits" for managers, such as conscientiousness, agreeableness, locus of control, confidence, and patience, and most of the other traits. It loads negatively on only a few traits, notably neuroticism, taste for authority, and procrastination. There is also a second factor for noncognitive skills, with eigenvalue just equal to 1. In robustness checks we have included this second factor, but it never predicts station performance, and leaves our other results unchanged. Thus, our main analysis focuses on using the first factor for noncognitive skills.

The third survey wave measured the same traits again, roughly one-year apart, allowing an assessment of within-manager-measurement error in the traits. A caveat is that there was only about 60 percent overlap in the second and third wave samples. Getting a sense of measurement error in cognitive skills is useful for understanding to what extent attenuation bias might make our results on how cognitive skills relate to various outcomes a lower bound. It also allows addressing another concern, which arises when we regress an outcome on both cognitive skills and noncognitive skills; measurement error in noncognitive skills could potentially bias the coefficient on cognitive skills.

Our measurement error calculations find greater measurement error for cognitive than noncognitive skills, and imply non-trivial attenuation. The values imply that a given correlation of an outcome with cognitive skills is attenuated by about 35 percent. The same calculation for noncognitive skills shows that the observed correlation is attenuated by about 17 percent. For regressions of outcomes on cognitive and noncognitive skills we can also check robustness to correcting for measurement error by instrumenting for the manager traits measured in one survey wave the same traits measured in the other survey wave, e.g., using the Obviously Related Instrumental Variables (ORIV) approach (Gillen et al., 2019; see also Stango and Zinman, 2020). Due to limited sample overlap, however, we lose a lot of data and have reduced power.

3 Cognitive skills and mental models

In this section we investigate whether manager cognitive skills influence mental models of competition. We begin by measuring what managers think are the key ways to be successful in terms of profits. Then, inspired by the behavioral literature on bounded rationality and competition, we investigate whether an underlying mechanism is how cognitive skills affect mental models of competitor behavior.

To measure the ideas that managers have about how they can influence a key aspect of success in their real competitive environment, oil profits, we adopted a “narratives" approach. This involves asking managers how they would explain an observed economic event, in this case, a manager consistently having high oil profits.[7] In our second survey wave we posed manager with the following prompt: “Some managers consistently have higher oil profits than other managers. What do you think are the most important practices that enable them to achieve this? Please be specific, providing examples if possible, and explain in complete sentences.”

Our main approach to classifying responses to the narratives measure involved human classification (as in Andre et al., 2023), but we check robustness to machine classification. In a first stage the researchers looked at a randomly drawn sub-sample of

[7]See Andre et al. 2023, who used this approach to understand consumers’ mental models of causes of high inflation.

3,000 responses, out of the total sample of more than 15,000. We accumulated a list of distinct categories of causes of high oil profits mentioned by the managers, e.g., keeping oil prices high to maintain high margins, or charging low prices to increase sales volume, or a manager putting in a lot of effort. We found that many of these causes could be conceptualized within the relationship $\pi = (p - c) * q$, namely as being related to either the profit margin component of profit, or to the sales volume component. Some categories, however, were distinct, e.g., effort or manager ability as causes did not clearly fit into either profit margin or volume.

We provided a team of undergraduate RA's with the categories we had identified, along with examples of text belonging to each, and a list of common keywords associated with each category (see appendix for the rubric). The RA's then categorized all 15,000 responses, with two RA's looking at each item of text. The agreement rate between RA's was about 75 percent. Conflicts in RA categorization were reconciled by the researchers, but we check robustness to only using narratives that were agreed upon by both RA's.

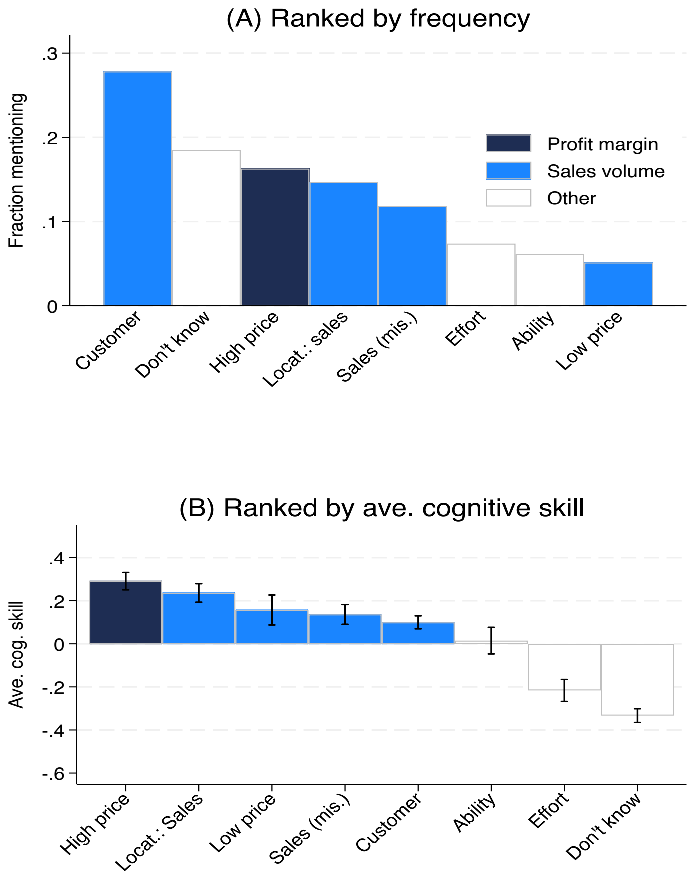
Panel (A) of Figure 2 shows the frequencies of different causes mentioned by managers, for a sample of roughly 14,700 managers. The figure excludes categories that were mentioned only very seldom, i.e., by less than 5 percent of managers; we show the frequencies of the full set of categories in the appendix (Panel (A) of Figure A.1).[8] The bars in Panel (A) are color-coded according to whether they fall into the profit margin (dark blue), sales volume (light blue), or other categories (white). We see that the most frequent category of narrative explanation, mentioned by more than 25 percent of managers, involves attracting customers, and falls into the sales volume group. The second most frequent category is some version of "I don't know." The third most frequent category attributes high profits to charging high prices, and is the only narrative from the profit-margin group that is mentioned by more 5 percent or more of managers.

To explore whether mental models of how to achieve high oil profits vary systematically with cognitive skills, Panel (B) shows causes ranked by the average cognitive skills of managers who mention them. A clear ordering emerges, of profit-margin causes (high price), then causes related to sales volume, and then the causes from the "other" category. Those who answer "don't know" have the lowest cognitive skills overall.[9] Notably, one of the sales volume causes explicitly attributes high profits to charging low prices, and categories related to having high sales may also reflect, implicitly, the idea of charging low prices. We thus see, emerging from the data, two opposing ideas about

[8]Most of the rarely mentioned causes are within the profit-margin category, such as "reduce costs" or sell "high-margin" products.

[9]As shown in the appendix, we see a similar ranking when we consider all categories of causes, with rarely mentioned causes within the profit-margin category being associated with high cognitive skills.

Figure 2: Narrative measure of mental models for high oil profits



Notes: Panel (A) shows the frequencies of managers mentioning different categories of causes of high oil profits, but excludes causes mentioned by less than 5 percent of managers. *Location: Sales* refers to narratives in which the location is favorable to high volume; *Low price* refers to high volume through low prices; *Sales (mis.)* indicates mentioning sales volume but without further explanation. Panel (B) shows the average cognitive skills of the groups of managers mentioning the respective causes. Error bars indicate 95% C.I.s.

the ideal pricing strategy for obtaining high oil profits, and managers with higher cognitive skills are more prone to favor the high-price approach.

The differences in average cognitive skills for those mentioning the high price cause relative to those those mentioning location and sales, or low price, or sales volume without further explanation, are all individually statistically significant.[10] In the appendix we report additional analysis. We show that the frequency of mentioning high price increases monotonically with (quintile of) cognitive skills (Figure A.2), and in Probit regressions, that the probability of mentioning the high price cause, relative to all other

[10]For the purposes of statistical tests we exclude managers who mention only one type of cause, so that observations are independent across the narrative categories (Wilcoxon tests; $p < 0.001$, $p < 0.001$, $p < 0.001$).

causes, sales volume causes, or specifically the low price cause, are all significantly increasing in cognitive skills, controlling for other manager traits of noncognitive skills, experience, gender, and age (Figures A.3 and A.4). These findings are consistent with cognitive skills mattering for mental models of success in competition, in a way that could generate different pricing behaviors and, potentially, profits.

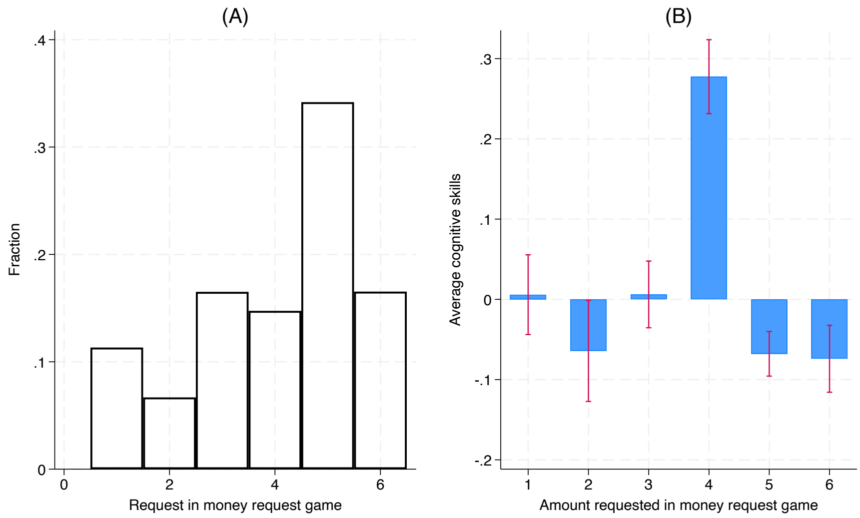
We have performed various robustness checks on the classification of narratives. Results are very similar if we eliminate researcher involvement in the classification, by only using the 75% of narratives that were agreed upon by both RA's (see Figures A.5 to A.8 in the appendix). As another robustness check, we used an NLP method to classify narratives, based on keywords. The procedure leads to a similar result that the high price narrative is ranked at the top in terms of average cognitive skills, whereas causes related to sales volume are ranked lower. More details are provided in the appendix (TBA).

What might explain the link between cognitive skills, and different ideas about optimal pricing? A hypothesis from the literature on bounded rationality and strategic competition is that bounded rationality may affect how well managers can model the behavior of competitors. We measure this ability in a tightly controlled strategic game, and investigate whether this ability is related to cognitive skills. The game isolates manager ability to predict what other managers will do as the cause of success, stripping away many other factors that can contribute to variation in success in real competitions, e.g., different managers facing different locations.

In our first survey wave with the managers, we presented managers with a hypothetical version of the money request game (Arad and Rubenstein, 2012; Fe et al., 2022): "Suppose you are matched with another station manager to play a game. Your opponent and you are going to ask for an amount of money from a referee for the game. The amount must be between \$1 and \$6. You will get the amount of money you ask for. However, you will get \$10 more if you ask for exactly \$1 less than your opponent. How much money do you ask for?" Behavior in this game can be viewed through the lens of level-k models of reasoning, or endogenous depth of reasoning models, with lower requests indicating a process of think through more levels of reasoning. Fundamentally, success in the game requires anticipating what other competitors will do. In our case, managers are asked to think about the types of individuals with which they compete in real life, namely other station managers. More than 13,600 managers responded to the survey and made a choice in the game.

Panel (A) of Figure 3 shows the distribution of requests for the station managers playing the game. The modal request is \$5, suggesting a strategy of hoping to undercut others who request \$6. Because so many managers request \$5, however, this is

Figure 3: Behavior in the money request game and cognitive skills



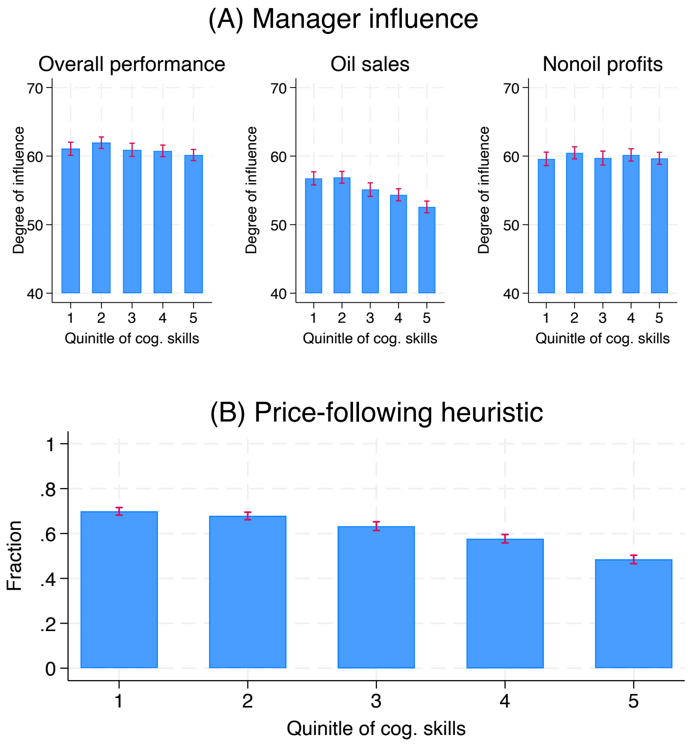
Notes: Panel (A) shows the distribution of requests in the money request game from our first survey wave. Panel (B) shows average cognitive skills for the group of managers making each of the possible requests. Error bars indicate 95% C.I.s.

not the request that maximizes the expected payoff. Instead, requesting \$4 is optimal (other, lower requests lead to lower expected payoffs). One might think that managers requesting \$4 are there due to luck rather than skill. When we look at the relationship of requests to cognitive skills, however, a clear pattern emerges that cognitive skills matter for success.

As shown in Panel (B) of Figure 3, average cognitive skills are significantly higher among managers choosing \$4 than among managers making other requests. In a regression where the dependent variable is an indicator for choosing \$4, and independent variables include manager traits, cognitive skills are highly significant, but other traits are unrelated to the probability of success. We also implemented the money request game in our second survey wave, along with our measures of cognitive skills, and we again replicate the same finding, that \$4 is the optimal choice, and those who make this choice have the highest cognitive skills (see appendix). Cognitive skills thus appear to be relevant for station managers having an accurate model of the strategic behavior of other station managers.

