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ORIGINAL PAPER

Pricing in firm-to-firm trade: evidence from a Danish multinational

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Abstract

We study pricing decisions in firm-to-firm trade. Using novel detailed transaction-level data from a Danish multinational firm, we uncover considerable price dispersion across countries, customers, and, surprisingly, within the same customer. In fact, we find that transaction-specific characteristics are the most important factors in explaining price variation. The extent of price dispersion within a customer relationship can be affected by the firm's price setting strategy. Our unique dataset allows us to examine the consequences of introducing price lists containing recommended and minimum prices. We find that prices converge towards the recommended price, and that price dispersion within a customer can decline if the price lists successfully narrow the pricing range for the products that the customer purchases.

Keywords Price discrimination · Firm-to-firm trade · Price list

JEL Classification F14 · L11 · L23 · D23

1 Introduction

A well-known reason for violations of the Law of One Price (LOP) is that firms engage in price discrimination across customers with varying willingness to pay. This type of price discrimination has been documented in both firm-to-consumer trade (Simonovska, 2015) and firm-to-firm trade (Fontaine et al., 2020). However, most firm-to-firm trade consists of repeated interactions between a sales agent and a customer, with sales agents often possessing some discretion in applying discounts.

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Therefore, the same product can be sold at different prices to the same customer, reflecting different characteristics of an order—such as quantities or urgency—or different willingness to pay of the customer across interactions. In spite of the widespread presence of these types of relationships, detailed firm-to-firm transaction level data is rare, resulting in limited evidence on price setting within customer-seller relationships. In this paper, we leverage unique barcode-level data on the universe of firm-to-firm transactions of a Danish multinational to investigate the deviations from the LOP within customers and to examine the firm's strategy for addressing these deviations.

First, we document substantial price dispersion across countries, customers, and even within the same customer-country. Notably, transaction-specific characteristics account for the largest fraction of price variation. While observed factors such as quantity discounts and bundling contribute to some of this variation, the majority is driven by unobserved transaction characteristics, which are at least partially related to the customer's willingness to pay and the interaction between the customer and sales agent. Second, our unique dataset allows us to study a change in the firm's pricing strategy following the introduction of a list of recommended and minimum prices. We find that these lists guide the pricing of sales agents and reduce price dispersion within the same customer. This indicates that the balance between delegation and centralization in price setting has tangible consequences for the prices customers pay and, ultimately, the observed deviations from the LOP. Furthermore, we find that the new price lists are applied differently across countries and customer types, suggesting a link between the degree of delegation to sales agents and price discrimination across customers and destinations.

To guide the empirical analysis and establish a theoretical foundation for the external validity of our findings, we build a simple model of transactions in firm-to-firm trade. In the model, a sales agent is able to observe only part of the willingness to pay of the customer. This variability in willingness to pay across transactions justifies the existence of price discrimination within the same customer. The presence of an unobserved component in the customer's willingness to pay warrants the introduction of minimum and recommended prices. Through numerical simulations, we show that the implementation of price lists can be profit-enhancing when minimum and recommended prices are appropriately selected, by altering the sales agent's objective function. Price lists enable sales agents to charge higher prices and extract more surplus from customers with a high willingness to pay. This outweighs the loss in profits for customers with low willingness to pay who choose not to make a purchase. We also show how the effectiveness of price lists varies with model parameters, reflecting differences in customers' demand or, more generally, in the market environment across destinations.

Our data contains the universe of transactions of life-saving equipment by Viking, a Danish multinational operating in 27 countries, with customers spanning various segments, such as cargo ships and offshore platforms. The data covers the 4-year period from 2015 to 2018. Viking's product portfolio is diverse, including items like lifebuoys and fire extinguishers. The products are defined at a highly granular level, equivalent to a barcode. This is a key advantage of our study, as datasets with more aggregate product definitions cannot rule out that price differences are driven by quality differences (Koren & Halpern, 2007; Fontaine et al., 2020). For this reason, our paper bridges the gap between the growing literature on firm-to-firm trade, which has generally limited information on the products exchanged (Dhyne et al., 2020; Grennan, 2013; Dhyne et al., 2022), and the literature on firm-to-consumer trade, which now benefits from highly detailed scanner data (Handbury & Weinstein, 2014; Hitsch et al., 2019; Feenstra et al., 2022).

In the first part of our empirical analysis, we quantify the contributions to price dispersion of customer, destination, time, product category, and transaction characteristics. We achieve this by performing a variance decomposition of price deviations for the same product across the listed dimensions. Transaction characteristics explain the largest portion of the variance, accounting for over 70%, while customer characteristics contribute for approximately 15% and destination characteristics to 3%. Although we find that a customer may be charged different prices for the same product due to quantity or bundling discounts, these factors only partially explain price dispersion. The majority of the variance is driven by unobserved transaction characteristics, which we speculate are likely related to shocks in the customer's willingness to pay. For instance, in the cargo ship segment, the sudden need to replace life-saving equipment due to usage or unexpected malfunctions can significantly increase a customer's willingness to pay, as ships must comply with safety requirements before leaving port. Consequently, the willingness to pay for a product may vary across different transactions for a single ship, and it may vary even more for customers with multiple ships managed by different employees. Finally, discounts might also be a response from sales agents to customers expressing a willingness to terminate the relationship.

These examples of transaction shocks are likely unobserved by the headquarters, as the price-setting decision is delegated to sales agents. However, firms can influence these decisions to varying degrees, such as by using price lists. In March 2018, Viking introduced a list of recommended and minimum prices for over 60% of its product range, intending to increase product prices and reduce their dispersion. If a sales agent charges a price below the minimum, they must justify the decision to a superior. Before March 2018, pricing decisions for the products analyzed were fully decentralized to the sales force. Full delegation of pricing decisions is relatively rare; a survey by Frenzen et al. (2010) found that only 11% of firms adopt such a strategy, while the majority of firms (58%) tend to delegate a significant degree of pricing authority while still maintaining some centralized control.[1]

In the second part of our empirical analysis, we evaluate the effects of this new pricing strategy by exploiting the heterogeneity in the recommended and minimum prices across destinations. We find that, after March 2018, prices moved towards the recommended price, with increases or decreases depending on the recommendation's level relative to the product's average price before 2018. Similarly, we find that implementing the price lists reduced price dispersion for products whose pre-2018 prices had greater dispersion than the range implied by the new price lists, but not for products with less dispersed prices. This indicates that the degree of centralization in price setting, as implied by the price lists, has an impact only when it

[1] A similar distribution of delegation decisions across firms is documented by Hansen et al. (2008).

effectively restricts the pricing range available to sales agents. This empirical finding aligns with our model's predictions.

Our results provide new insights into price discrimination across customers and destinations. Our analysis of price lists reveals that price discrimination is significantly influenced by the pricing strategy firms employ in managing firm-to-firm trade. For example, the price of an item in country A might be higher than in country B not only due to differences in recommended prices but also because the countries vary in their adherence to those recommendations. This phenomenon also occurs across customers: while Viking typically offers larger discounts to customers making larger purchases, we find that the new pricing strategy is only applied to a limited extent for these larger customers. This suggests that it is more challenging to adjust the prices charged to larger customers.

Related literature Our paper contributes to the multidisciplinary literature on price discrimination. The textbook case of price discrimination across consumers has garnered significant attention in the industrial organization literature, particularly in terms of the welfare effects of such discrimination (Robinson, 1933; Schmalensee, 1981; Varian, 1985; Katz, 1987; Holmes, 1989; Valletti, 2003; Stole, 2007; Gerardi & Shapiro, 2009). Additionally, the international trade literature has highlighted the importance of price discrimination across destinations, where trade costs and income differences play a role (Goldberg & Verboven, 2005; Atkeson & Burstein, 2008; Alessandria & Kaboski, 2011; Simonovska, 2015; Jäkel, 2019). Our analysis reveals that firms also engage in price discrimination across transactions for the same customer-destination, controlling for quantity and the number of products within an order. We investigate the determinants of this additional channel and focus on the role of price lists in controlling the degree of price discrimination.

Our paper relates to the growing literature that leverages highly detailed data obtained from a limited number of firms. For instance, Haskel and Wolf (2001) use data for Ikea, Cavallo et al. (2014, 2015) for Apple, Ikea, H &M, and Zara, and Simonovska (2015) for Mango. These papers build on publicly available information, as prices in firm-to-consumer trade are easily accessible. By contrast, obtaining detailed information on prices for identical products in firm-to-firm trade is more challenging due to their sensitive and strategic nature. Our paper fills this gap and sheds light on pricing in firm-to-firm relationships, which can inform the burgeoning theoretical literature on firm-to-firm trade (Huneeus, 2018; Bernard et al., 2019; Dhyne et al., 2022, 2020; Bernard et al., 2021). Furthermore, our study is the first to examine the role of price lists, a prevalent tool used by firms to set prices (Hansen et al., 2008; Frenzen et al., 2010).

Our papers most closely relates to Koren and Halpern (2007) and Fontaine et al. (2020), who study deviations from the LOP and price discrimination in firm-to-firm trade using international data from Hungary and France. Our paper broadens the evidence provided by these papers and provides insights on firm-to-firm trade by documenting a more comprehensive set of price determinants. Although our data focuses solely on one firm, our product definition is more detailed than any of the cited studies.[2] A similar level of disaggregation is also found in Grennan (2013), who explores pricing in domestic firm-to-firm trade for a single product, coronary stents, using information on both buyers and sellers.[3]

Our paper is also related to the organizational economics literature on decision delegation. Largely driven by principal-agent models, this literature has primarily focused on the causes and consequences of decision delegation from a theoretical perspective.[4] As noted by Foss and Laursen (2005), empirical research on delegation within a firm is limited. Both Foss and Laursen (2005) and Frenzen et al. (2010) document a positive relationship between environmental uncertainty and price delegation. Lo et al. (2016) explore the degree of delegation as a function of sales agent ability and experience.[5] Our contribution to the literature is to assess the effects of one common centralization tool: price lists. Instead of concentrating on the rationale behind the extent of pricing decision delegation, we examine the impacts of a reduction in delegation across all sales agents.