We also included in our survey some other, more structured survey questions to shed additional light on manager's mental models about competitors, in the context of their real job. One measure was inspired by the intuition from level-k models that lower cognitive skills may lead to overconfidence in strategic competition: We asked managers how much they think different aspects of station performance can be influenced by the manager, as opposed to performance being determined by external factors. Inspired by models of endogenous depth of reasoning, we also asked managers a question about whether they follow a simple heuristic in their pricing, of following competitor prices. This can be thought of as indicating the manager not being sure how to model competitor behavior, and instead just deciding to copy what competitors do. The intuition from endogenous depth of reasoning models is that such heuristics are more likely to be used by those with lower cognitive skills.

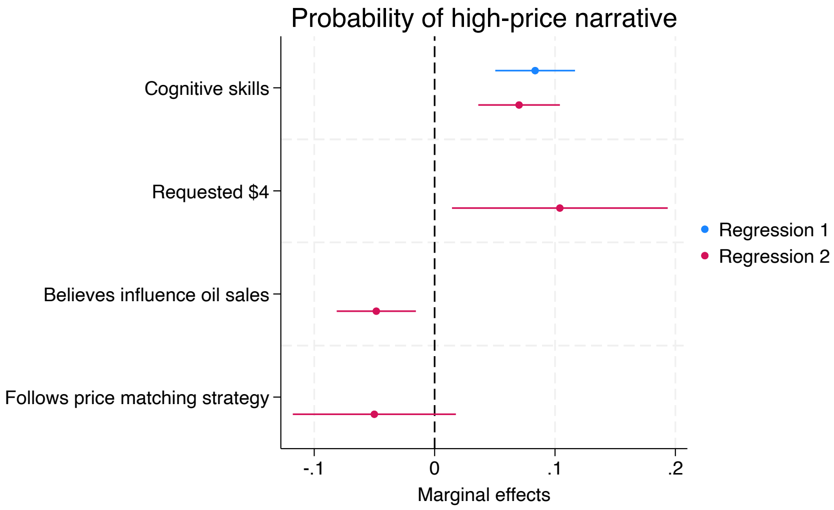
Figure 4: Mental models of competitors and cognitive skills



Notes: Quintile 5 is the best. In Panel (A), beliefs about manager influence were measured on a scale from 0 (only external factors matter) to 100 (only manager matters). Panel (B) shows the frequency of managers replying in the affirmative when asked whether they set prices by matching what competitors do. Error bars indicate 95% C.I.s.

Figure 4 provides some support for both the level-k and endogenous depth of reasoning intuitions, for how cognitive skills shape mental models of competition. Panel (A) shows that managers with lower cognitive skills are *more* confident about the ability of managers to influence performance, particularly for oil sales, compared to high ability managers. This could reflect overconfidence about ability to "win" price competitions through strategies of cutting prices. Panel (B) shows that lower cognitive skills also increase the frequency of using the price-following heuristic. This is consistent with some low-skill managers realizing that they are not as sophisticated as competitors, but not knowing how to model their behavior, and thus adopting a simple heuristic.

Figure 5: High price narrative, cognitive skills, and mental models of competitors



Notes: The figure plots marginal effects from Probit regressions, with 95% C.I.s. The dependent variable is an indicator for whether a manager mentioned the high price cause. The first model reports the coefficient for cognitive skills but also controls for other manager traits: noncognitive skills, experience, gender, and age. The second model includes these traits but adds three measures of mental models of competitors.

The different ideas about optimal pricing by cognitive skills suggest that this may reflect the differences we have seen in mental models of competitors. In Figure 5 we show results from Probit regressions explaining the probability that a manager mentions the high price narrative. The first model shows the coefficient on cognitive skills, controlling for other manager traits, which is positive and highly significant. The second model shows that the coefficient on cognitive skills is reduced by about 22 percent when we add mental models about competitors. Furthermore, each of these mental models has explanatory power for mentioning high price. Those who make the optimal choice in the money request game are more likely to favor the high price strategy for oil profits, suggesting that the high price approach reflects a relatively sophisticated ability to predict competitor behavior. Those who think they can strongly influence oil sales, however, and those who tend to simply imitate competitor prices, are less likely to mention high price as a way to achieve high oil profits. This suggests the reasons managers differ in their views about optimal pricing can be attributed in part to their ability to model competitor behavior, and this helps explain the link to cognitive skills.

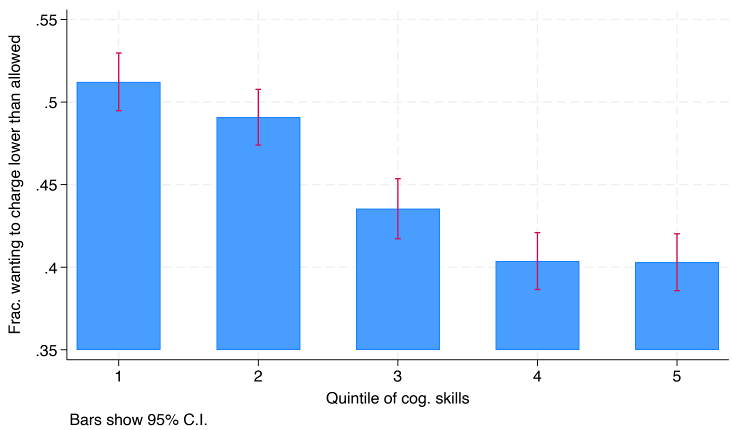
In the next section we turn to self-reported and actual observed pricing decisions, and test whether these are related to cognitive skills in the way we would expect based on the mental model results.

4 Cognitive skills and pricing behavior

4.1 Cognitive skills and self-reported pricing behaviors

Before exploring the relationship between managers' cognitive skills and their actual pricing behaviors, we first examine the connection between their self-reported pricing strategies and cognitive abilities. In the second survey wave, we asked managers: (1) If they tend to charge lower prices than the default set by upper level management (the default typically being the price ceiling); (2) about the frequency of their requests to reduce listed prices. The former is relevant for districts where managers have discretion to change oil prices directly; the latter is relevant only for districts requiring proposals to cut prices.

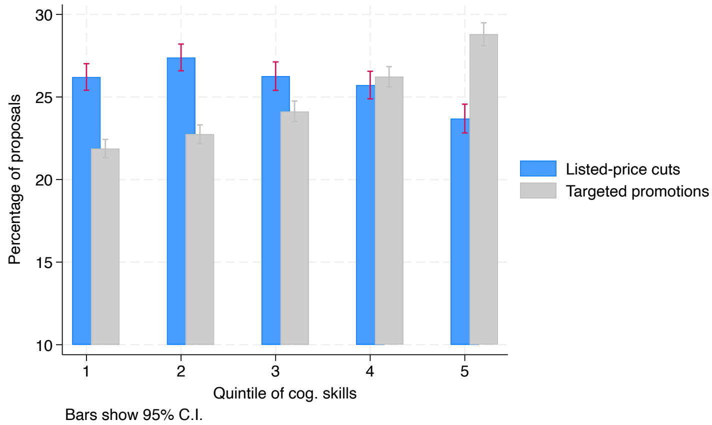
Figure 6: Cognitive Skills and Desire to Cut Prices



Notes: Proportion of managers preferring to charge a lower oil price than the default suggested by upper management, categorized by quintiles of cognitive skills.

As depicted in Figure 6, managers with lower cognitive skills are significantly more inclined to charge lower prices compared to those with higher cognitive skills. Over half of the managers in the lowest cognitive skill quintile prefer to charge less than the default price suggested by upper level management, in contrast to only 40% in the highest quintile. Notably, this preference is not driven by self-interest. When queried about their reasons, a majority (82%) indicated that a lower price would be advantageous for the company, a statement consistently stated across all cognitive skill levels. This suggests that managers with lower cognitive abilities are more likely to perceive the prices suggested by upper management as sub-optimally high and believe that reducing them would benefit the company. Indeed, if we correlate an indicator for the manager thinking that high prices are a cause of high oil profits, with desire to cut prices, we see a significant negative relationship (see also Figure B.1 in the appendix). This reinforces that the different price setting desires of low and high cognitive skill managers are due to different ideas of how to be successful.

Figure 7: Cognitive Skills and Types of Requests



Notes: Percentages of various request types made to upper-level management, categorized by quintiles of manager cognitive skills. 'Listed-price cuts' refer to requests for reducing the listed oil prices, while 'Targeted promotions' represents proposals for specific price promotions aimed at selected consumer groups. The heights of the bar represent the proportion of a particular request type among all requests made to upper-level management.

In districts requiring proposals to change oil prices, we also see that managers with lower cognitive skills more frequently propose to upper-level management reductions in listed oil prices, as shown by the blue bar in Figure 7. Conversely, the figure shows that managers with higher cognitive skills adopt a different strategy. Rather than seeking across-the-board reductions in listed oil prices, they are more prone to propose targeted promotions aimed at specific consumer segments. We also find that these different self-reported pricing behaviors, in the form of proposals, are explainable by different ideas about what causes high oil profits. Managers who mention high price as a cause of profits report a lower percentage of proposals about price cuts, and a higher percentage of proposals about targeted promotions (see Figure B.2 in the appendix).

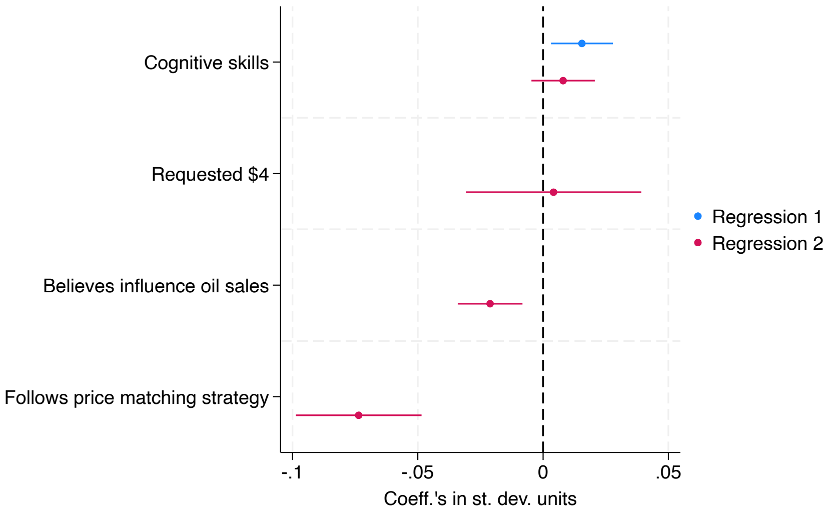
We also find that self-reported desire to cut prices, and frequency of proposing price cuts, are both significantly negatively related to cognitive skills if we control for other manager traits. Furthermore, this relationship appears to be partly mediated by mental models of competitors as captured by requesting $4 in the money request game, belief about ability to influence oil sales, and adopting a price follower strategy (see appendix Figures B.3 and B.4).

4.2 Relationship of actual pricing to manager cognitive skills

So far we have seen that cognitive skills matter for whether managers think low prices are a good idea, and for whether managers report seeking to lower price. In this section, we analyze the relationship between cognitive skills and actual, observed oil product prices. Additionally, we explore whether this relationship is explained by the mental models managers have about competitors.

In studying pricing behavior, we use our monthly panel data on the pricing behavior of gas station managers. Due to varying price ceilings and the diverse pricing of different oil products, the company computes a metric to measure a station's overall pricing for a month. This metric compares the monthly average price of each oil product to its respective ceiling, weighting each product by its sales volume at the station in that month. A ratio of 1 indicates pricing equal to the ceiling for all products. This price ratio incorporates all forms of discounts, including reductions in listed prices and all types of coupons and promotions.

Figure 8: Pricing behavior as a function of cognitive skills and mental models

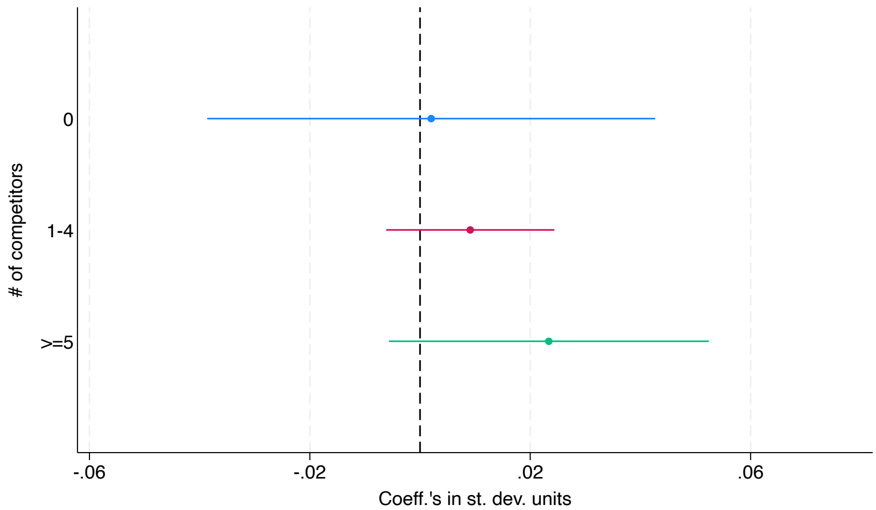


Notes: Coefficients from OLS regression, with 95% confidence intervals based on robust standard errors clustering on station. Controls in all regressions include noncognitive skills, experience, gender, age, station location indicators, station ownership type, station size, open 24 hours, number of competitors, market share, and interacted day and district fixed effects. Results are from monthly price data.

In Figure 8, Regression 1 presents regression results of the monthly average price ratio against manager traits. We account for local market competition, controlling for different types of competitor stations (although results are consistent when controlling for total number). The analysis reveals that managers with lower cognitive skills tend to set significantly lower oil product prices relative to the ceiling. Interestingly, male managers also tend to set lower prices. Our findings thus show that cognitive skills matter systematically for a fundamental market outcomes, the level and distribution of prices. An important question is whether this effect persists with experience, or whether managers learn to charge higher prices over time. Including an interaction term between cognitive skills and experience, we find a small and not significant coefficient, so there is no evidence of experience changing the effect of cognitive skills on pricing strategies.[11]

We also find that the impact of cognitive skills on pricing is partly mediated through mental models. In Figure 8, Regression 2 demonstrates that managers who employ a price-matching heuristic, exhibit higher confidence in their ability to influence oil sales, and perform poorly in the money request game, tend to set lower prices. While the coefficient for the money request game indicator is imprecisely estimated, the three mental models are highly jointly significant (F-test; $p < 0.001$). Comparing these results with regressions excluding mental model measures (Regression 1), we observe a 30% reduction in the cognitive skills coefficient upon including mental models. This provides more direct evidence that mental models of competitors help explain the link between cognitive skills and pricing. It also suggests that lower cognitive skills lead to lower prices through different approaches to competing, rather than as a reaction to their competitive environments.

Figure 9: Pricing behavior as a function of cognitive skills: by number of competitors



Notes: Coefficients from OLS regression, with 95% confidence intervals based on robust standard errors clustering on station. Controls include location indicators, station ownership type, station size, open 24 hours, market share, and interacted day and district fixed effects. Results are from monthly price data.

To provide further evidence on whether the effect of cognitive skills on pricing is through how managers handle competition, we investigate whether the impact of cognitive skills on pricing behavior varies with the intensity of local market competition.

[11]We check robustness of these results to correcting for measurement error in cognitive and noncognitive skills using the ORIV approach, to make sure that measurement error in noncognitive skills is not biasing the cognitive skills coefficient upwards. Cognitive skills and are no longer statistically significant, due to loss of power (we lose about 40 percent of the sample), but the point estimate is about 30 percent larger, showing the effect of correcting for attenuation bias, reassuring that the positive coefficient for cognitive skills is not an artifact of measurement error in noncognitive skills.

Figure 9 presents the coefficients from an OLS regression of price ratios on cognitive skills, categorized by the number of competitors in the local market. We control for the characteristics of the station, including the location indicators, the market share, the station size, etc., to deal with potential differences between stations facing different numbers of competitors. We see that the effect of cognitive skills on pricing is approximately zero and not statistically significant in markets with no competitors. The effect becomes positive, however, when there are moderate number of competitors and the magnitude of this effect becomes the largest when there are many competitors (larger or equal than 5). Appendix Figure B.6 displays the relationship between managers' cognitive skills and price ratios depending on the market share. The pattern is similar: the positive effect of cognitive skills on prices is strongest when the market share is the lowest, and the effect is close to zero when the market share is larger than 50%. Although the estimates are not sufficiently precise for the differences across different market conditions to be statistically significant, these findings provide suggestive evidence that the effect of cognitive skills on pricing operates through how managers are responding to more intense competition. This is consistent with our other findings that a reason for cognitive skills to matter is through mental models of competitors.

4.2.1 Robustness check on causality: Event study

The main threat to identification in our main analysis is omitted variable bias. For instance, if managers with lower cognitive skills happen to be assigned to stations or locations with less favorable unobserved characteristics, this could lead them to charge lower prices. To provide a tougher test of causality, we therefore turn to an event-study design.

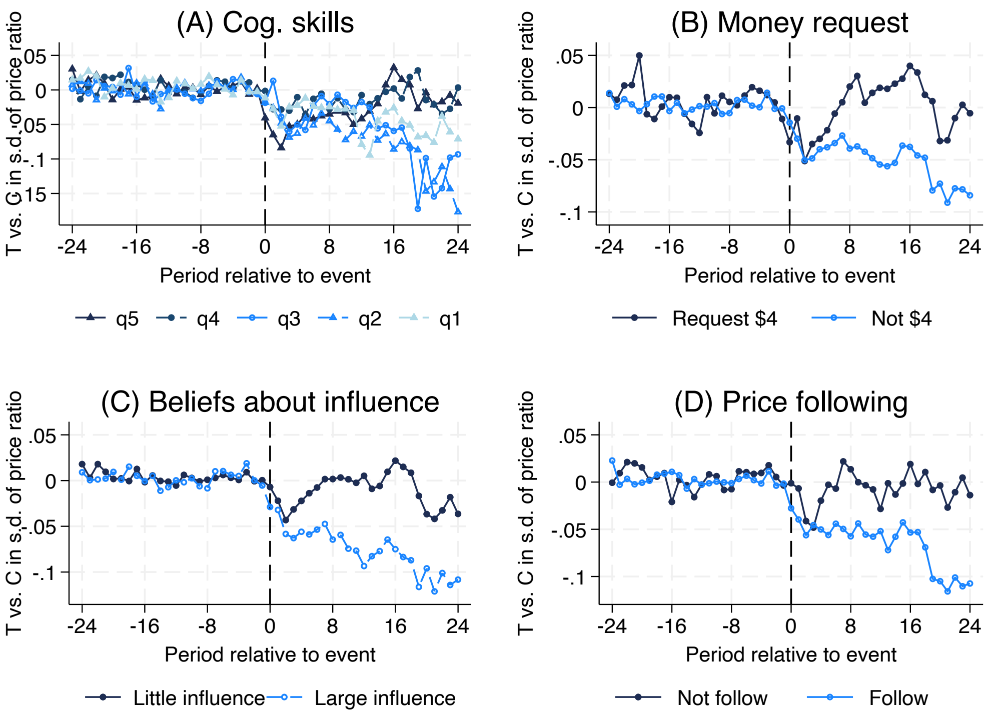
Our approach is to identify stations that have a change in managers, and for which we measure the traits of the new manager. We define the treatment event as the arrival of this new manager.[12] We can compare performance before and after the new manager arrives, to assess the impact of the manager, holding all time-invariant aspects of the station and location constant. And, we can relate this difference to traits of the new manager, to see if arrival of a high skill manager is associated with increasing prices, and a low skill manager with decreasing prices. This before-after difference could, of course, be confounded by time trends. To address this, we would like to also difference with respect to a control station, which has similar time trends before the event, but does not experience a change in manager. A challenge, however, is finding individual control stations that have similar pre-trends to our treated stations.

To achieve a good control group for our difference-in-differences analysis, we there-

[12]There are 4,569 manager change events in our dataset.

fore turn to the method of synthetic difference-in-differences (SDID), as discussed in Arkhangelsky et al. (2022). This method takes the set of all candidate control stations – those that do not ever have a change in manager during the sample period – and constructs for each treated station a weighted average of the control stations that has the best fitting pre-trends, i.e., a synthetic control. Unlike synthetic control methods (see, e.g., Abadie et al., 2015), synthetic difference-in-differences does not require the level of treatment and control to be the same in the pre-treatment periods, just that the trends be parallel.

Figure 10: SDID treatment effects, cognitive skills, and mental models



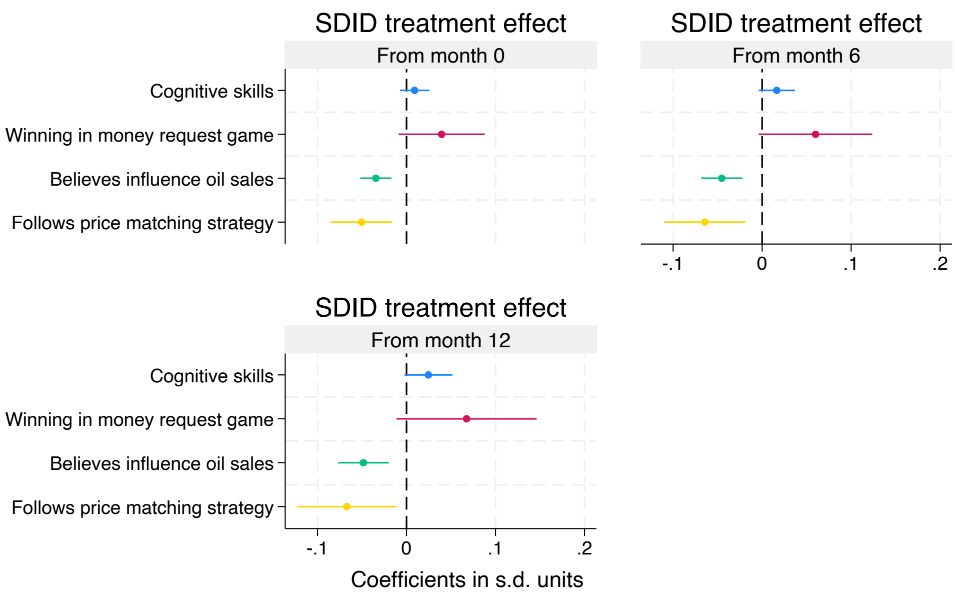
Notes: Treatment effects on price ratio versus the synthetic control stations from SDID regressions, by traits of the *new* manager. These are categorized in Panel (A) by quintiles of cognitive skills (quintile 5 is the best), in Panel (B) by requesting $4 in the money request game or requesting a different amount, in Panel (C) by above or below median belief in ability to influence oils sales in the middle panel, and in Panel (D) by whether a manager uses the price following heuristic in the bottom panel.

Figure 10 shows results of the SDID analysis for price ratios depending on the traits of the *new* manager. Panel (A) shows the SDID treatment effects by cognitive skills of the new manager. Specifically, it graphs the average post-treatment versus pre-treatment difference in price ratio of the treated stations relative to their synthetic control stations by the quintile of cognitive skills of the new manager. In the pre-period, these treatment effects are close to 0, regardless of the traits of the new manager, indicating that our SDID method is successful in achieving parallel trend in pre-periods. After they take over the station, however, we see that the prices charged by managers in the top two quintiles of cognitive skills tend to be higher than prices charged by managers with lower cognitive skills. This becomes pronounced starting at around 12 months, suggesting that it takes some time for the traits of the new manager to matter.

Panels (B) through (D) of Figure 10 shows a similar analysis, but according to the mental models about competitors of the new manager. We see that bringing in a manager who makes the right choice in the money request game leads to higher prices, compared to managers who do not. Likewise, bringing in a manager who believes he or she can influence oil sales, or who adopts a price follower heuristic, leads to lower prices. These effects start already after a few months.

Given that manager treatment effects may be estimated with varying degrees of precision due to differences in the number of observations per manager and potential noise in the data, we employ empirical Bayes (EB) shrinkage to account for sampling error (Kane et al., 2008; Jacob and Lefgren, 2008; Angrist et al., 2017; DellaVigna and Gentzkow, 2019). Our results to robust to this adjustment, as shown in Appendix Figure B.7.

Figure 11: Regressions of SDID T.E. on cognitive skills, and mental models



Notes: OLS coefficients with 95% CIs. The dependent variable is the SDID treatment effect of the new manager on the price ratio. The first coefficient in each panel is for cognitive skills. Subsequent coefficients are from separate regressions on the given mental model measure, cognitive skills, and controls. Controls in all regressions include noncognitive skills, experience, age, gender, location indicators, station ownership type, station size, open 24 hours, number of competitors, market share, and district fixed effects.

We also performed regression analysis, regressing the SDID treatment effects on traits and mental models of the new manager. In each panel of Figure 11, the first coefficient is for cognitive skills, controlling for other manager traits, and station characteristics. Subsequent coefficients are for each of the mental model measures, each based on a separate regression, controlling for cognitive skills, other traits, and station characteristics. The different panels consider the entire treatment period, the period starting after 6 months, and the period starting after 12 months. The regression analysis is a hard test in that the dependent variable is an estimated variable, and thus contains noise that makes it less likely to have statistically significant explanatory variables. We address heteroscedasticity in the dependent variable by using robust standard errors (Lewis and Linzer, 2005).

The results in Figure 11 show a consistent pattern: having a new manager with low cognitive skills is associated with lower prices, with the difference becoming (marginally) statistically significant if we consider 12 months after the change. The mental model measures are generally significant or marginally significant even including the periods before 12 months, but point estimates get larger considering time frames 6 months, or 12 months, after the change. The coefficients show that bringing in a manager who won the money request game leads to higher prices, while having a new manager who believes managers can influence oil sales, or is a price follower, causes lower prices. If we include all three mental models in the regression simultaneously, along with cognitive skills, these are highly jointly significant (F-test; $p < 0.001$). These results are robust to empirical Bayes shrinkage, as shown in Appendix Figure B.8. In summary, the SDID analysis helps adds further evidence that cognitive skills cause differences in pricing, and this is due in part to how this leads to different mental models of competitors.

5 Cognitive skills and price wars

So far we have shown that managers with higher cognitive skills tend to charge a higher price at their station. More broadly, does the impact of bounded rationality on individual stations further spillover to the local market? We use our daily price data from one region to study the relationship between cognitive skills and market outcomes. The dataset comprise around 900 gas stations with daily price information of all types of oil products and it includes the prices of competitors in the local market. Because the data include competitor prices, we can analyze whether manager cognitive skills are related to being involved in price wars with competitors.

The market condition facing stations in this region is best characterized as the coexistence of two "premium brands", the company we study and another big company, and a competitive fringe of much smaller firms offering a lower quality brand. The government imposes a price ceiling for each oil product. The two large companies choose this price ceiling as their default price in the gas markets. Small company stations, by contrast, often charge gas prices substantially below the ceiling, consistently undercutting the larger, "premium brand" companies. The diesel market is different, with all competitors pricing more frequently below the price ceiling (for our stations, about 40 percent price regularly below the ceiling).

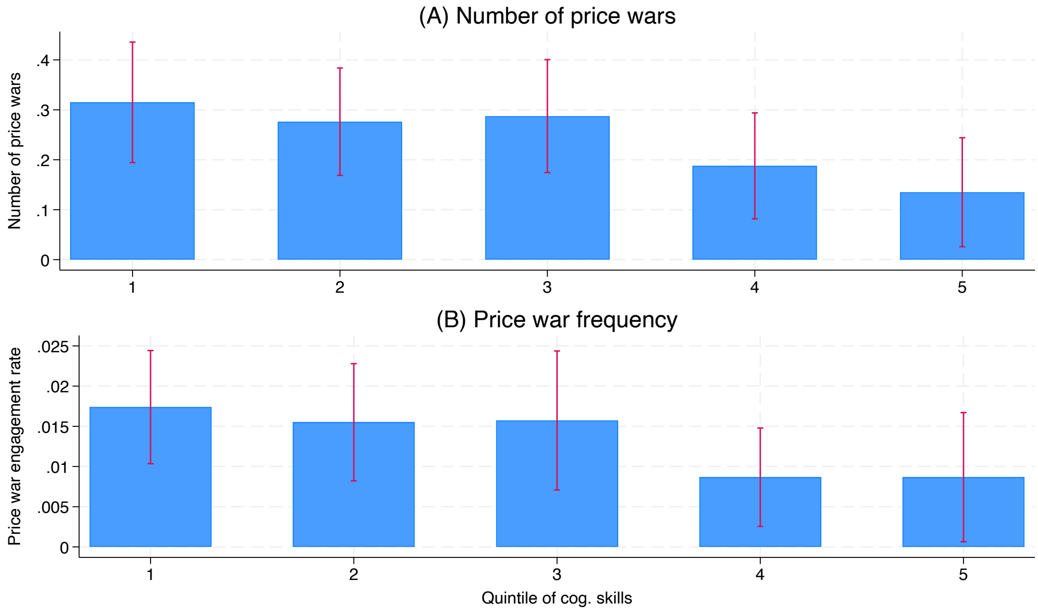
We define a price wars as "mutual price cuts of at least 30 cents from the price ceiling for a period of 14 days or more." Our results are qualitatively consistent if we choose a higher or lower cutoff of price cuts, or if we consider a shorter or longer periods of consecutive price cutting. Here "mutual price cuts" means a station belongs to the company we study and at least one rival station in the local market were involved in the war. For an graphical illustration of the price war, see Appendix Figure B.9.