The paper is organized as follows: Sect. 2 presents the model. Section 3 describes the dataset, Viking, and the introduction of the new price lists. Section 4 analyzes the degree of deviations from the LOP in Viking's transactions. Section 5 evaluates the impact of Viking's new price lists. Section 6 concludes.

2 A simple model of pricing

In this section, we build a simple model of the pricing decision of a sales agent, to understand the motivation for price discrimination within a customer relationship and evaluate the effects of Viking's introduction of minimum and recommended prices. The environment of the model is the individual transaction between an agent and a customer, which constitutes the largest source of variation in prices, as we document in Sect. 4.

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[2] Firm-to-firm trade is also studied by Ignatenko (2019) using data from Paraguay and by Cajal-Grossi et al. (2019) using data from Bangladesh. The most disaggregate product definition in the literature is in Ignatenko (2019), who combines the Harmonized System 8-digit codes with brand names and detailed product description. The other papers mentioned examine goods defined at the 8- or 6-digit level. Due to the more aggregated data used in the literature, price differences for the same product across buyers may reflect product differentiation. However, in our paper, price differences for a product are solely attributed to price discrimination.

[3] Grennan (2013) focuses on alternative pricing configurations from the point of view of buyers while our paper is focused on sellers. Always in a domestic context, Grennan and Swanson (2020) have information on a wider set of health products purchased by a large number of hospitals. However, the authors cannot study price discrimination and focus on the effects of information on buyers' prices.

[4] See, for instance, Dessein (2002). Alonso et al. (2008) study the circumstances under which coordination across organizations requires the centralization of decision rights. In our case, coordination across sales organizations (destinations) is not relevant for the pricing strategy.

[5] Lo et al. (2016) measure the extent of delegation by the maximum discount off a price list that a sales agent is allowed to offer without having to report to its manager.

2.1 Benchmark

We start with a model of a decentralized pricing strategy, where sales agents have full control over the price they charge and have complete knowledge of the customers' willingness to pay. Our focus is on the pricing decision for a generic item requested by the customer at time t. Demand for the item in the benchmark model (denoted with superscript b) has the following general form:

$$d_t^b = a_t - \frac{p_t^\gamma}{\gamma} \tag{1}$$

where a_t is a demand shifter which varies with t and can be interpreted as the customer's willingness to pay. In our data, the demand shifter varies across destinations, customers, and interactions. In this model, we concentrate solely on its variation across interactions, which we show to be quantitatively more significant. The parameter γ captures the demand curvature, and we constrain it to be positive.

For simplicity, we assume that the demand shifters a_t are *i.i.d.*. Furthermore, we assume that customers cannot store the items or, equivalently, that the items are perishable and, hence, an item purchased in t cannot be used in $t + 1$. This assumption is supported by the data, as Viking's items are typically purchased directly by end users (e.g., ships in port, offshore platforms, etc.) and are not generally stored in warehouses.[6] Finally, we assume that unit costs for the item equal zero.

The sales agent maximizes profits $\pi_t = d_t p_t$ choosing price p_t. The optimal price equals:

$$p_t = \left(\frac{\gamma a_t}{\gamma + 1}\right)^{\frac{1}{\gamma}} \tag{2}$$

If the demand shifter a_t varies across transactions and the sales agent observes these variations, she will optimally charge a different price for each transaction. Notice that changes in a_t result in a change in demand elasticity, which is reflected by the differing optimal prices.[7]

2.2 Unobserved willingness to pay

Under perfect information and no misaligned incentives between the sales agent and the firm, the chosen price maximizes profits and there exist no better alternative pricing strategy. If a firm introduces price lists, profits can only increase if some of these conditions are violated. For instance, price lists can boost profits if customers prefer sellers with lower price volatility. Another possible rationale for price lists

[6] Note that varying prices over time can also be optimal in a model with forward-looking buyers and durable goods. For instance, see Conlisk et al. (1984) and Garrett (2016).

[7] An equivalent but less analytically tractable approach is to allow the demand curvature γ to vary across interactions. We do not model bargaining and instead assume that the sales agent makes a take-it-or-leave-it price offer. We abstract from bargaining because, in our data, we would not be able to distinguish between bargaining ability and willingness to pay.

is to prevent collusion between the sales agent and the buyer, who might share the applied discounts with each other. In this section, we consider the simplest possible mechanism by which price lists can improve profits, which relies on the imperfect ability of sales agents to observe a customer willingness to pay.

Consider the following version of the demand function (denoted with superscript u for the unobserved willingness to pay):

$$d_t^u = a_t + \mu_t - \frac{p_t^\gamma}{\gamma} \tag{3}$$

The customer's demand shifter depends on two components: a_t is observed by the sales agent and μ_t is unobserved. Without loss of generality, we assume that the expected value of the unobserved component is zero, i.e., $E[\mu_t] = 0$. The sales agent is risk-neutral and chooses the price to maximize profits given the expected demand $E[d_t^u] = a_t - \frac{p_t^\gamma}{\gamma}$. Thus, the expected profits for the sales agent are given by: $E[\pi_t] = E[d_t^u]p_t$. The optimal price charged by the sales agent is identical to the case of full information in Eq. (2). Since there are no price lists, we refer to this as decentralized pricing strategy.

The quantities exchanged depend on the realization of the unobserved component of the customer willingness to pay, μ_t. In particular:

$$d_t^u = \max\left\{\frac{a_t}{\gamma + 1} + \mu_t; 0\right\} \tag{4}$$

If $\mu_t < 0$ and has a large enough magnitude, the customer can reject the offer, and no quantity is exchanged. This is in contrast with the case of full information, where demand is always positive. The realized profits are given by $\pi_t = d_t^u p_t^u$.

2.3 Minimum and recommended prices

We model minimum and recommended prices by augmenting the objective function of the sales agent in Sect. 2.2 with two additional costs associated with charging a price different from the recommended price p_R or below the minimum price p_{min}. In particular, the expected objective function for the sales agent become:

$$E[\pi_t] = \left(a_t - \frac{p_t^\gamma}{\gamma}\right)p_t - m\mathbb{1}_{p_t<p_{min}} - \theta(p_t - p_R)^2$$

If the agent charges a price below the minimum price p_{min}, she must incur a cost m. In the Viking case, this cost is associated with having to justify the pricing decision to the local manager. Furthermore, we model another cost which is proportional to how different the charged price is from the recommended price p_R. In the Viking case, information on these costs is not known to the researcher.

The first order condition yields the following implicit solution for the optimal price p_t^*[8]

$$\frac{\gamma+1}{\gamma}(p_t^*)^\gamma + \theta p_t^* - \theta p_R - a_t = 0 \tag{5}$$

For $\theta = 0$, the price is the same as (2), while for $\theta \to \infty$, the price equals p_R.

If the optimal price found in (5) is less than the minimum price, the sales agent compares her expected objective function evaluated at a price p_t^*, $E[\pi_t(p_t^*)]$, which includes the minimum price penalty m, to the objective function evaluated at the minimum price $E[\pi_t(p_{min})]$. The pricing rule is:

$$p_t = \begin{cases} p_t^* & \text{if } [\pi_t(p_t^*)] > E[\pi_t(p_{min})] \\ p_{min} & \text{otherwise} \end{cases} \tag{6}$$

The customer's realized demand is $d_t = \max\left\{a_t + \mu_t - \frac{p_t^\gamma}{\gamma};0\right\}$, and the realized profits for the firm are $\pi_t = d_t p_t^*$.

2.4 Results

We simulate the model and evaluate the effects of the new pricing strategy on price dispersion and profits. We draw a large number of observed and unobserved demand shifters from a normal distribution and apply the pricing equations discussed above. In the figures, we present the average and 95% CIs of price dispersion and profits over the demand shifters. The details of the simulation and additional figures are in "Appendix 1". In Fig. 1, we show the ratio of total profits obtained with the use of price lists relative to the decentralized pricing strategy discussed in Sect. 2.2. The two scenarios only differ in the pricing strategy: The parameters and the draws of demand shifter are identical in each case. We vary the minimum and recommended price separately in the two panels.

Profits exhibit a non-monotonic, hump-shaped relationship to the level of the minimum and recommended prices. Increasing the minimum price increases the profitability of the average sale and the total profits, but only up to a certain point. Once the minimum price is above the optimal level, average and total profits begin to decline as agents sacrifice sales due to the high minimum price, until they become lower than in the decentralized strategy. A similar pattern occurs with the recommended price. However, the mechanism is slightly different, as higher levels of the recommended price increase the profitability of each sale. At a high level of the recommended price, a larger number of sales is not concluded, and this reduction in the number of sales generates the hump-shaped relationship between recommended prices and profits in the new strategy relative to the old one.

[8] In the case of linear demand (i.e., $\gamma = 1$), we can find an explicit solution for prices, which equal a weighted average of the price in the decentralized strategy (2) and the recommended price: $p_t^* = \frac{2}{\theta+2}\left(\frac{a_t}{2}\right) + \frac{\theta}{\theta+2}(p_R)$.

The positive effect of minimum and recommended prices on the company's profits is due to the asymmetric effects of the unobserved demand shifter. In fact, while there is no upper limit to the profits that the firm can obtain from customers with high willingness to pay, the lower bound for profits is zero. For some values of our parameters, charging higher prices extracts more surplus from customers with high willingness to pay, which more than offsets the loss in profits for customers with low willingness to pay, who do not make a purchase.[9]

Figures 3 and 4 show that values of the minimum price and recommended price that increase total profits also cause an increase in the average price, as sales agents follow the new price rules. This is the key prediction of the model and we test it in Sect. 5.1 of the empirical analysis. Furthermore, minimum prices cause a decline in price dispersion, as both the standard deviation of prices and the 95/5 percentile ratio decrease while total profits increase. The effect of the recommended price on price dispersion is less clear, as higher p_R leaves the 95/5 percentile ratio almost unchanged but increases the standard deviation of prices due to the higher average price. In Sect. 5.2 of the empirical analysis, we test whether the effect of minimum prices dominates and whether price dispersion falls with the implementation of the price lists.[10]

The level of certainty that the sales agent has about the customer's willingness to pay is also an important determinant of the overall effect of minimum and recommended prices. In Fig. 7, we show that minimum and recommended prices have a larger impact when the dispersion in μ_t is greater. The dispersion in μ_t can reflect both the agent's and the customer's characteristics. In particular, we would expect this variance to be lower for repeat customers, whose willingness to pay the sales agent has had the opportunity to learn, and for large customers, who make up a significant share of the company's sales and need to be kept satisfied. Therefore, we expect these types of customers to be less affected by a push towards price centralization. In our empirical analysis, we test for this hypothesis by considering the heterogeneous impact of price lists on customers of different classes. Furthermore, we show that a higher demand curvature, γ, is associated with lower expected profits from the price lists (see Fig. 8). Differences in the demand curvature across items or customers suggest that firms may optimally enforce the new price lists differently. Finally, we show that our results are robust to having the demand shifter be log-normally or Pareto distributed (see Fig. 9).

In "Complements and substitute items" of "Appendix", we consider an extension of our baseline model in which the sales agent sells two items that can be either substitutes or complements. In the decentralized case, we show the textbook result

9 Since total profits depend on the realized demand shifters, it is difficult to gauge the optimal minimum and recommended price, and whether the two pricing tools are complements or substitutes. To gather some intuition, we consider the average profits across 100 iterations of our simulations in Fig. 6. We find that using both pricing tools generates larger profits than using only one. Furthermore, it appears that the two pricing tools are imperfect substitutes in the neighborhood of the optimal values. For instance, increasing the minimum price reduces the level of the recommended price that generates the largest average profits.

10 Fig. 5 shows the effects of varying the minimum price penalty m and the recommended price penalty θ on total profits.

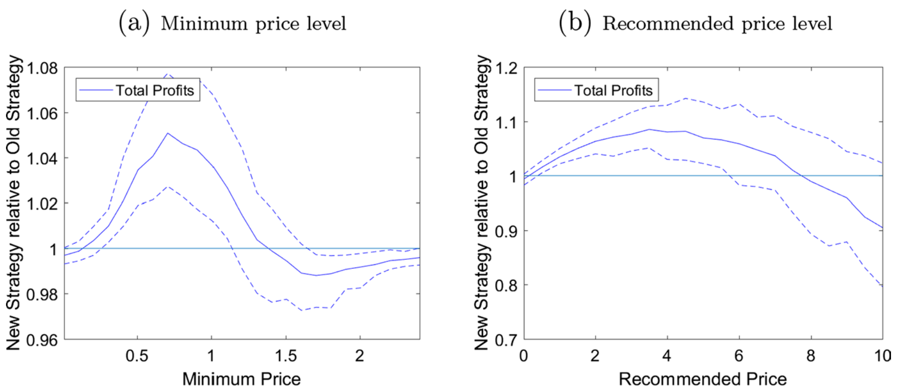


Fig. 1 Performance of price lists relative to decentralized strategy: profits. Notes: total profits with the price lists relative to the decentralized pricing strategy and 95% CI resulting from model simulation for a range of values for the minimum price level (**a**) and the recommended price level (**b**). Details in "Appendix 1"

that the sales agent optimally charges higher prices for substitute items and lower prices for complement items, reflecting the difference in cross-price elasticities for the two goods. In the following sections, we will test this prediction by analyzing prices of items within the same product category. Furthermore, we show that the effects of price lists are heterogeneous across the two types of goods: When goods are complements price lists have a larger effect on total profits than when goods are substitutes.

3 Viking and the introduction of price lists

Viking Life-Saving Equipment A/S is a large Danish multinational firm that operates in the maritime, offshore, and fire safety sectors. Viking's core production includes lifeboats, evacuation systems, and life-rafts. In March 2018, Viking introduced a new global pricing strategy by providing its sales organizations with price lists that include minimum and recommended prices for various items. This section describes the dataset provided by Viking and the nature and implementation of the new pricing strategy.

3.1 Data

The data contain transaction-level information on prices and quantities for all trade products sold by Viking in 27 countries between 2015 and 2018. The name of trade products refers to a range of safety-related items that are not part of Viking's production of lifeboats, evacuation systems, and life-rafts. These items are not manufactured by Viking and can be considered as carry-along trade (Bernard et al., 2018). Examples of these products include fire extinguishers, lifebuoys, signal lights, first aid kits, navigation equipment, and more. Although these items do not constitute

Viking's primary activity, the company sells over 3500 of them annually, generating revenues exceeding EUR 15 million, which accounts for about 6% of total revenues. Typically, demand for these items arises when customers need to stock or replace them due to usage, breakage, or expiration (e.g., fire extinguishers).

Viking assigns a unique identifier to each item, which can be considered analogous to a barcode in retail trade. These items are then aggregated into 333 product categories. For example, one product category is "light lifebuoy", which includes various types of light lifebuoys. While Viking products are subject to multiple regulations in each country, there is considerable variation in product pricing and characteristics within each product category, indicating a degree of vertical and horizontal differentiation. Viking sells its products to 27 destinations worldwide, with the US, Germany, and Denmark accounting for the largest sales.

Consistent with the literature on multi-product firms (Arkolakis et al., 2021), product sales are skewed towards a small fraction of best performing products: In 2018, the top 1% of products account for 50% of total sales.[11] Table 10 presents yearly sales, transactions, customers, and products, with panel B highlighting a significant degree of product churning, as more than 1300 new products were introduced and a similar number were discontinued each year.[12] The distribution of sales by customer is also highly skewed, with the top 1% of customers accounting for 26% of total sales in 2018. Additionally, there is a significant degree of customer churning, with a thousand new customers appearing every year and a smaller number of customers making their final purchase each year.

Viking assigns an identifier to each customer. Viking sells to more than 2500 customers every year, and the number has increased from 2015 to 2018. While there are some customers who purchase from Viking in multiple destinations (3% of customers in 2017), the majority of customers are firms that only purchase in one country. However, some of these firms may be divisions or subsidiaries of larger multinationals, such as a shipping company with separate Danish and Norwegian divisions and distinct employees and demand. For this paper, we treat these divisions as separate customers, as Viking classifies them.[13]

Viking records additional characteristics for its customers, including their classification into four classes: VIP, A, B, and C. These classes are determined by the customers' size and past sales revenue and each class accounts for a quarter of Viking's sales. Customer types are ranked according to their average sales, with VIP customers spending an average of EUR 40k from 2015 to 2018, while C customers spent an average of EUR 2.4k (see Table 12). Furthermore, customers are divided into seven segments based on their operation: cargo, defense, fire, fishing, offshore, passenger, and yachting. The cargo segment is the largest accounting for 48% of total

[11] See online appendix A for the distribution of sales by product and customer.

[12] A large share of product churning occurs within product categories, likely reflecting new products replacing older ones. Figure 14 shows the distribution of net product introduction (i.e., the difference between the number of new products and the number of discontinued products) by product category, with nearly 40% of product categories experiencing zero net entry in 2016 and approximately 73% of categories having a net entry of products between −1 and 1.

[13] Table 11 in the "Appendix" provides the list of destinations with the associated sales, number of customers, and products.

sales, followed by offshore (18%) and passenger (12%) segments. Customers in the defense segment tend to be the largest buyers (see Table 13).

Viking provides an identifier of the latest employee responsible for the orders of each customer, although this information is only available for about 70% of customers. The dataset does not include any changes in the employee responsible for each customer and only reports the latest recorded. In other words, we have information about the last sales agent involved in a transaction with a customer, but not which sales agent was responsible for previous transactions. There are 220 recorded employees, with the number ranging from 2 in Panama to 25 in Singapore. On average, this amounts to around 65 orders managed per employee in 2018 across countries. In each destination, there is a highly skewed distribution of orders, as only a few employees are linked to the majority of orders.

3.2 The introduction of price lists

In March 2018, Viking introduced price lists to its sales organizations in all destinations, containing minimum and recommended prices for a large group of items. The primary objective of the price lists was to increase product prices and reduce their dispersion. The lists vary across destinations in terms of both the products they cover and the type of strategy employed (e.g., minimum and recommended price, either, or neither). The incentives associated with the new pricing structure are unknown and likely destination-specific. Prior to March 2018, pricing decisions were fully decentralized to the sales force, but after, sales agents must justify any decision to charge below the minimum price to their superior. Although the official introduction time of the price lists is March 2018, we cannot rule out the possibility of informal circulation of price lists before that time or delays in implementing the new strategy.[14]

To describe and analyze the price lists, we restrict the dataset in order to focus on items sold before and after the implementation of the price lists by destination. We focus on items by the destination where they are sold, i.e., item-destinations. Around 19% of the transactions occur after the implementation of the strategy change, and approximately 96% of transactions involve items that are included in the price lists. However, only about 83% of all items are included in the price lists, which implies that the products in the price lists are sold more frequently.[15] While minimum and recommended prices have a high coverage in the price lists, they are not overlapping, as 99% of items have a recommended price, while 93% have a minimum price.