Price wars are present for both markets, but are relatively rare. We observe 72 price wars in 707 non-monopoly gas markets between 2018 and 2021. Among the 707 managers, 40 of them experienced one or more gas price wars. On average, a gas price war lasted 29 days (median 21 days) and the station belongs to the company we studied lowered their prices by 50 cents in the price war period. Prices wars are more frequent in the diesel market. Among the 617 non-monopoly diesel markets in our dataset, there were 326 price wars between 2018 and 2021 and 121 managers were involved. The diesel price wars also lasted longer (average 39 days; median 27 days) and were more intensive in price cutting (0.55 cents). One likely reason for the different pricing environment for diesel and gas is that diesel customers are more price sensitive, being mainly truck drivers.

Figure 12 plots the relationship between managers' cognitive skills and their propensity to engage in price wars, combining data from both the gas and diesel markets. The top panel depicts the number of wars each quintile of cognitive skills was involved in between 2019 and 2021. While managers in the lowest cognitive skill quintile had around 0.4 price wars over the three years, the number of wars steadily decreased to 0.2 for managers in the highest cognitive skill quintile. The frequency of price wars, displayed in Panel B, which is defined as the ratio of the number of days a gas station engages in a price war to the total number of days observed, shows a similar pattern. Managers in the lowest quintile of cognitive skills engaged in a price war around 2% of the time, while managers in the highest quintile engaged in a price war about half as often. These findings suggest that managers with higher cognitive skills are less prone to engaging in price wars compared to their lower-skilled counterparts. Roughly speaking, about half of the price wars are by lower ability managers and thus might plausibly reflect mistakes.

To deal with the concern that the observed relationship between cognitive skills

Figure 12: Cognitive skills and price wars

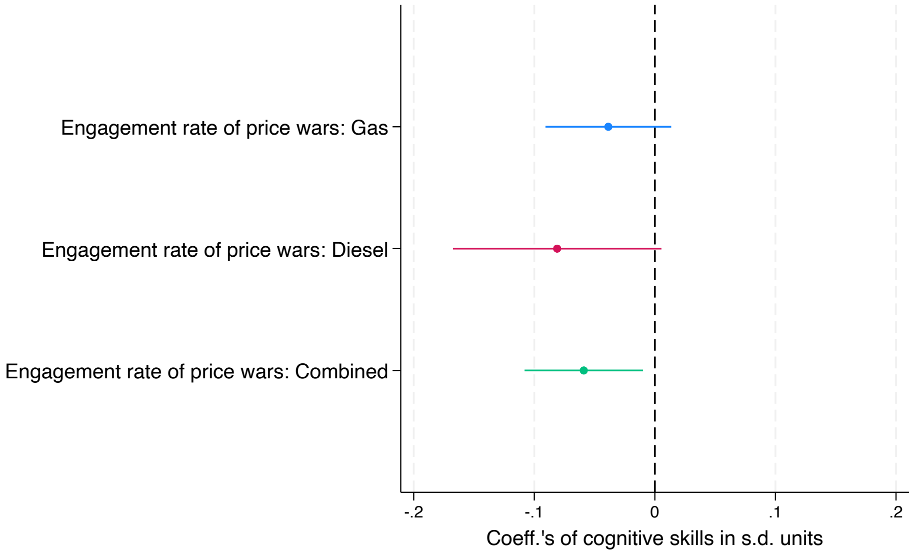


Notes: Relationship between cognitive skills and the number and the frequency of price wars between July 2019 and January 2021. The horizontal axis shows quintiles of cognitive skills, with 1 being the lowest and 5 being the highest. In Panel (A), the vertical axis represents the average number of price wars for managers in each cognitive skill quintile. The 95% confidence intervals for the mean number of price wars are shown as error bars. In Panel (B), the vertical axis is the ratio of the number of days a gas station engages in a price war to the total number of days observed.

and price wars could be the outcome of smart managers being assigned to stations where competition is less fierce, we also run a regression of the frequency of price wars on cognitive skills and controlling for the market conditions (number and type of competitors, location indicators, etc). Figure 13 displays the coefficients from the OLS regression of cognitive skills on the engagement rate of price wars. After controlling for the observable market conditions, we still find that managers with higher cognitive skills are significantly less engaged in price wars, in both the gas and the diesel markets.

Next, we explore the profit consequences of engaging in a price war. For a price war to be beneficial, a necessary condition is that competitors charge a higher price after the war than before the war. To test whether this necessary condition is satisfied, we compare the average competitors prices 14 days before a price war to the average competitors prices 14 days after a price war. Appendix Figure B.11 shows the competitor prices in the gas market and diesel markets. In the top-left and bottom-left panels, we observe that the price war does not have a significant effect on average competitor prices in both the gas and the diesel markets. The competitor prices barely change in the post-war two weeks compared to the pre-war two weeks. Thus, price wars are plausibly a mistake if the demand of the stations we studied depend on the prices of all

Figure 13: Frequency of price wars as a function of manager traits



Notes: Coefficients from OLS regressions, with 95% confidence intervals based on robust standard errors clustering on the station. Controls include noncognitive skills, experience, age, gender, location indicators, station ownership type, station size, open 24 hours, number of large competitor stations, number of own company competitors stations, number of small company competitor stations, market share, and interacted day and district fixed effects.

competitors or an average competitor.

The top-right and the bottom-right panels of Appendix Figure B.11 display the prices of the competitors that were involved in the price war, where involvement is defined as cutting the price by at least 30 cents relative to the price ceiling during the entire price war period. A first observation is that the involved competitors had already lowered their prices prior to the beginning of the price war, which suggests that they initiated the price war and the stations we studied responded to the price cut in most cases. Second, there is an increase in their prices after the war ends compared to the pre-war level in both types of markets. However, the increase is modest (2 percentage points), and the involved competitors still charge substantially lower prices than the average competitor level after the war. Interestingly, the involved stations only raised their prices to the level before they started to cut the prices, which suggests that a war with them is unlikely to be a way to establish coordination on high prices. One interpretation is that managers with lower cognitive skills are more prone to react to being undercut by lowering their prices, even though this does not have strategic benefits when the competitors are the low-price stations.

In summary, we do not find a strong effect of price wars on raising the prices of competitors. Given the cost incurred during the price war, it is difficult to determine whether price wars are beneficial or not, and further, whether charging low prices is a good strategy. In the next section, we study the relationship between the pricing strategies of managers with low and high cognitive skills and the profits of their stations.

6 Pricing strategies and profits

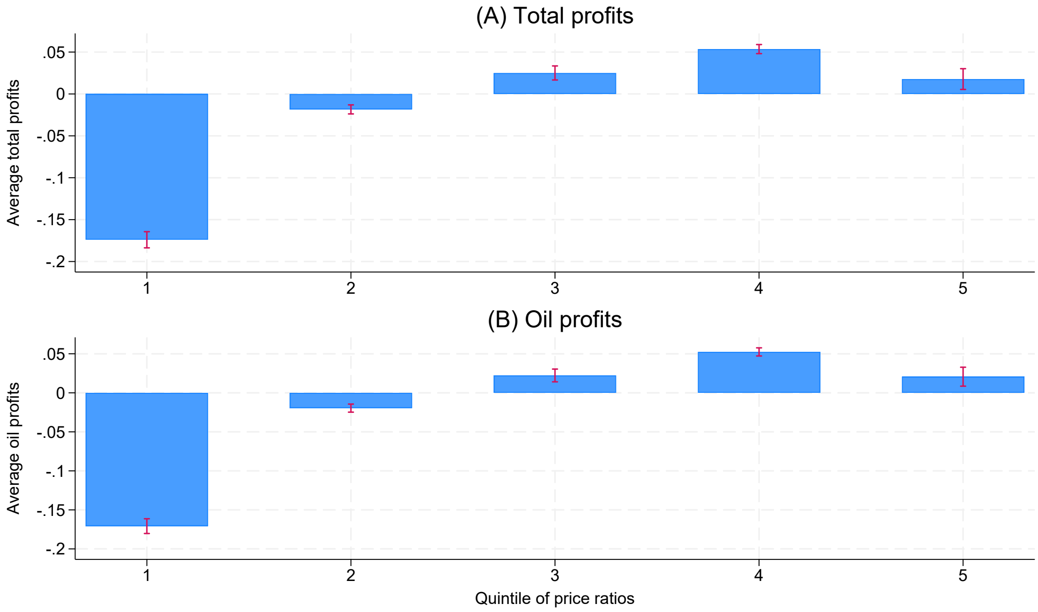
We have established that managers with different cognitive skills have different mental models regarding the optimal pricing strategies and indeed charge different prices in line with these models. The next question is whether the strategy to charge a lower price adopted by managers with lower cognitive skills is less beneficial to the company. It is challenging as researchers to know exactly what is the optimal price for a given station at a given point in time, not least because the environment is one of strategic competition rather than perfect competition. For example, charging low prices could lead to low profits in the short run, if the fall in revenues outstrips the gain in sales volume, but there could be a long-run benefit if this helps discipline competitors and encourage coordination on, e.g., pricing at the price ceiling. Another issue is the possibility of reverse causality. If managers with lower cognitive skills have lower profits for some other reason, they might try to mitigate this by charging low prices (although it is not obvious that lowering price is a good remedy for low profits).

In this section we provide several pieces of evidence that suggest the more aggressive pricing of managers with low cognitive skills may, in fact, be a mistake that contributes to low profits. A first observation is that it is already suggestive that lower prices are being chosen by those with lower cognitive skills; since cognitive skills are related to ability to predict competitors, and are a measure of decision quality, there is already a reason to think that pricing strategies associated with low cognitive skills may be less beneficial.

We can also see that the lower prices charged by managers with low cognitive skills are strongly, negatively correlated with contemporaneous profits. As shown in Panel (a) of Figure 14, total profits are substantially lower for price ratios that are in the bottom quintile (this corresponds to a roughly 5.5% reduction in price relative to the price ceiling). The data suggest that the optimal price is either very close to, or at, the price ceiling, which is notably consistent with the company policy to make the price ceiling the default price. Panel (b) shows that this is driven by how prices influence oil profits. By contrast, nonoil profits are higher for lower price ratios, which makes sense given that low oil prices can attract more customers to the store, but this relationship is relatively weak and is dominated by the negative relationship with oil profits.

As shown in Figure 15, managers with lower cognitive skills are significantly more likely to implement the deep price cuts associated with low contemporaneous profits.

Figure 14: Average profits by quintile of price ratio



Notes: Results are from monthly price and profit data for 25 regions.

These results do not rule out that deep price cuts could have long run benefits, but on the other hand, if we regress profits on cognitive skills we have seen that managers with lower cognitive skills have lower average profits during their careers as managers. Thus, it does not seem that their lower prices have long-run benefits that outweigh short run downsides.

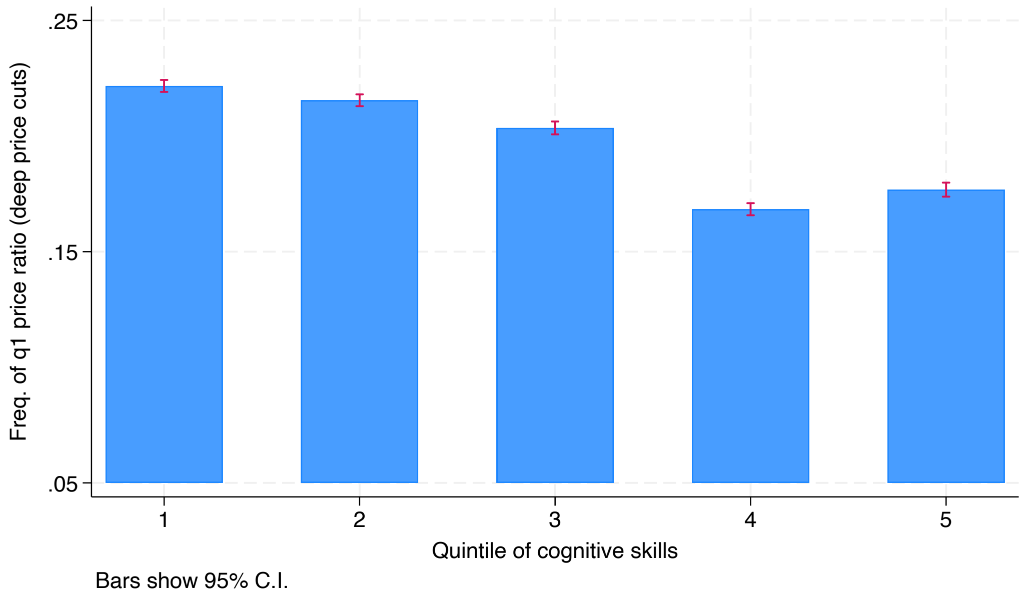
Table 3: Views of district level managers about the optimality of price cuts

If station managers have full autonomy over price setting, do you think the price will be:	Frequency	Percentage
Higher than the current price	11	3%
Same as the current price	91	27%
Lower than the current price	236	70%
If station managers have full autonomy over price setting, do you think the price will be:		
A price that is too high	28	8%
The optimal price	53	16%
A price that is too low	257	76%

Notes: Results are from a survey with 353 district level managers.

Another type of evidence comes from our survey of district level managers, where we asked for their views on the pricing strategies of station managers. As shown in table 3, the district managers overwhelmingly say that station managers have a tendency to cut prices, if they are given more autonomy over price. Furthermore, when asked whether the price chosen by station managers would be too high, about right, or too low, roughly 75% say too low. We also asked district managers an open-ended question, about whether it was a good idea to compete aggressively by lowering price and undercutting competitors. Coding the text responses, we see that roughly 70% of the district managers think this is a bad idea, and the most common reason given is concern about

Figure 15: Frequency of deep price cuts by quintile of cognitive skills



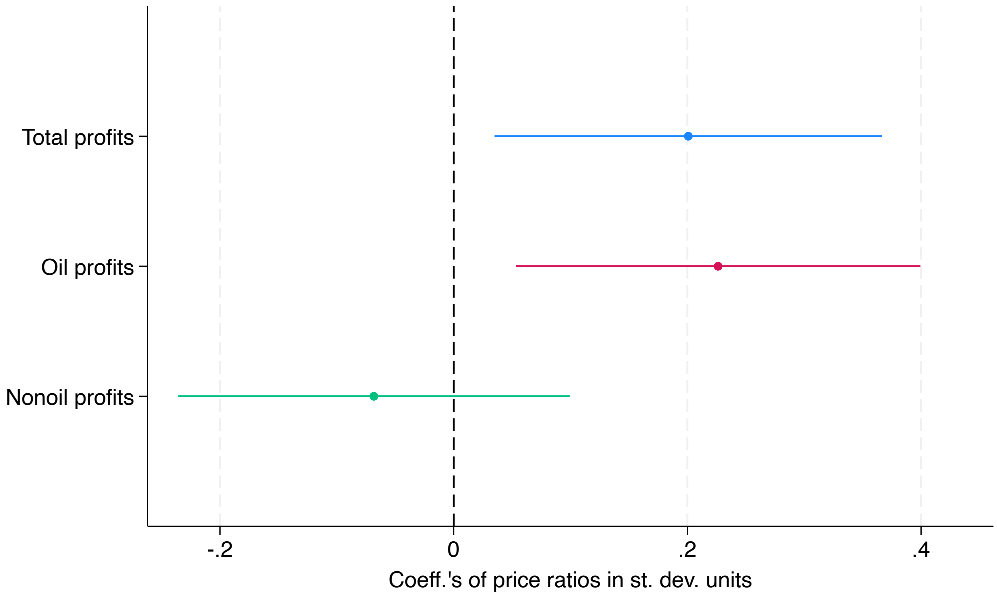
Notes: Results are from daily price data for one region.

price wars. Thus, district level managers seem to be concerned that station managers may make a mistake by being overly aggressive with price cuts. This raises doubts that price cuts have long run benefits, and also suggests district managers see causality going from price cuts to low profits. In Section 5, we also saw that there is little evidence of price wars having long-run benefits in terms of establishing high prices in the long run, in the sense that competitor prices are typically not very different after the price war compared to before.

To further establish the causal relationship between price charged by managers and the profit of the station, we adopt an instrumental variables approach. We use the measures of mental models, namely the performance in the money request game, the price-matching heuristic, and the confidence in influencing oil profits, to instrument for the price ratio. We have shown in Figure 8 that the mental models are strongly correlated with price ratio and highly jointly significant, providing a strong first stage. In addition, all three measures we use are relatively narrowly focused on pricing, and thus it is plausible that they influence profits only through prices, thereby satisfying the exclusion restriction.

Figure 16 shows the results of two-stage least squares regressions, explaining station performance with instrumented price ratio. We see that total profits are positively related to price ratio, and the effect is significant at the 5% level. This positive relationship is mainly driven by higher oil profits. The point estimate is negative for nonoil profits, consistent with low oil prices increasing nonoil profits, but this is not statisti-

Figure 16: Profits as a function of instrumented price



Notes: Coefficients from 2SLS regression, instrumenting price with mental models, with 95% confidence intervals based on robust standard errors clustering on station. Controls include cognitive skills, noncognitive skills, experience, age, gender, location indicators, station ownership type, station size, open 24 hours, number of competitors, market share, and interacted month and district fixed effects. Results are from monthly data from 25 regions.

cally significant. Taken together, our results suggest that the more aggressive pricing of managers with lower cognitive skills can lead to lower profits.

7 Why boundedly rational managers are allowed to set prices?

Our results indicate that managers with different cognitive skills charge different prices in line with their mental models, and the low prices charged by managers of low cognitive skills lead to more price wars and lower profits. A natural question arising is why the upper-level management still give station managers the autonomy to set prices? Does this reflect a bounded rationality at the upper-level management's side or is it an outcome of a trade-off faced by the upper-level management?

First, it is noteworthy that the upper-level management indeed put restrictions on the autonomy of the managers, especially on pricing. As shown in Figure 1, managers are required to make a proposal to the district-level management if they want to change the oil prices in more than of the districts. There is often a pre-specified range of allowed prices even when station managers have the autonomy to change the prices without reporting. When station managers make a proposal to change prices, xxx% of their proposals are rejected by the district-level managers as reported by the station managers in the survey. Thus, it is not the case that the autonomy of station managers are unrestricted.

Second, there are evidence suggesting that district-level managers are aware and concerned about some managers' low-pricing strategies. The restrictions on the pricing autonomy of station managers can be seen as a sign of such a concern. More directly, as shown in Table 3, the majority of district managers state in the survey that they believe station managers would charge a price lower than the current level if they were given full autonomy, and that the price charged by them would be lower than what is optimal.

Third, given they are aware of the issue and are putting restrictions on station manager's pricing autonomy, the next question is why do district-level managers not centralize pricing? There are two potential reasons against centralized pricing. First, from a strategic perspective, giving station managers no autonomy and committing to a price will allow the competitors to undercut slightly and overtake the whole market. Giving station managers the possibility to respond to competing station could be beneficial strategically. Second, it is also unclear what is the optimal pricing level at different stations. Even though setting the prices high near the ceiling is, on average, better than setting prices substantially below the ceiling, setting it at the ceiling is not always optimal. Elasticity varies a lot at the station level. For example, the elasticity in #92 gas ranges from close to 0 to -4, and the elasticity in #0 diesel ranges from close to 0 to -8. Thus, the optimal level of pricing for a specific station at a specific time might require local knowledge. Setting the prices at the ceiling all the time also leaves money on the table, as shown by DellaVigna and Gentzkow (2019). Another important dimension of local knowledge is the strategy and sophistication of the competitors in the local market. It is hard for the district-level manager but relatively easy for the station managers to know the marginal costs of the competitors, their current promotion policies, how sophisticated their managers are, whether they have autonomy to change prices, and so on. In fact, the most important reason to give autonomy to station managers as stated by the district-level managers is their local knowledge.

8 Implications of boundedly rational pricing policies for welfare and measured market power

In this section we assess how the different pricing strategies associated with low and high cognitive skills affect PS, CS, DWL and measured market power. As discussed below, our calculations require making some additional assumptions. We provide further details in Appendix B.6.

To measure the impacts of price changes on surplus and efficiency, we follow a previous literature evaluating the efficiency implications of gas price changes due to, e.g., gasoline tax, by assuming a constant elasticity demand function (see, e.g., Davis, 2014). In particular, we assume that there is such a demand function facing a typical, individual station. This enables calibrating the demand function using relatively little data: An estimate of the price elasticity of demand for an individual station, and also observed average volume sold at the average price.

Estimating the price elasticity of demand is challenging for the well-known reason that observed equilibrium prices are jointly determined by demand and supply. Finding plausible instruments for price is often challenging. A useful feature of the market we study, however, is that variation in the price ceiling provides exogenous variation in prices. Using the region where we observe daily prices and volume sold, we regress the natural log of the average daily volume of oil products sold (the average is across all types of oil products sold by a station) on the average price of oil products, instrumenting for price with the price ceiling. The coefficient on price gives the demand elasticity. We find that the price elasticity of demand for oil products is -0.98 (in our data, gasoline is less elastic than this average, and diesel is more elastic).[13]

We use a calibrated version of the demand function to calculate the observed impact of cognitive skills on oil prices. We also assume constant MC, and consider a range of plausible values for MC. The impact on PS is simply the difference in $p_i * q_i - mc * q_i$ for the high and low skill managers, with $i \in \{h, l\}$. Going from one of the highest skilled managers to one of the lowest (2 s.d. difference in cognitive skills) decreases the PS provided by the station by \$5,211 per year given the average value for marginal cost. Lower prices imply, however, a higher CS. The change in CS is given by the area to the left of the demand curve between the higher and lower prices implied by the difference in cognitive skills. We calculate an increase in CS of about \$6,199 per year from having a manager with low cognitive skills. The resulting impact is a reduction in DWL of about 7 percent.

Turning to standard measures of market power based on the markup of price over marginal cost ($\frac{p-mc}{p}$), we can assess the impact of cognitive skills under plausible assumptions about marginal cost. We calculate that the lowest ability managers have a markup that is about 4 percent lower than for the highest ability managers. This means that the same gas station facing the same market conditions can have substantially more or less measured market power depending on the cognitive skills of the manager. As an-

[13]In our data, demand for gasoline is less price elastic than diesel. Although methodologies and estimates of elasticities for oil products differ in previous literature, Brons et al. (2008) provide a meta-analysis for gasoline and report a short-run price elasticity of -0.34, which is very similar to our estimate for 92 gas, -0.33.

other benchmark, we can compare the impact of cognitive skills on price to the impact of having an additional gas station competitor; the effect of replacing the high ability manager with a low ability manager is about one-tenth of the effect of adding an entire new gas station competitor in the local market (for this benchmark we use an estimate from Hastings, 2004).

9 Conclusion

In conclusion, our analysis reveals that variation in cognitive skills is a significant factor in explaining the mental models that decision makers have about ways to be successful in competition, and about competitor behavior. In particular, lower cognitive skills are associated with gas station managers viewing low prices as a path to success, and mediating factors are a worse ability to model the behavior of competitors. Importantly, the influence of cognitive skills is durable; it does not dissipate with increased experience. This difference in mental models in turn leads to systematic effects on pricing strategies, with lower cognitive ability leading to more aggressive price cuts for oil products and more price wars. This strategy contributes to lower profits, seemingly because it reduces short run profits without any long run benefit. Consumers benefit, however, from the presence of such managers, due to lower prices for oil products, and market efficiency is plausibly improved. Measured market power, an important diagnostic for market competitiveness, varies substantially with cognitive skills of decisions makers setting prices.

Our study has implications for both economic theory and policy. The presumption of perfect rationality among firms, a common fixture in economic models, may distort interpretations of market data. Our findings advocate for the incorporation of firm heterogeneity with respect to rationality into economic models. Our findings support modeling bounded rationality as leading firms to underestimate the sophistication of competitors, with implications for pricing behavior and profits. From a policy perspective, the role of information in shaping market behavior becomes particularly salient, given that mental models appear to matter for strategic behavior, although our results suggest that differences in mental models are resistant to the accumulation of experience. Conventional indicators of aggressive competition, such as price cuts and price wars, may not necessarily signify successful collusion, which implies a need for a nuanced understanding of competitive market signals in policy formulation. Moreover, the shift toward algorithmic pricing raises important questions about the potential for increased prices, market structure and consumer welfare.

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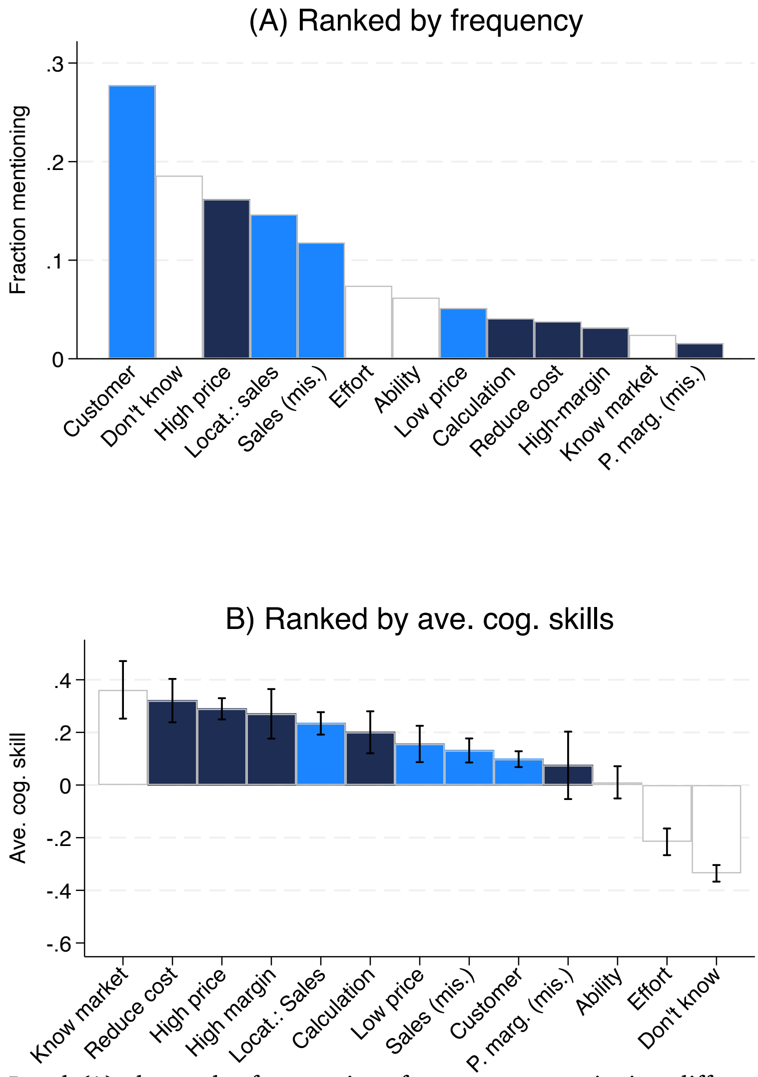
A Mental models

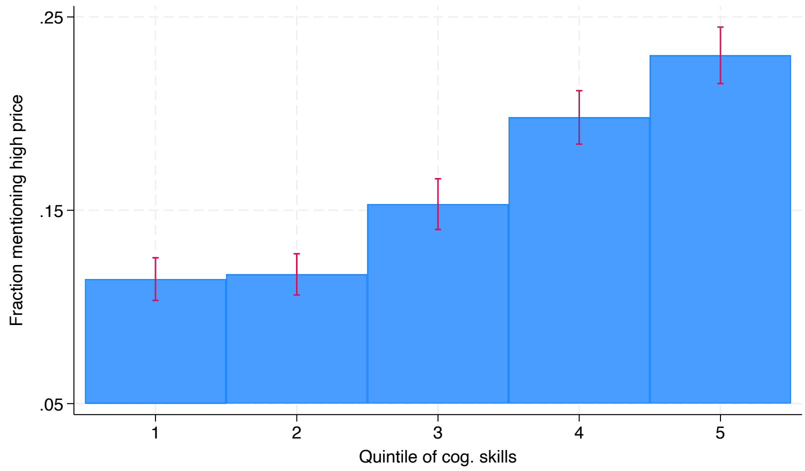
A.1 Additional results on mental models

Figure A.1: Narrative measure of mental models for high oil profits, all narratives