In Figs. 2 and 13, we show how minimum and recommended prices compare to average prices in all destinations. Given that the items sold and customers serviced

[14] An interesting aspect of the pricing decision of Viking is the fact that variation of prices for the same product within a client may discourage the client from coming back to Viking. To fully explore the retention effects of the pricing decisions of Viking, we would need information about the total purchases of clients of life-saving equipment regardless of whether they were acquired from Viking or not. Such data is not available.

[15] Appendix Table 34 confirms this: The average total quantity sold of items not in the price lists is about one fourth of the quantity sold of items in the price lists.

vary across time and destinations, we regress the log of real prices of items included in the price lists over month dummies, controlling for item-customer fixed effects and transaction characteristics for each destination.[16] We plot the constant plus the coefficients of the time dummies and compare them with the log of minimum (in red) and recommended prices (in green) net of item-customer fixed effects. We also include 95 percent confidence intervals.

In most destinations, the recommended prices are very close to the pre-March 2018 average price. However, in Estonia, Turkey, South Africa, and in Panama, prices are closer to the minimum price, suggesting that price lists in these countries had the more complicated role of steering prices up. There are large differences across destinations between the variance of prices and the new pricing range implied by the minimum and recommended prices. In Spain, Singapore, and Sweden, the pricing strategy implies a much smaller range than the observed pricing range, while in most other countries, the pricing range is similar or larger than the observed one. In Panama, Singapore, and the US, prices were decreasing pre-change, while in Iceland, Germany, and Italy, prices were on an upward trend. There is no obvious common trend in prices post-March 2018: While in most destinations there is no change, the figures suggest at least a temporary rise in Germany, Iceland, US, and South Africa.

Overall, Fig. 2 suggests that price lists were implemented differently across destinations, with substantial variation in the level and distance between minimum and recommended prices relative to price variance, thus ideally providing sales agents with a different range of options. Appendix Figs. 11 and 12 depict how minimum and recommended prices compare to average prices by customer class and trade segment. Unclassified customers, who tend to be smaller and non-returning, pay prices close to the minimum price, while all other classes pay above the minimum price. This trend is confirmed by Fig. 12, where we observe that sectors with smaller customers (Fishing and Yachting) pay prices close to the minimum price. Recommended prices tend to be higher than prices paid, particularly for customers of class C and sales in Cargo, Fire, and Yachting.

4 Price dispersion in firm-to-firm trade

4.1 Facts on price dispersion

In this section, we provide some basic facts on the price dispersion of Viking products. First, we provide information on the distribution of price dispersion to allow for a comparison of our findings with the literature. We show that a significant fraction of an item's price dispersion occurs within the same customer relationship. Second, we confirm the result using a fixed effect regression model: The standard deviation of prices within item-customer-destinations is more than half of the standard deviation of prices within items.

[16] To compute real prices, we divide the price of a product in a transaction by the corresponding monthly CPI for G20 economies from Eurostat.

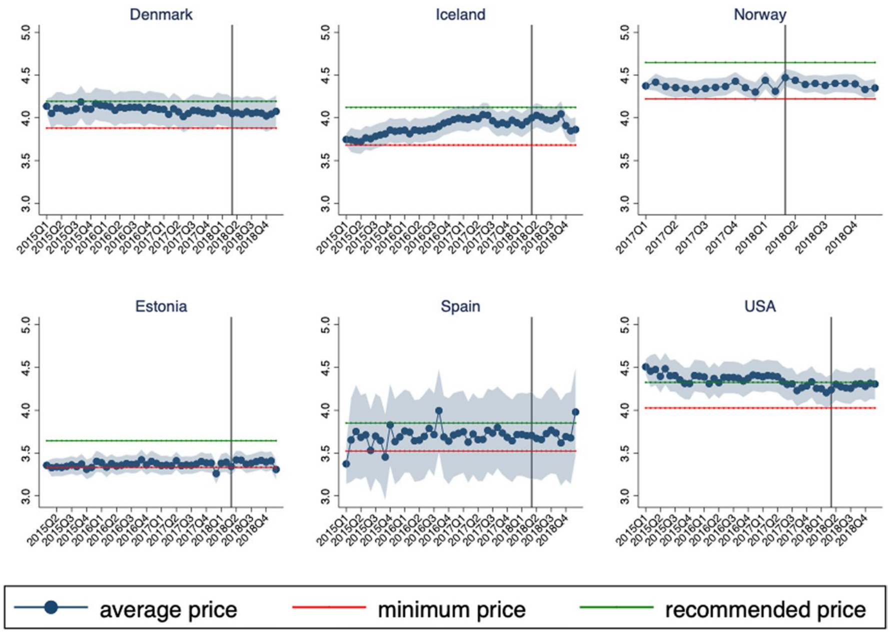


Fig. 2 Minimum and recommended prices, by destinations (selected countries). Notes: sample: all transactions in the period 2015–2018 of products sold continuatively in 2016–2018 in Denmark, Iceland, Norway, Estonia, Spain, and the USA. Figure 13 includes all destinations where we observe above 500 transactions over the period, excluding UAE and Australia. We exclude products in sale organizations where the minimum price is assigned to be above the recommended price. Source: Viking Life-Saving Equipment A/S. For each destination: OLS of log of real prices over month dummies, item-customer fixed effects and transaction characteristics, including a dummy for if the product is sold in a bundle with other products, and the revenue of the sale in thousands of real March 2018 euros. Sample includes all items included in the price lists with both recommended and minimum prices. In blue, the estimated constant plus the coefficients of the time dummies, 95% CI. Minimum prices (in red) and recommended prices (in green) net of fixed effects. Black vertical lines: the official implementation of the new pricing strategy (colour figure online)

We begin by measuring price dispersion using three methods: (1) the coefficient of variation of prices, calculated by dividing the yearly standard deviation by the mean price of an item, (2) the standard deviation of log prices for an item in a year, and (3) the ratio of the 95th percentile to the 5th percentile of the price of an item in a year. We define a product as either an item, an item-destination (to remove cross-country differences in prices), or an item-destination-customer (to remove cross-customer differences in prices). We also consider the case of products defined as item-destination-customer and, further, only select transactions where such products are sold as single products in one order. By doing this, we can control for bundling discounts that may occur within the transaction.[17] We restrict the sample for each

[17] We cannot exclude the possibility of bundling discounts occurring in different transactions within a short time span. However, further restricting the sample to products sold in single-product orders that occur in different months leaves us with too few observations to compute the various measures of dispersion. Nonetheless, we explore the impact of this type of bundling in Sect. 4.2.

product definition to include only those with at least 10 observations in the year considered.[18]

In Table 1, we present the distribution measures for the three price dispersion methods in 2018. For the sample with all items, the average coefficient of variation is 0.21 and the median is 0.2. When we define a product as an item-destination to remove cross-country differences, the coefficient of variation reduces to 0.15. Price dispersion still persists even when we consider products within a customer. Defining a product as an item-destination-customer yields an average coefficient of variation of 0.10. When we consider only products sold as single products (SP in the table) within a customer, we find similar measures of dispersion. This indicates that the dispersion in the price of the same product for the same customer is not solely driven by bundling discounts within the transaction, i.e., the fact that products are often sold together with varying discounts.

The results are similar when we consider the other two measures of price dispersion. The average standard deviation is 0.19, which reduces to 0.13 when controlling for price differences across destinations and to 0.09 when controlling for price differences across customers. This latter value does not change when we only consider items sold as single products in an order. Finally, we examine the 95/5 percentile ratio, which has an average of 2.5. Eliminating cross-country and cross-customer differences reduce the average to 2.2 and 1.5, respectively. When we only consider products sold individually, the percentile ratio reduces to 1.36.[19]

Our results align with the limited literature on price dispersion in firm-to-firm trade. Ignatenko (2019) documents a coefficient of variation of prices for the same good across buyers ranging from 0.2–0.4 depending on the sample. Similarly, Fontaine et al. (2020) reports an average coefficient of variation of 0.3 for products across buyers. However, when examining the firm-to-consumer literature, we find that prices within Viking exhibit more dispersion than prices across U.S. retailers. Hitsch et al. (2019) reports an average standard deviation of approximately 0.16, which is slightly smaller than our estimate of 0.19. However, the 95/5 percentile ratio reported by Hitsch et al. (2019) is around 1.5–1.7, much smaller than our measure of 2.5.

Our results are generally consistent across years (see Tables 14, 15, and 16 in the "Appendix"). We also consider two additional samples in Table 17 in the "Appendix": The top 1% of items by revenues and the items purchased by the top 1% of customers by revenues. For these two subsamples, we define a product as an item. Even when focusing on the top items and top customers, the average 95/5 percentile ratio is around 1.7. Interestingly, top items and items for top customers exhibit a smaller dispersion than the sample of all items at all percentiles of the distribution.

To further illustrate the significant portion of price variance that occurs within the same customer relationship, we run the following regression:

[18] In 2018, our sample includes 617 items, 900 item-destinations, 333 item-destination-customers that meet this criterion, and 68 item-destination-customers which are sold as the only product in at least 10 orders.