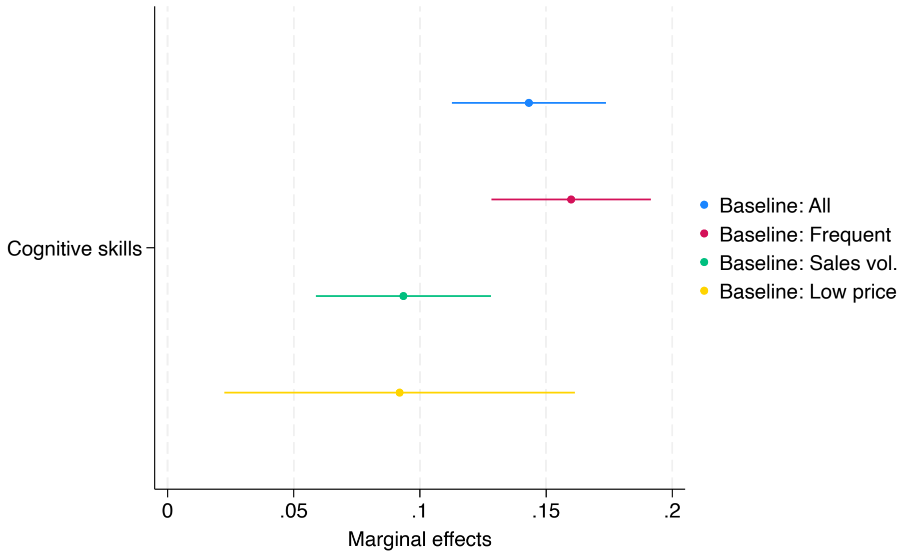
Notes: Panel (A) shows the frequencies of managers mentioning different categories of causes of high oil profits. *Location: Sales* refers to narratives in which the location is favorable to high volume; *Low price* refers to high volume through low prices; *Sales (mis.)* indicates mentioning sales volume but without further explanation. P. marg. (mis.) indicates mentioning profit margin without further explanation. Panel (B) shows the average cognitive skills of the groups of managers mentioning the respective causes. Error bars indicate 95% C.I.s..

Figure A.2: Frequency mentioning high price cause by quintile of cognitive skills



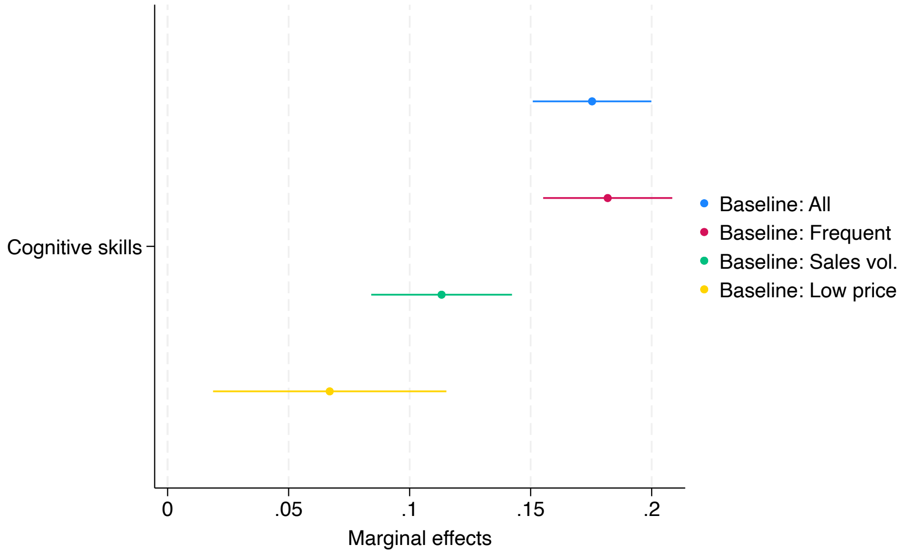
Notes: Error bars show 95% C.I.'s.

Figure A.3: Probability of mentioning high price cause and cognitive skills, managers mentioning a single cause



Notes: Marginal effects from Probit regressions with 95% C.I.'s and robust s.e.. Each coefficient is from a separate regression, and shows how a 1 s.d. increase in cognitive skills translates into the probability of mentioning the high price cause, relative to mentioning a cause from the respective baseline group, controlling for other manager characteristics. The sample is restricted to managers who mention only a single cause. *All* uses all managers who mention either high price, or one alternative cause. *Frequent* only uses managers who mention either high price or one of the relatively frequent alternative causes. *Sales vol.* uses managers who mention either high price or a single cause from the sales volume category. *Low price* only uses managers who mention either high price or the low price cause. All regressions control for noncognitive skills, experience, gender, and age.

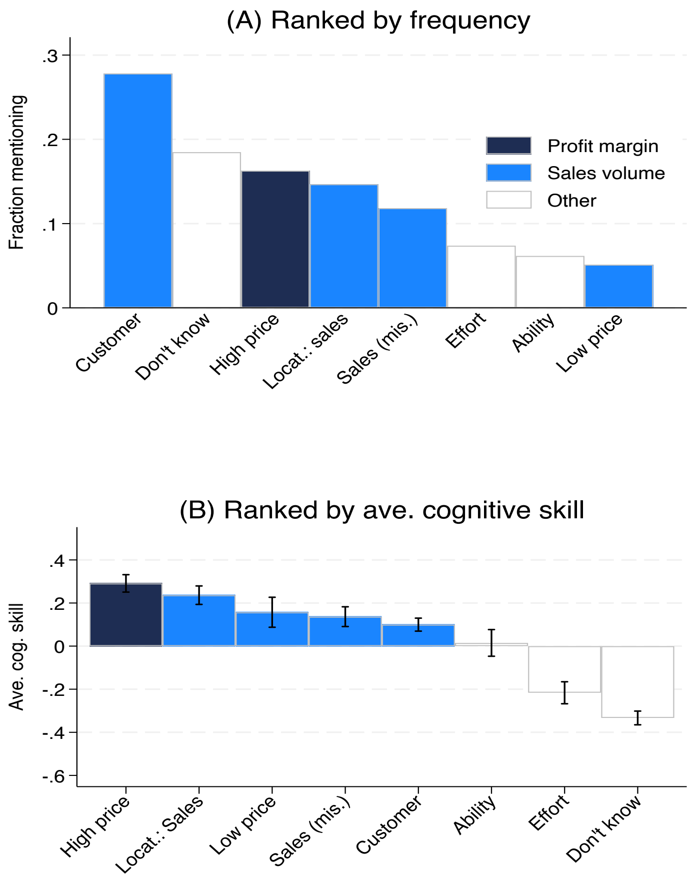
Figure A.4: Probability of mentioning high price narrative and cognitive skills, including managers mentioning multiple causes



Notes: Marginal effects from Probit regressions with 95% C.I.'s. Each coefficient is from a separate regression, and shows how a 1 s.d. increase in cognitive skills translates into the probability of mentioning the high price narrative, relative to instead mentioning one or more causes from the respective baseline group of causes, controlling for other manager characteristics. *All* uses all managers and tests whether cognitive skills matter for whether a manager mentions the high price cause instead of or in addition to other causes. *Frequent* excludes managers who mentioned one or more of the infrequent causes. *Sales vol.* excludes managers who mentioned one or more causes besides high price or causes from the sales volume category. *Low price* only uses managers who mention either high price or low price or both. All regressions control for noncognitive skills, experience, gender, and age.

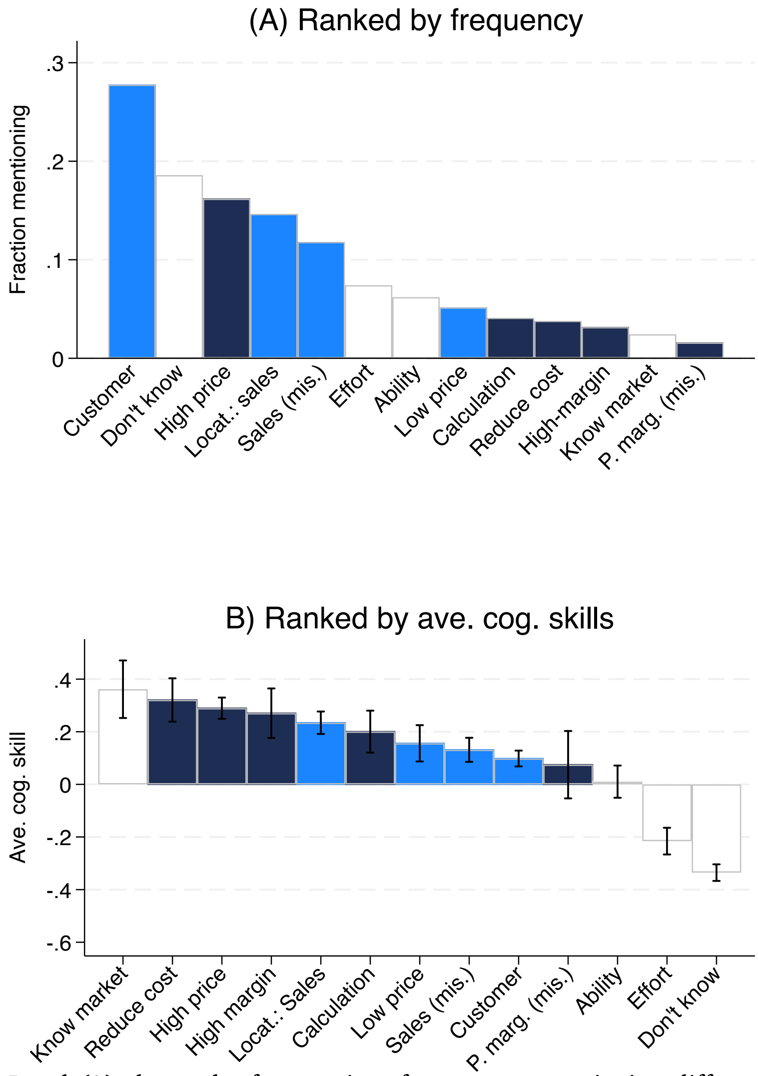
A.2 Robustness checks on mental models

Figure A.5: Narrative measure of mental models for high oil profits, frequent narratives (RA's agree)



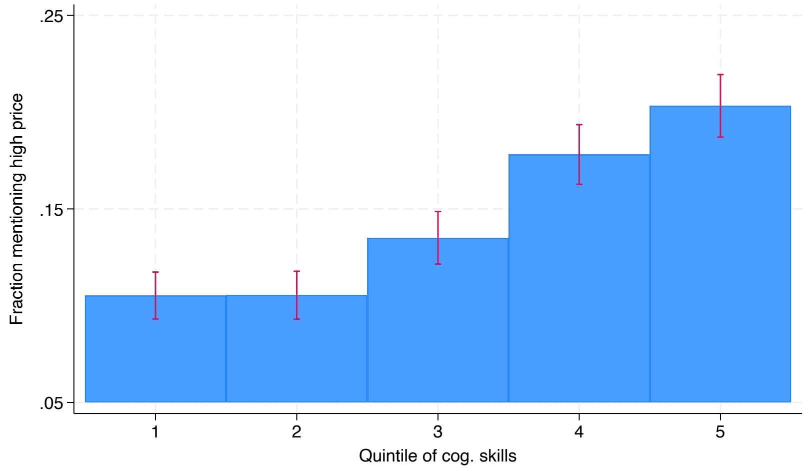
Notes: Panel (A) shows the frequencies of managers mentioning different categories of causes of high oil profits, but excludes causes mentioned by less than 5 percent of managers. The figure only shows the 75% of cases with full RA agreement. *Location: Sales* refers to narratives in which the location is favorable to high volume; *Low price* refers to high volume through low prices; *Sales (mis.)* indicates mentioning sales volume but without further explanation. Panel (B) shows the average cognitive skills of the groups of managers mentioning the respective causes. Error bars indicate 95% C.I.s.

Figure A.6: Narrative measure of mental models for high oil profits, all narratives (RA's agree)



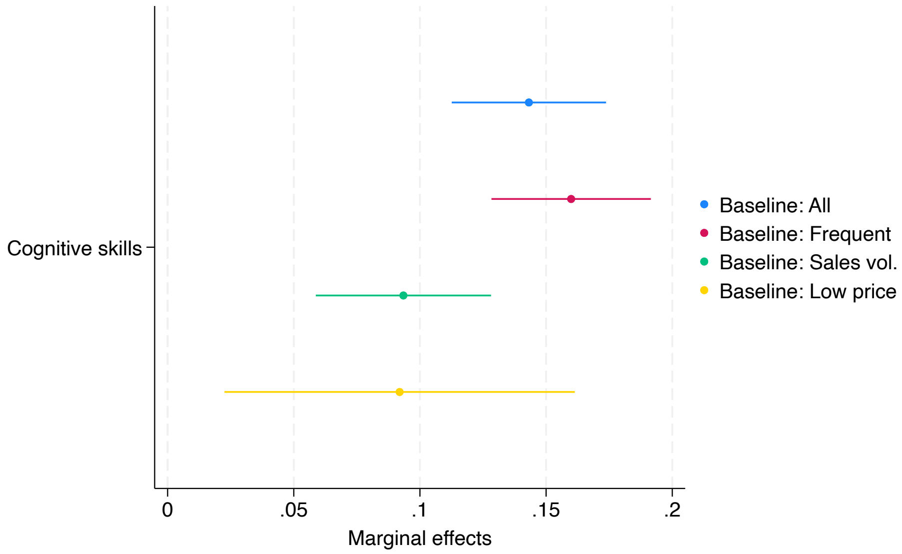
Notes: Panel (A) shows the frequencies of managers mentioning different categories of causes of high oil profits, based on the 75% of narratives agreed upon by RA's. *Location: Sales* refers to narratives in which the location is favorable to high volume; *Low price* refers to high volume through low prices; *Sales (mis.)* indicates mentioning sales volume but without further explanation. P. marg. (mis.) indicates mentioning profit margin without further explanation. Panel (B) shows the average cognitive skills of the groups of managers mentioning these respective causes. Error bars indicate 95% C.I.s..

Figure A.7: Frequency mentioning high price cause by quintile of cognitive skills (RA's agree)



Notes: Classification of high price cause includes only the 75% of cases with full RA agreement. Error bars show 95% C.I.'s.

Figure A.8: Probability of mentioning high price cause and cognitive skills, managers mentioning a single cause (RA's agree)

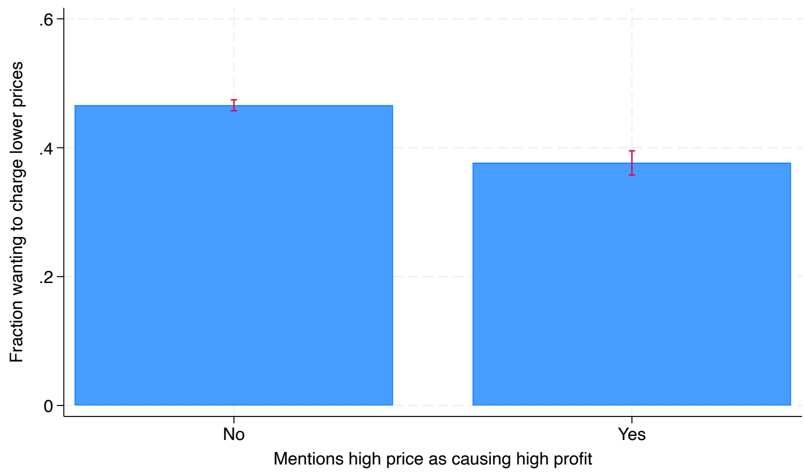


Notes: Marginal effects from Probit regressions with 95% C.I.'s and robust s.e.. Classification of high price cause includes only the 75% of cases with full RA agreement. Each coefficient is from a separate regression, and shows how a 1 s.d. increase in cognitive skills translates into the probability of mentioning the high price cause, relative to mentioning a cause from the respective baseline group, controlling for other manager characteristics. The sample is restricted to managers who mention only a single cause. *All* uses all managers who mention either high price, or one alternative cause. *Frequent* only uses managers who mention either high price or one of the relatively frequent alternative causes. *Sales vol.* uses managers who mention either high price or a single cause from the sales volume category. *Low price* only uses managers who mention either high price or the low price cause. All regressions control for noncognitive skills, experience, gender, and age.

B Pricing behavior and cognitive skills

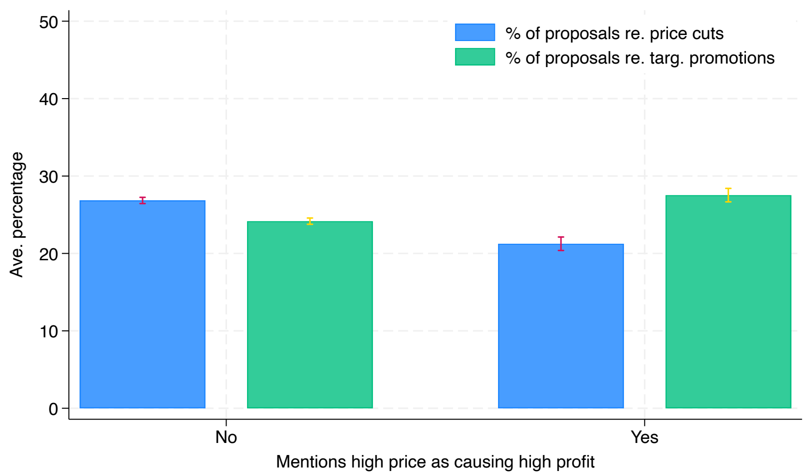
B.1 Additional results on self-reported pricing

Figure B.1: Self-reported tendency to cut prices and belief that high price fosters high oil profits



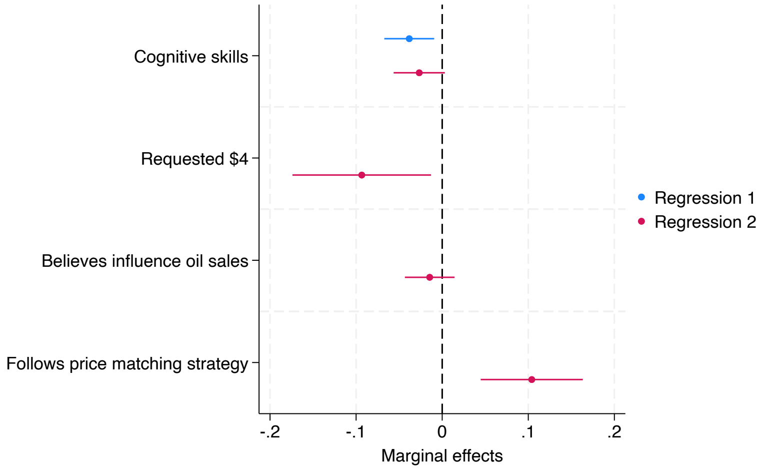
Notes: The figure shows the fraction of managers reporting a tendency to charge lower price than the default suggested by upper level management, according to whether they mentioned high price as a cause of high oil profits in the narratives measure. Error bars show 95% C.I.'s.

Figure B.2: Self-reported frequency of proposing price cuts, versus targeted promotions, by belief that high price fosters high oil profits



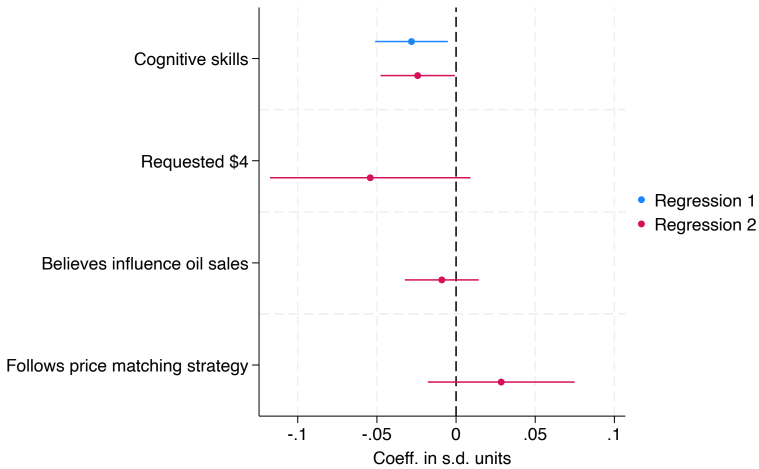
Notes: The bars show the average self-reported percentage of proposals that a manager makes, which are about requesting direct oil price cuts, or about launching targeted promotions. These percentages are show according to whether or not the manager mentioned high price as a cause of high oil profits in the narratives measure. Error bars show 95% C.I.'s.

Figure B.3: Probability of stating a desire to cut prices as a function of cognitive skills, mental models, and other traits



Notes: Marginal effects from Probit regressions with 95% C.I.'s and robust s.e.. The dependent variable equals 1 if the manager reports a tendency to cut prices relative to the default price suggested by upper management. The first model reports the coefficient for cognitive skills but also controls for other manager traits: noncognitive skills, experience, gender, and age. The second model includes these traits but adds three measures of mental models of competitors.

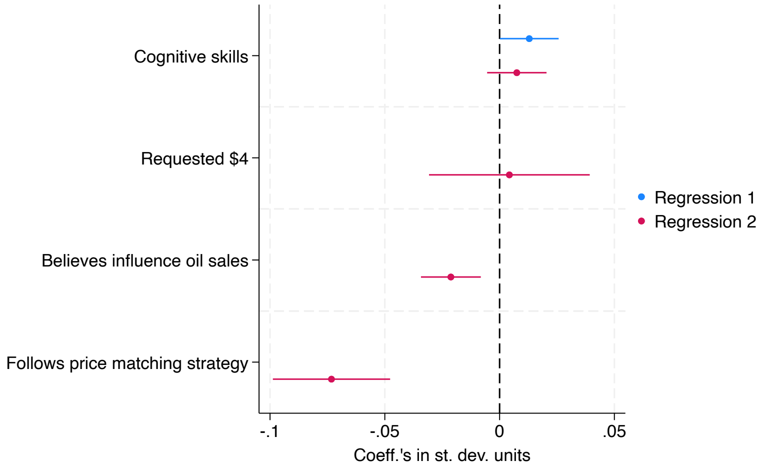
Figure B.4: Self-reported percentage of proposals that are about cutting oil prices as a function of cognitive skills, mental models, and other traits



Notes: Coefficients from OLS regressions with 95% C.I.'s and robust s.e.. The dependent variable is the self-reported percentage of proposals that the manager makes that are to cut oil prices. The first model reports the coefficient for cognitive skills but also controls for other manager traits: noncognitive skills, experience, gender, and age. The second model includes these traits but adds three measures of mental models of competitors.

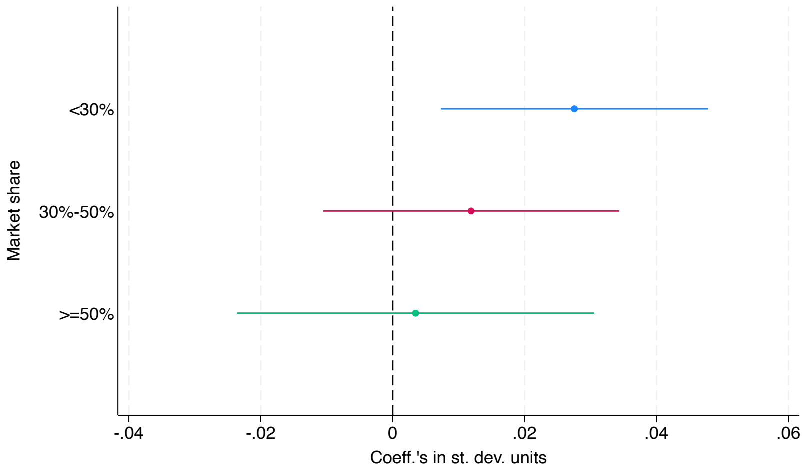
B.2 Additional results on actual pricing

Figure B.5: Pricing behavior as a function of cognitive skills: controlling for non-cognitive skills separately



Notes: Coefficients from OLS regression, with 95% confidence intervals based on robust standard errors clustering on station. Instead of controlling for the non-cognitive factor, we control for all individual non-cognitive skills. Controls also include gender, age, experience, station location indicators, station ownership type, station size, open 24 hours, number of competitors, and interacted day and district fixed effects. Results are from monthly price data.

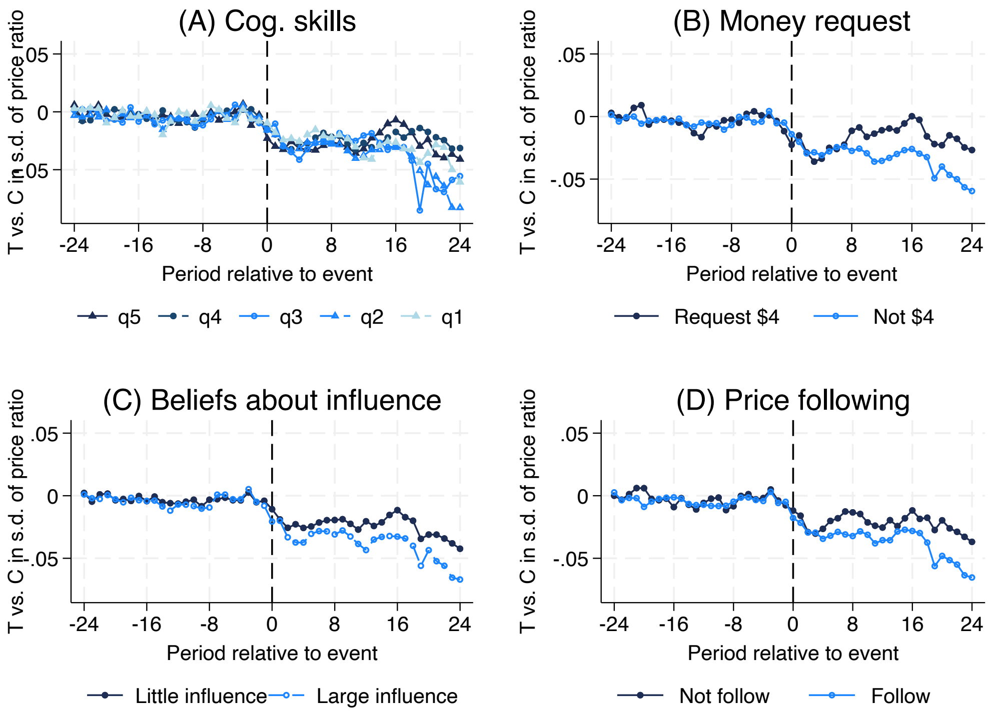
Figure B.6: Pricing behavior as a function of cognitive skills: by market share



Notes: Coefficients from OLS regression, with 95% confidence intervals based on robust standard errors clustering on station. Controls include noncognitive skills, experience, gender, age, location indicators, station ownership type, station size, open 24 hours, number of competitors, and interacted day and district fixed effects. Results are from monthly price data.

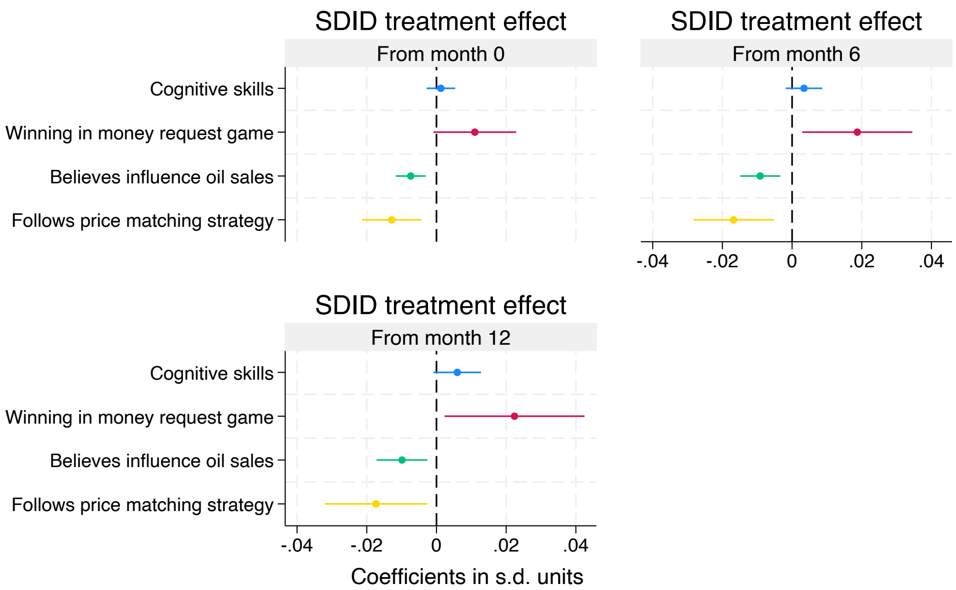
B.3 Additional results on synthetic difference-in-differences

Figure B.7: SDID treatment effects, cognitive skills, and mental models after Bayesian shrinkage



Notes: Treatment effects on price ratio versus the synthetic control stations from SDID regressions, by traits of the NEW manager. These are categorized in Panel (A) by above or below median cognitive skills, in Panel (B) by requesting $4 in the money request game or requesting a different amount, in Panel (C) by above or below median belief in ability to influence oils sales in the middle panel, and in Panel (D) by whether a manager uses the price following heuristic in the bottom panel.