[19] For a graphical representation of the distributions summarized in Table 1, see Fig. 15 in the "Appendix".

$$\ln p_{jdcto} = \text{Fixed Effects} + \epsilon_{jdcto} \tag{7}$$

where we regress the log price of item j, sold in destination d, to customer c, in month t, in transaction o, on a vector of fixed effects and calculate the standard deviation of the error term ϵ_{jdcto}. In Table 2, we report the results. Unlike in Table 1, we do not place any restrictions on the sample of transactions used. For reference, we also run a regression with only item fixed effects and report the standard deviation of the residual in the first row of Table 2, which is 0.32.

When we include item, customer, destination, and time fixed effects in the regression, the standard deviation of the error term reduces to 0.27, a value comparable to the reference value. However, when we interact the fixed effects and consider item-customer-destination fixed effects, the standard deviation decreases to 0.18, which is more than half of the reference value.[20] This finding further confirms the substantial variation of prices within the same customer relationship. In fact, if a customer always received the same price for the same item, the standard deviation would be zero.

Finally, when we include item-customer-destination-time fixed effects, the standard deviation of the residual is still a substantial 0.13.[21] Notably, with this set of fixed effects, we are controlling for shocks that affect the price of an item in a given month, such as seasonal changes in demand. This result implies that the same item can be priced differently for the same customer within the same month. However, this tends to occur for a relatively small fraction of customers. In fact, roughly 64% of items are sold to the same customer at the same price within a given month; it is only the remaining occurrences, in which prices vary, that drive the result. By contrast, when we consider items sold to the same customers in any month, only 16% of item-destination-customers exhibit no changes in their prices. Thus, while deviations from the LOP within customers are common, deviations from the LOP within customers and month are rarer but not impossible. This suggests that, at least for some customers, there is variability in the willingness to pay perceived by Viking within the same month. To further illustrate this point, consider the example of a shipping company that needs to purchase the same fire extinguisher for different ships in the same month. The price difference may be due to a different level of urgency required or due to the fact that different employees are responsible for the purchase of equipment for each ship.

[20] It is worth noting that this combination of fixed effects is also used in Sect. 5, where we investigate the effects of price lists within the same item-customer-destination.

[21] The number of observations in Table 2 decreases as we drop a larger number of singleton observations when we interact fixed effects. However, the results barely change if we restrict the sample so that the number of observations is the same in all four specifications. See Table 18 for details. Additionally, we have verified that daily exchange rate movements are not driving the results by repeating the analysis in Table 2 with a sample of transactions invoiced in local currency only, Danish kroners only, and euro only. See Table 19 for details.

Table 1 Price dispersion measures

Sample	Mean	Median	P1	P5	P10	P25	P75	P90	P95	P99	# Products
Coefficient of variation of prices											
All items	0.21	0.20	0.00	0.05	0.08	0.12	0.33	0.55	0.75	1.39	617
Item-Dest	0.15	0.14	0.00	0.04	0.06	0.09	0.21	0.39	0.55	1.08	900
Item-Dest.-Cust	0.10	0.06	0.00	0.00	0.00	0.03	0.10	0.19	0.26	0.78	333
Item-Dest.-Cust. (SP)	0.10	0.05	0.00	0.00	0.01	0.03	0.13	0.19	0.21	0.25	68
Standard deviation of log prices											
All items	0.19	0.19	0.00	0.05	0.12	0.30	0.42	0.53	1.18	2.49	617
Item-Dest	0.13	0.13	0.00	0.04	0.09	0.21	0.30	0.38	0.58	2.18	900
Item-Dest.-Cust	0.09	0.06	0.00	0.00	0.03	0.10	0.18	0.24	0.60	1.54	333
Item-Dest.-Cust. (SP)	0.09	0.05	0.00	0.00	0.03	0.12	0.17	0.18	0.25	1.36	68
95/5 percentile ratio											
All items	2.49	1.81	1.01	1.19	1.26	1.45	2.48	3.74	5.86	19.80	617
Item-Dest	2.18	1.49	1.01	1.12	1.20	1.31	1.86	2.77	3.58	6.06	900
Item-Dest.-Cust	1.54	1.20	1.00	1.00	1.00	1.08	1.40	1.72	2.13	4.63	333
Item-Dest.-Cust. (SP)	1.36	1.17	1.00	1.01	1.04	1.10	1.42	1.69	1.75	1.95	68

Sample: all transactions in the year 2018, samples restricted to products that have at least 10 observations in 2018. Source: viking life-saving equipment A/S. Product definition: all items, items by destination, item by destination by customer. Mean is the sales-weighted average. Item-Dest.-Cust. (SP) denotes the sample in which products are defined as item-destination-customer and restricted to only the transactions in which such products are sold as single products in one order. Measures of price dispersion: coefficient of variation of prices of a product in a year (σ/p); standard deviation of log prices of a product in a year; ratio of 95th percentile to 5th percentile of the price of a product in a year

Table 2 Standard deviation in the residual

Fixed effect	SD	Observations
Item	0.32	163,399
Item, Dest., Cust., Time	0.27	161,813
Item-Dest.-Cust, Time	0.18	121,183
Item-Dest.-Cust.-Time	0.13	48,286

Sample: all transactions. Source: Viking life-saving equipment A/S. Product definition: all items. We compute the standard deviation of the residuals from Eq. (7), in which we regress $\ln p_{jdcto}$ on various combinations of fixed effects

4.2 Determinants of price dispersion

To investigate the determinants of the deviations of prices from the LOP, we conduct a variance decomposition exercise. First, we demean the log price of each item by its average $\bar{p}_j$, computed across all transactions. Second, we decompose the log of the demeaned price of item j, sold in destination d, to customer c, in month t, in transaction o, of product category h as follows:

$$\ln\left(\frac{p_{jdctoh}}{\bar{p}_j}\right) = FE_c + FE_d + FE_t + FE_h + \epsilon_{jdctoh} \tag{8}$$

where FE denotes a fixed effect. We estimate (8) with customer, destination, time (month–year), and product category fixed effects.[22] We assume that the remaining price dispersion not explained by these factors is attributable to transaction-specific characteristics. We also consider further refinements of the model and allow interactions between fixed effects to assess the robustness of the explanatory power of transaction characteristics. To account for the variance of the price deviations explained by each fixed effect, we use the variance decomposition approach developed by Hottman et al. (2016) and Bernard et al. (2021): We regress the estimated fixed effect on $\ln\left(\frac{p_{jdctoh}}{\bar{p}j}\right)$ without a constant term, and the resulting coefficient represents the percentage of variance of the log prices explained by the fixed effect in question. We report the explanatory power of each variable in Table 3.[23]

Customer characteristics account for 14.9% of the variation in prices, suggesting that Viking practices price discrimination across customers. This finding is consistent with the results of Ignatenko (2019), who found that 20% of price variance can be explained by buyer characteristics, and Cajal-Grossi et al. (2019), who report a larger value of 33%. On the other hand, destination characteristics account for only about 3% of price variation. This result is in line with Koren and Halpern (2007) who find that destination characteristics account for 6% of the price variation, and buyer characteristics account for 14%. The low explanatory power of destination characteristics is partly due to the fact that few customers purchase across multiple destinations, and some of the variation in destination characteristics is captured by the customer fixed effects. The product category accounts for 1% of the variance, while the month and year of the transaction accounts for 0.5%. The residual, which includes the interactions between fixed effects and transaction-specific characteristics, accounts for the majority of price variation (80%).[24]

To test the robustness of our finding, we adopt more restrictive specifications of (8) and interact fixed effects together. The goal is to show that even reducing the variation left in the residual as much as possible, such variation still accounts for a large fraction of price dispersion. In column (1) of Table 4, we repeat the specification of Table 3. In column (2), we include customer-destination fixed effects,

[22] As we are interested in deviations from the LOP and have already demeaned the log prices, we do not need to include item fixed effects. We present the results this way for clarity since there is a large variation of prices across items, which range from fire extinguishers to boats. However, as a robustness check, we also obtain the residuals from regressing the log price on item fixed effects and use these residuals as the dependent variable in (8). The results are reported in Table 28 in the “Appendix”.

[23] To use the *reghdfe* Stata command to its full potential, we first regress $\ln\left(\frac{pjdctoh}{\bar{p}_j}\right)$ on a constant term, and then perform the variance decomposition as described above. This initial step is necessary to fully attribute the variance to the fixed effects in question, since without it, part of the variance would be absorbed by the constant of the regression.

[24] Tables 1 and 2 also show that a large portion of price dispersion occurs across transactions between the same customer. The results from the variance decomposition of Table 3 and, more generally, of Sect. 4.2 robustly confirm this finding and additionally document the importance of various determinants (observed and unobserved) in explaining deviations from the LOP.

which aligns with the analysis of Sect. 5. The explanatory power of the transaction-specific characteristics remains relatively unchanged. The explanatory power of the customer-destination fixed effect is 18% (see Table 20). In column (3), we introduce destination-time fixed effects, which capture time-varying demand factors in the destination and changes in competition. Destination-time fixed effects only account for 3% of the variance (see Table 21), and they further reduce the variance of prices in the residual by 2.3 percentage points. Finally, in column (4), we consider a model with customer-destination-time fixed effects, which captures time-varying characteristics of a customer in a destination, such as the type of the match. In this case, the variance left in the residual, which only captures transaction-specific characteristics, is 66%, while the explanatory power of customer-destination-time is 33% (see Table 22).[25]

As mentioned in Sect. 3.1, we are unable to control for sales agent fixed effects since we lack information on the agent that managed a particular order. We only have information on whether a customer has an assigned employee and who the last responsible employee was. Thus, we cannot dismiss the possibility that the observed price discrimination is due to different sales agents charging different prices. However, since the number of employees relative to the number of orders is small, and few employees in each destination are attached to most of the orders, it is likely that price dispersion also occurs within sales agents.[26]

4.2.1 Transaction-specific characteristics

Since our primary empirical finding is a significant deviation from the LOP within the same product and customer, this section aims to investigate which observable transaction characteristics determine price dispersion. To achieve this, we consider the following regression of the demeaned price on a vector of transaction characteristics X_{oj}:

$$\ln\left(\frac{p_{jdctoh}}{\bar{p}_j}\right) = \beta X_{oj} + FE_c + FE_d + FE_t + FE_h + \epsilon_{jdctoh} \tag{9}$$

The vector X_{oj} consists of

- Quantity of item j in transaction o.
- Total sales in transaction o, excluding sales from item j.
- Total number of items in transaction o.
- A dummy variable which equals 1 if the invoice currency of transaction o is the destination currency, and 0 otherwise.

[25] As a robustness test, we also control for any time-varying characteristics at the product category level with product-category-time fixed effects, which control for demand and supply shocks common to all items within a product category (e.g., seasonality in the demand for fire extinguishers of all types). The results are in Table 23. These fixed effects' explanatory power accounts for 8% of the variance. Even in this case, the variance in the residual remains large and equal to 59%.

[26] See "Robustness" of "Appendix" for a set of sensitivity analyses to the analysis in this section.

Table 3 Variance decomposition

	(Customer)	(Destination)	(Time)	(Category)	(Transaction)
% of log price variance	0.149***	0.033***	0.005***	0.011***	0.802***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Observations	164,576	164,576	164,576	164,576	164,576

Sample: all transactions in the period 2015–2018. Source: Viking life-saving equipment A/S. The % of log price variance are the coefficients from OLS of the estimated fixed effects and residual of Eq. (8) on $\ln\left(\frac{p_{jdctoh}}{\bar{p}_j}\right)$. Product definition: item. Standard errors in parentheses

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 4 Variance decomposition: variance of prices in the residual

	(1)	(2)	(3)	(4)
% of log price variance	0.802***	0.800***	0.777***	0.656***
	(0.001)	(0.001)	(0.001)	(0.001)
# Observations	164,576	164,479	164,462	152,346
Additional controls				
Customer FE	Yes	No	No	No
Destination FE	Yes	No	No	No
Time FE	Yes	Yes	No	No
Category FE	Yes	Yes	Yes	Yes
Customer-destination FE	No	Yes	Yes	No
Destination-time FE	No	No	Yes	No
Customer-destination-time FE	No	No	No	Yes

Robust standard errors in parentheses. Sample: All transactions in the period 2015–2018. Source: viking life-saving equipment A/S. The % of log price variance are the coefficients from OLS of the residual of different specifications of Eq. (8) on $\ln\left(\frac{p_{jdctoh}}{\bar{p}_j}\right)$. Equation (8) ran with different combinations of fixed effects: (1) baseline customer, destination, time, and product category, (2) customer-destination, time, and product category, (3) customer-destination, destination-time and product category, (4) customer-destination-time and product category. The number of observations varies across the three columns as more singleton observations are dropped with interacted fixed effects. Product definition: item

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

- The average log price of products sold in the same transaction o that belong to the same product category h as item j, excluding item j itself. The variable equals zero if no other product in the same category is sold in the same order as product j.
- The average log price of products sold in the same transaction o that belong to a different product category $h' \neq h$ than item j. The variable equals zero if no product is sold in a different category in the same order.

Our ability to control for transaction-specific characteristics is limited by the available data. For instance, we lack information on the order's urgency or the requested delivery time of the products, which could reveal the customers' willingness to pay. Nevertheless, the variables at our disposal account for crucial channels of price discrimination: Price variations for the same product and customer can result from differences in value across orders, together with the presence of discounts. Additionally, bundling discounts may also play a role: The price of a product depends on the number of other products the customer purchases. We excluded the relevance of this channel in Table 1.

In Table 5, we present the results of the regression, which reveal that Viking applies quantity discounts. Doubling the units sold leads to a 5% reduction in the price per unit. Additionally, Viking employs discounts that depend on the other items sold in the same order: Larger transaction values are associated with lower prices of the items within the transaction, and transactions involving a larger set of items tend to receive discounts. Doubling the number of products in a transaction results in an almost 3% reduction in the price of the items within that transaction, which suggests the presence of bundling discounts.[27] Finally, transactions invoiced in the local currency tend to be 5% cheaper.

A higher average price of products in the same product category is associated with higher prices, indicating some degree of substitutability between items in the same product category.[28] Conversely, the coefficient on the average price of items outside the category to which item j belongs is negative and significant, indicating that items across product categories tend to be complements.

As evidenced by the R^2 of the regressions, these additional variables explain up to 11% of the variance remaining in the residual after accounting for customer, destination, time, and category fixed effects. To further validate the robustness of these results, in column (7) of Table 5, we control for all possible fixed effects interactions and discover that a significant portion of the variance remains unexplained.

Another explanation for the high degree of price dispersion within the same customer relationship may be attributed to the type of transaction. Several of the items sold by Viking are part of mandatory safety requirements and, as mentioned in Sect. 3.1, demand for these items may arise when a customer needs to replace them due to usage, breakage, or expiration. In some cases, the customer may have a tight schedule for the replacement and may be willing to pay more for prompt service. For instance, a cargo ship may be stuck in Panama until all mandatory security items are

[27] As bundling discounts may occur through multiple transactions that occur within a short span of time, we consider alternative measures for the number of products as a robustness exercise. In particular, we examine the number of products sold in a month to a customer-destination and the number of products sold in a quarter to a customer-destination. The results are available in Table 32. The coefficients of the new measures are negative and statistically significant, and their magnitudes are similar to the baseline result. Furthermore, using these variables causes the effects of sales order and local currency to become significant in the specification with all variables included. However, the R^2 of the regression remains unchanged with the new measures.

[28] In an extension to the model in "Complements and substitute items" of "Appendix", we demonstrate that the firm optimally charges higher prices when two products are substitutes. We confirm that this finding is robust to alternative definitions of product category in Table 31.

stocked, and the wait could be costly. However, as previously stated, we lack information on the type of transaction to verify this mechanism.

The large dispersion in prices within the same customer motivates our focus on price lists in the following sections. These transaction-specific shocks are unknown to both the researchers and Viking's headquarters, who do not closely monitor all interactions between sales agents and customers. The variation in prices depends not only on the unobserved customers' willingness to pay but also on how Viking handles the transaction shocks. The pricing decisions of sales agents are constrained by recommended and minimum prices, and we aim to examine whether these tools ultimately impact price dispersion.

4.2.2 Customer characteristics

To understand the relationship between prices and customer characteristics, we consider the following regression of the demeaned price on a vector of customer characteristics X_c:

$$\ln\left(\frac{p_{jdctoh}}{\bar{p}_j}\right) = \beta X_{cj} + FE_d + FE_t + FE_h + \epsilon_{jdctoh} \tag{10}$$

The vector X_{cj} consists of

- Total sales on customer c, where we exclude sales of item j in transaction o.
- Total number of items purchased by customer c.
- Total number of transactions by customer c.
- A dummy variable that equals one if customer c has an associated Viking's employee at the end of the data period.
- A dummy variable that equals one if customer c did not purchase from Viking in the previous year (new customer).
- A dummy variable that equals one if customer c did not purchase from Viking in the following year (lost customer).

The results are reported in Table 6. Larger customers generally receive lower prices, which confirms the findings of Ignatenko (2019). In fact, customers who purchase higher values, a greater number of items, or larger transactions are offered lower prices. Viking provides more substantial discounts to customers who buy many products, controlling for their value and the number of orders [column (5)]. Customers assigned to an employee receive a 4% discount. Lost customers and new customers are offered prices that are 3% higher than other customers.

There is evidence of price discrimination across customer segments and customer classes. To show this, we run regression (10) by incorporating the division of customers into classes and segments as dummy variables and present the results in Table 33 of the "Appendix".[29] Using the complete set of controls for customer

[29] For these results, we drop any customer who is not assigned to a class or a segment.

Table 5 Prices and transaction characteristics

Dep. var.	Log of demeaned price						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log(Quantity)	− 0.051***					− 0.046***	− 0.043***
	(0.008)					(0.007)	(0.008)
Log(1+ Trans. Value -j)		− 0.008***				0.002	0.000
		(0.002)				(0.002)	(0.002)
Log(# Prod. in Trans.)			− 0.027***			− 0.042***	− 0.045***
			(0.005)			(0.004)	(0.005)
Local currency				− 0.047**		− 0.041	− 0.060
				(0.022)		(0.025)	(0.045)
Avg. Price In Cat					0.323***	0.304***	0.123**
					(0.049)	(0.048)	(0.045)
Avg. Price Outside Cat					− 0.404***	− 0.412***	− 0.545***
					(0.053)	(0.050)	(0.063)
R^2	0.21	0.20	0.20	0.20	0.29	0.31	0.47
Observations	164,576	164,576	164,576	164,576	164,576	164,576	152,346
Additional controls							
Customer FE	Yes	Yes	Yes	Yes	Yes	Yes	No
Destination FE	Yes	Yes	Yes	Yes	Yes	Yes	No
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	No
Product-Category FE	Yes	Yes	Yes	Yes	Yes	Yes	No
Cust.-Dest.-Time-Cat. FE	No	No	No	No	No	No	Yes

Cluster-robust standard errors in parentheses. Cluster: destination country. Sample: All transactions in the period 2015–2018. Source: Viking Life-Saving Equipment A/S. Results from OLS of Eq. (9) of $\ln\left(\frac{p_{jdctoh}}{\bar{p}_j}\right)$ on transaction characteristics described in the main text. Customer, Destination, Category, and Time fixed effects in (1)–(6). In (7), Customer-Destination-Category-Time Fixed Effect. Product definition: item

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

characteristics, we find that, relative to the yachting segment, the offshore and passenger segments are offered higher prices. Holding quantities and the number of products purchased constant, VIP customers are charged higher prices than class C customers. This outcome implies that Viking assigns to the VIP category customers with a high willingness to pay, or that Viking provides VIP customers with additional services, which justify higher prices. The variables we investigated in this section only account for a small portion of the explanatory power of customer characteristics on prices. Indeed, the R^2 of our regressions barely surpasses 9%, which is close to the combined explanatory power of destination, time, and product category characteristics.