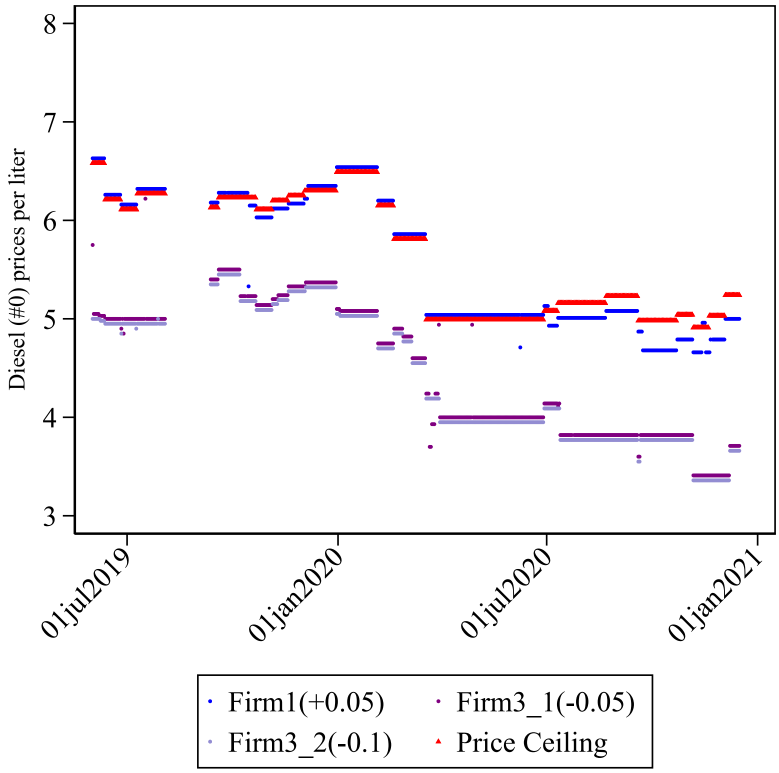
Figure B.8: Regressions of SDID T.E. on cognitive skills, and mental models after Bayesian shrinkage



Notes: OLS coefficients with 95% CIs. The dependent variable is the SDID treatment effect of the new manager on the price ratio. The first coefficient in each panel is for cognitive skills. Subsequent coefficients are from separate regressions on the given mental model measure, cognitive skills, and controls. Controls in all regressions include noncognitive skills, experience, age, gender, location indicators, station ownership type, station size, open 24 hours, number of competitors, market share, and district fixed effects.

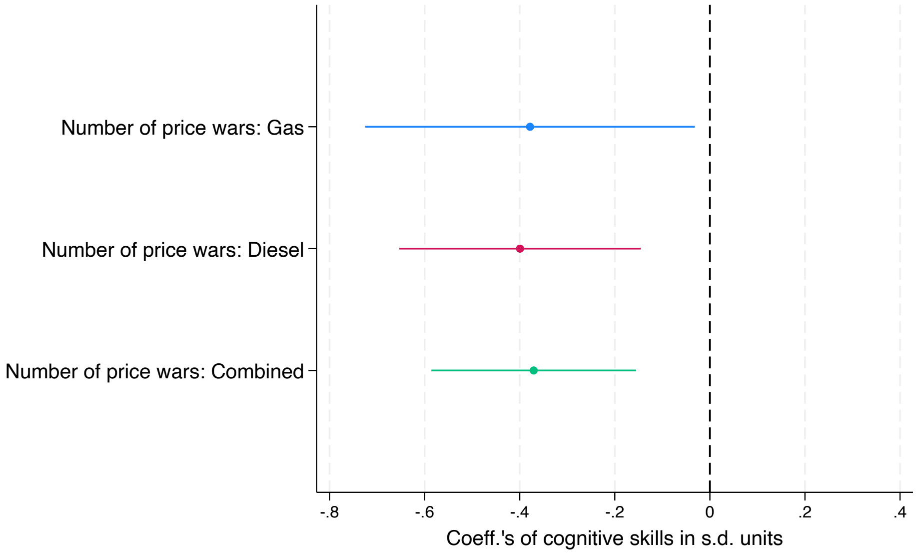
B.4 Additional results on price wars

Figure B.9: Price competition in a local diesel market



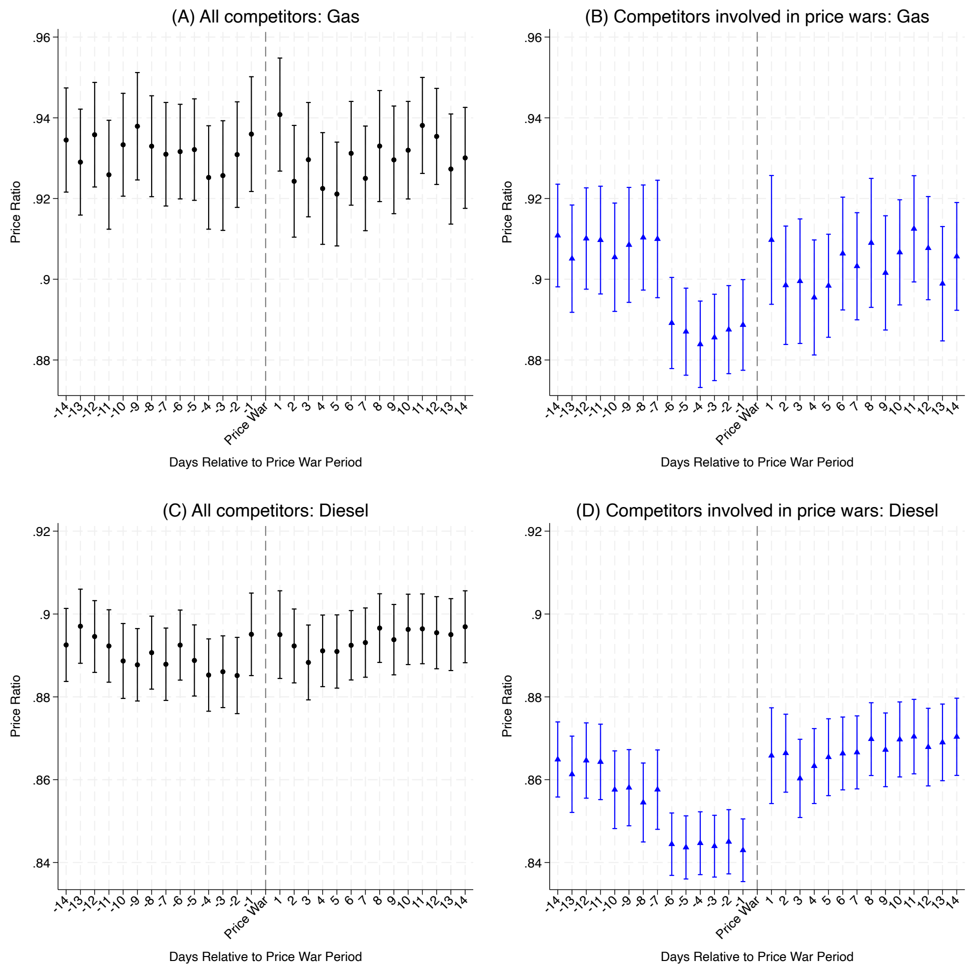
Notes: This figure depicts number 0 diesel prices per liter for three firms in a local market from July 1, 2019 to January 1, 2021. The red triangle shows the government-imposed price ceiling. The prices of Firm 1 (+0.05), the company studied in this paper, and two small competitor stations, Firm 3_1 (-0.05) and Firm 3_2 (-0.1), are plotted as dots. The prices for each firm are slightly shifted vertically for visual clarity, with the amount of shift indicated in parentheses next to the firm's name.

Figure B.10: Number of price wars as a function of manager traits



Notes: Coefficients from negative binomial regressions, with 95% confidence intervals based on robust standard errors clustering on the station. Controls include noncognitive skills, experience, gender, age, location indicators, station ownership type, station size, open 24 hours, number of large competitor stations, number of own company competitors stations, number of small company competitor stations, market share, and interacted day and district fixed effects.

Figure B.11: Competitor prices before and after price wars



Notes: Average competitor prices 14 days before a price war and 14 days after a price war. Panel (A) and (C) display the average prices of all competitors. Panel (B) and (D) display the average prices of competitors that were involved in price wars. Here involvement means charging a price at least 30 cents lower than the price ceiling on each day during the price war.

B.5 Estimation of demand elasticity

B.6 Details on calculations of PS, CS, DWL, and markups

We assume a station faces a constant elasticity (residual) daily demand curve, $q = a * p^{\epsilon}$. To calibrate demand we first estimate the price elasticity of demand, ϵ, using our data from the region with daily price and sales quantity data. We regress the natural log of daily sales volume of oil products on the natural log of price and controls, instrumenting for price with the price ceiling (as expected the first stage is very strong, with a t-statistic for the price ceiling of $t = 145.5$). We obtain an average price elasticity of $\epsilon = -0.98$. We can then rearrange the demand function to obtain $a = \frac{q}{p_1^{\epsilon}}$, and solve for a using average price and daily sales volume of oil products. This leads to our calibrated demand function.

To calculate the impact on producers surplus of having a manager with lower cognitive skills, we calculate the difference $(p_1 * q_1 - MC * q_1) - (p_0 * q_0 - MC * q_0)$ under a range of assumptions about marginal cost. We denote by p_1 and q_1 the price and quantity for the high skill manager and by p_0 and q_0 the corresponding values for the low skill manager. We consider a plausible range of marginal cost values, based on information from the partner firm that these range from 80 to 90 percent of the price ceiling. Using the average price ceiling, this gives a range of values for MC. Our calculations indicate that the price decrease associated with a 2 s.d. decrease in cognitive skills translates into a reduction in producer surplus ranging from roughly \$5,020 to \$5,640 per year, depending on whether marginal cost is at the low or high end of the plausible range, respectively.

Turning to CS, the change in daily consumer surplus from a price reduction is given by the area to the left of the demand curve, between the high price of a high skill manager (p_1) and the lower price of a low skill manager, p_0:

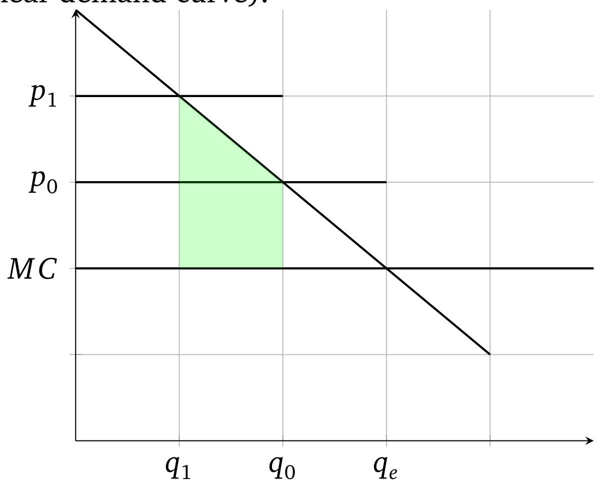
$$\Delta CS = -\int_{p_0}^{p_1} a p^{\epsilon} dp$$

$$= (1+\epsilon)^{-1} a p_1^{1+\epsilon} - (1+\epsilon)^{-1} a p_0^{1+\epsilon}$$

$$= (1+\epsilon)^{-1} a (p_1^{1+\epsilon} - p_0^{1+\epsilon})$$

The resulting calculation of the change in consumer surplus (note that this does not depend on MC) implies that having one of the lowest skilled managers leads to an increase in consumer surplus of roughly \$6,200 per year.

Assuming price is higher than marginal cost initially, and that a lower skill manager reduces price to a level that is still above marginal cost, there is a reduction in DWL to a positive but smaller amount. This is given by the area beneath the demand curve, from the original to the new quantity, minus the area below marginal cost and between the two quantities. The shaded area in the figure below illustrates the change in DWL (for a linear demand curve).



To calculate the percentage change in DWL we can calculate the DWL of the manager with high cognitive skills and compare the the DWL of the manager with lower cognitive skills. The former is given by

$$DWL_h = -\int_{q_1}^{q_e} (a^{-1}q)^{\frac{1}{\epsilon}} dq - MC(q_e - q_1)$$

The DWL for the manager with low cognitive skills is given by

$$DWL_l = -\int_{q_0}^{q_e} (a^{-1}q)^{\frac{1}{\epsilon}} dq - MC(q_e - q_0)$$

Taking the integrals, we can evaluate the resulting expressions using the same values as for calculation of PS, along with daily sales volume corresponding to the intersection of MC with the demand curve, q_e. This leaves MC as the remaining unknown. For our plausible range of marginal costs, the impact on DWL of having one of the lowest skill managers compared to the highest is a reduction ranging from 6 percent to 12 percent.

We compare price markups for high and low skill managers using $\frac{p_1 - MC}{p_1}$ and $\frac{p_0 - MC}{p_0}$. Going from highest to lowest cognitive skills, the percentage reduction in the markup ranges from 3 percent to 7 percent, depending on assumptions about marginal cost. As another benchmark, we can compare the effect size of cognitive skills on price, to the effect size reported in Hastings (2004) of a station having a plausibly exogenous increase in the number of competitor stations. The effect of decreasing cognitive skills by 2 s.d. on price is equivalent to one-sixth of the effect of adding one additional competitor.