Table 6 Prices and customer characteristics

Dep. var.	Log of demeaned price						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log(Tot. Sales)	− 0.011*				0.001		− 0.000
	(0.006)				(0.003)		(0.004)
Log(Tot. # Products)		− 0.022**			− 0.022***		− 0.020**
		(0.010)			(0.006)		(0.007)
Log(# Orders)			− 0.015*		− 0.001		− 0.002
			(0.009)		(0.008)		(0.010)
Employee resp				− 0.043***	− 0.044**		− 0.047**
				(0.010)	(0.017)		(0.018)
New customer						0.032**	0.004
						(0.013)	(0.021)
Lost customer						0.032**	0.002
						(0.012)	(0.014)
R^2	0.10	0.10	0.10	0.09	0.10	0.10	0.10
Observations	166,168	166,168	166,168	166,168	166,168	80,871	80,871
Additional controls							
Destination FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product-category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Cluster-robust standard errors in parentheses. Cluster: destination country. Sample: All transactions in the period 2015–2018. Source: Viking Life-Saving Equipment A/S. Results from OLS of Eq.(10) of $\left(\frac{p_{jdctoh}}{\bar{p}_j}\right)$ on customer characteristics described in the main text. All columns include destination, time, and product category fixed effects. Product definition: item. In columns (6) and (7), we restrict the sample to the years 2016 and 2017 since we cannot define new customers for 2015 and lost customers for 2018

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

4.2.3 Destination characteristics

To understand the relationship between prices and destination characteristics, we consider the following regression of the demeaned price on per capita income, GDP, and the destination's distance from Denmark:

$$\ln\left(\frac{p_{jdctoh}}{\bar{p}_j}\right) = \beta_1 \ln(\text{Pc. Income})_{dt} + \beta_2 \ln(\text{GDP})_{dt} + \beta_3 \ln(\text{distance})_d + FE_c + FE_t + FE_h + \epsilon_{jdctoh} \tag{11}$$

We collect per capita income and GDP data from the World Development Indicators and distance information from CEPII. Table 7 shows a negative relationship between GDP and prices: Larger economies pay lower prices for Viking's products. On the other hand, Viking charges higher prices to richer destinations, even controlling for GDP. The two coefficients become statistically significant when we control for distance. This is largely driven by the fact that in the sample of countries where Viking

Table 7 Prices and destination characteristics

Dep. var.	Log of demeaned price				
	(1)	(2)	(3)	(4)	(5)
Log(PC. income)	0.020			0.097***	− 0.058
	(0.022)			(0.030)	(0.037)
Log(GDP)		− 0.025		− 0.035***	− 0.007
		(0.016)		(0.011)	(0.010)
Log(distance)			0.020	0.051***	0.012**
			(0.013)	(0.016)	(0.004)
R^2	0.03	0.03	0.03	0.05	0.20
Observations	164,578	164,578	164,578	164,578	164,576
Additional controls					
Customer FE	No	No	No	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Product-category FE	Yes	Yes	Yes	Yes	Yes

Cluster-robust standard errors in parentheses. Cluster: destination country. Sample: All transactions in the period 2015–2018. Source: Viking Life-Saving Equipment A/S, WDI and CEPII. Results from OLS of Eq. (11) of $\ln\left(\frac{p_{jdctoh}}{\bar{p}_j}\right)$ on destination characteristics described in the main text. All columns include time and product category fixed effects, column 5 includes also customer fixed effects. Product definition: item

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

operates, the richer countries are also the ones closest to Denmark. This result is in line with the evidence of Fontaine et al. (2020) for firm-to-firm trade and from pricing in firm-to-consumer (Simonovska, 2015). When we control for customer fixed effects, both variables lose their statistical significance (column 4). This result is likely due to the fact that only 3% of customers purchase from more than one destination. The coefficient on distance is positive: Prices are higher in more distant destinations from Denmark. However, this does not appear to be the result of trade costs, as the items examined here are not produced by Viking and are bought by the local sales organizations in each country.

5 Impact of the price lists

This section evaluates the impact of minimum and recommended prices on Viking's pricing behavior. We leverage the varying recommended and minimum price levels across items and countries to conduct our analysis. Our approach consists of two parts. First, we examine the effect of price lists on prices, using the dataset described in Sect. 3.2. Second, we investigate the impact of price lists on price dispersion at the item-destination-customer level.

Although we are not privy to the precise reasons behind Viking's decision to include or exclude items from their price lists, we can infer that it was a move to optimize or rectify their previous pricing strategy. Consequently, we expect that the items included in and excluded from the price lists will differ somewhat. In Appendix Table 34, we present the summary statistics for items on and off the price lists, and with and without minimum prices. The items not included in the price lists tend to be pricier, and are less likely to receive significant discounts. Conversely, the items on the price lists sell more frequently, and might require a clearer pricing strategy. Additionally, the items on the price lists with only minimum prices could be items that were previously sold at prices that were too low. Figure 2 shows that minimum and recommended prices vary across sales destinations and align with the existing price trends. These factors suggest that we should exercise caution when interpreting our results in this section as causal. Nevertheless, they provide a valuable insight into how the introduction of the new pricing strategy influenced prices within Viking.

Our focus is on the variations between items with recommended and minimum prices that are either higher or lower than the average price before 2018. Our findings show that prices tend to move in the direction indicated by the minimum and recommended prices. For instance, items with an average price before March 2018 that was lower than the minimum price tend to experience an increase in price, while items with an average price above the recommended price tend to experience a decrease in price. Furthermore, we document a reduction in price dispersion that occurs for those items that previously had prices outside the pricing range suggested by the minimum and recommended prices. Although we cannot examine the effect of the price lists on Viking's profits, these results align with the model's predictions in Sect. 2.

5.1 Impact of the price lists on prices

5.1.1 Empirical strategy

Our baseline regression equation for studying the impact of Viking's new pricing strategy on prices is the following:

$$\ln\left(p_{jdcto}\right) = \beta \mathrm{Post}_t \times \text{New Strategy}_{jd} + FE_{jdc} + FE_t + X_{jdcto} + \epsilon_{jdcto} \tag{12}$$

where $\ln\left(p_{jdcto}\right)$ is the log of the real price of item j, sold in destination d, to customer c, in month t, in transaction o. Post_t is a binary variable that equals one if the new pricing strategy is active in month t, when month t is March 2018 or later. New Strategy$_{jd}$ indicates whether the item is covered by the new pricing strategy or not.[30] We define New Strategy$_{jd}$ in several ways. Our preferred definition splits the treatment into the possible scenarios generated by the difference between the average price charged before 2018 (p_{pre}), and the new recommended and minimum prices (p_{rec} and p_{min}). There are three scenarios listed here[31]:

[30] Note that the item-destination-customer fixed effects and the time fixed effects include controls for New Strategy$_{jd}$ and Post_t that we would normally have in a difference-in-differences strategy.

[31] We exclude a few observations for which the assigned recommended price is lower than the minimum price as it is probably a mistake in the data.

1. $p_{rec} > p_{pre}$, $p_{min} > p_{pre}$. As both recommended and minimum prices are higher than the average price, we expect the price for these products to increase.
2. $p_{rec} < p_{pre}$, $p_{min} < p_{pre}$. As both recommended and minimum prices are lower than the average price, we expect the price for these products to decrease.
3. $p_{rec} > p_{pre}$, $p_{min} < p_{pre}$. The effect of the new pricing strategy in this case is ex-ante ambiguous. In fact, the price can increase to become closer on average to the recommended price, or it can decrease because of the larger margin for discounts.

Therefore, we split New Strategy$_{jd}$ into four different treatments: (1) both recommended and minimum prices above the average unit price (10% of item-destinations), (2) both recommended and minimum prices below the average unit price (26%), (3) recommended price above and minimum price below the average unit price (52%), (4) items lacking the minimum or recommended price (12%).

The main coefficient of interest is β, which measures the effect of the interaction between the new pricing strategy and the Post indicator. A positive coefficient for the first scenario above would indicate that the introduction of the minimum and recommended prices is linked to an increase in the price of items whose historical average was lower than the minimum price.

For completeness, we consider two additional measures for New Strategy$_{jd}$. First, we use a dummy which equals one if the item-destination is in the price list. With this specification, we compare items in the price lists to items not in the price lists using the entire dataset. Second, we narrow the sample down to only include items on the price lists and compare items with a minimum price to those without.[32]

As in Sects. 3.2 and 4, we control for item-destination and customer-specific characteristics with item-destination-customer fixed effects. These capture any product, destination, and customer characteristics that, alone or interacted, affect the price setting for a product in the same way across time. As each customer belongs to only one segment, item-destination-customer fixed effects automatically control for segment characteristics. Additionally, we include month fixed effects. Finally, X_{jdcto} is a vector of additional controls that includes a dummy variable for whether the product is sold in a bundle with other products and the revenue generated from the sale, measured in thousands of real March 2018 euros.

Pre-trends. If we are comparing prices of items that followed distinct trends before the price lists were implemented, we might be concerned that our findings are driven by these trends rather than the introduction of the pricing lists. To address this, we display the trend of average log prices for items on and off the price lists in panel (a) of Appendix Fig. 16. Both follow similar increasing trends, with the average prices for items not on the price lists being less stable due to the lower transaction volume. Intriguingly, post-March 2018, there appears to be a flattening of both time series and, at least temporarily, a decrease in the prices of items not on the price lists. In panel (b) of Fig. 16, we run regression (12), interacting the dummy for the new pricing strategy with month dummies rather than Post$_t$, and plot the estimated coefficients. Net

32 Only 1.2% of items in the price lists lack a recommended price. Therefore, the two are almost equivalent in the dataset.

of item-destination-customer fixed effects and transaction characteristics, the prices of items on and off the price lists do not appear to consistently diverge or converge over the time period. Post-March 2018, there is not a significant change, and if anything, the prices of items on the price lists decrease slightly. In panels (c) and (d) of Fig. 16, we repeat the above analysis by comparing prices of items on the price list with and without a minimum price. Items on the price list with and without a minimum price follow the same trend before March 2018 and appear to flatten post-March 2018.

In our preferred specification, we focus on the differences between items with recommended and minimum prices above and/or below the pre-2018 average unit price. Thus, we repeat the price trend analysis for items in the price lists with minimum and recommended prices below and above the average pre-2018 unit price in panels (e) and (f) of Fig. 16. Panel (e) displays the raw trends, indicating that prices of items with an average pre-2018 unit price below the minimum or above the recommended prices were flat over the period. By contrast, prices of items with a pre-2018 price between the minimum and recommended prices demonstrated an upward trend before 2018. After controlling for item-destination-customer fixed effects in panel (f), we find that the trends are less apparent in 2015–2017. While there was some price convergence starting in 2017, prices for the three types of items in 2017 were comparable, and we observe a clear price convergence after 2018, notably due to a rise in prices of items with a pre-2018 unit price below both the minimum and recommended price. Overall, although the implementation of the price lists is non-random, the analysis of pre-trends is reassuring.

5.1.2 Results

Table 8 presents the results of Eq. (12). In columns 1 and 2, we compare prices before and after March 2018 for items on and off the price lists. Columns 3 and 4 present outcomes for the sample of items on the price lists, comparing prices before and after March 2018 for items with and without a minimum price. In columns 2 and 4, we present the findings for our preferred specification, with the treatment split into four scenarios, as discussed in Sect. 5.1.1.

We find that there is no effect of the introduction of the price lists or of the minimum price for items on the price lists. However, this overall zero effect conceals substantial heterogeneity based on whether the average price of the item-destination was above or below the minimum and recommended prices. We find that prices of items above (below) both recommended and minimum prices before 2018 decreased (increased) by 6%, while prices of items between the minimum and recommended prices saw a small and barely significant increase of between 1 and 2%.[33]

[33] We ran the specification in Eq. (12) using the quantity of the item sold in the transaction and its revenue as outcomes. We do not find significant effects of the price lists on quantity overall, even if the coefficient in the specification equivalent to columns 1 and 2 in Table 8 are quite large and positive (implying an increase of 4 units per transaction post-2018). We find an 8.3% increase in log-revenue for items with a minimum price compared to items without a minimum price, driven in particular—unsurprisingly—by items with pre-2018 prices below the minimum price and items with pre-2018 prices between the minimum and recommended prices. Tables are available in the online appendix.

We are also interested in understanding if the implementation of the price lists affects price discrimination across customers, segments, and destinations. To investigate this, we estimate Eq. (12) with the specification of column (4) of Table 8 by customer classification, trade segment, and destination. We separate item-destination-customer fixed effects and control for item-destination and customer-specific characteristics with item-destination and customer fixed effects. The results are presented in Fig. 17. The first blue bar in panels (a-c) represents the result for the entire sample. Our findings suggest that the application of the new pricing strategy is not uniform across customers and destinations. Although prices converge towards the range between the recommended and minimum prices, this convergence is not uniform: for VIP customers, it is only suggestive and not significant, while it is clear and significant for customers of classes B and C. The results by trade segment follow a similar pattern, with the defense sector being the only outlier, while the pattern by destinations is not clear. The overall results suggest heterogeneity in the enforcement and application of the new price lists across countries and customers, leading to differences in price setting across customers and destinations and partially driving price discrimination.

5.2 Impact of the price lists on price dispersion

5.2.1 Empirical strategy

To study the effect of imposing recommended and minimum pricing directly on price dispersion, we consider the following baseline regression:

$$d_{jdcq} = \beta \text{Post}_q \times \text{New Strategy}_{jd} + FE_{jdc} + FE_q + X_{jdcq} + \epsilon_{jdcq} \tag{13}$$

where d_{jdcq} is an indicator of dispersion of the real price of item j, sold in destination d, to customer c, in quarter q. Our main indicator of price dispersion is the coefficient of variation measured as the standard deviation of the price of an item j, sold in destination d, to customer c, in quarter q divided by the average price, all multiplied by 100. As an alternative measure of price dispersion we use the log of the 95/5 percentile ratio of the quarterly price.[34]

Post_q is a binary variable that equals one if the new pricing strategy is active in quarter q, i.e., starting in the second quarter of 2018.[35] Our main coefficient of interest is β, which quantifies the effect of the interaction between the new pricing strategy and the Post indicator. As in the Sect. 5.1.1, we consider different measures of New Strategy_{jd}, including dummies for whether the item is included in the price lists.

As previously discussed, the effectiveness of the new pricing strategy depends on the distribution of prices before the implementation of the price lists, in relation to the

[34] We restrict the dataset to item-destination-customer combinations that appear in at least two quarters and at least two times per quarter in both the period 2015–2017 and 2018. This reduces the dataset to 1067 item-destination-customers for a total of 24,980 transactions. Then, we collapse this dataset at the quarterly level for a total of 6983 observations. Relative to the dataset used in Sect. 3, we can be less strict with the continuity requirements since we need a quarterly dataset.

[35] The official implementation of the pricing strategy is March 2018, so our quarterly indicator is off by 1 month. Our results are robust to starting the post-period in the first quarter of 2018.

Table 8 Impact of price lists on log prices

Dep. var.	Log of real prices			
	(1)	(2)	(3)	(4)
Explanatory variables				
Post-March 2018×in price list	0.005			
	(0.015)			
Post-March 2018×minimum price			0.011	
			(0.009)	
Post-March 2018×				
$p_{pre} > p_{rec} > p_{min}$		−0.066***		−0.061***
		(0.015)		(0.010)
$p_{rec} > p_{pre} > p_{min}$		0.012		0.017*
		(0.015)		(0.009)
$p_{rec} > p_{min} > p_{pre}$		0.059***		0.064***
		(0.015)		(0.009)
Observations	104,285	104,285	99,938	99,938
Sample	Full	Full	In price list	In price list
Additional controls				
Item-destination-customer FE	Yes	Yes	Yes	Yes
Year–month FE	Yes	Yes	Yes	Yes
Transaction characteristics	Yes	Yes	Yes	Yes

Standard errors in parentheses. Sample: All transactions in the period 2015–2018 of products sold continuatively in 2016–2018 in destinations where we observe above 500 transactions, excluded UAE and Australia. We exclude observations where the minimum price is assigned to be above the recommended price. Columns 3–4: only items included in price lists. Source: Viking Life-Saving Equipment A/S. Outcome: the log of the price in real March 2018 euros. OLS of the log of real prices on interactions of a dummy for post-March 2018 with: (col. 1) a dummy for the item being in the price list in the destination responsible for the sale; (col. 3) a dummy for the item being in the price list with a minimum price; (cols. 2 and 4) dummies for having both recommended and minimum prices below the average unit price charged in 2015–2017, recommended price above and minimum price below the average unit price, both recommended and minimum prices above the average unit price, and a dummy for having only minimum or recommended price (not shown). Other controls include: item-destination-customer fixed effects, year–month fixed effects, and transaction characteristics (a dummy equal to one if the item is sold in a bundle with other products, the revenue of the transaction in thousands of real March 2018 euros)

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

minimum and recommended prices within the new pricing range. Intuitively, if the price distribution before 2018 was outside the new range, we would expect a reduction in price dispersion. Conversely, if the price distribution before 2018 was already within the new price range, we would expect no effect on price dispersion, or possibly an increase. Therefore, we have created two indicators to determine whether the observed price range in the years before 2018 was inside or outside the pricing range implied by the new minimum and recommended prices. We have defined the price range using the 5th and 95th percentiles of the distribution, and we have run robustness checks using the 1st and 99th percentiles, as well as the 10th and 90th percentiles. The two price ranges are defined as follows:

1. In range: $p5_{pre} > p_{min}$, $p95_{pre} \leq p_{rec}$
2. Out of range: $p5_{pre} \leq p_{min}$, $p95_{pre} > p_{rec}$

As the recommended price is not a maximum price, the range defined above is skewed towards the lower end. Consequently, we have conducted robustness checks using the recommended price multiplied by 1.5 and 2 as the upper bounds of the new price range.

5.2.2 Results

Table 9 shows the results of Eq. (13) for both our indicators of price dispersion,[36] Table 9 shows that the coefficient of variation of items that before the implementation of the new pricing strategy had a p5–p95 range outside of the minimum-recommended price range showed a significant decrease of 3.5 percentage points relative to the other items. This finding is further supported by the 10% reduction in the ratio between the 95th and the 5th percentiles of the quarterly real price distribution. These results suggest that the new pricing strategy had an effect on price setting by reducing price dispersion for item-destination-customer combinations that had prices outside of the desired range.

On the other hand, we find that the coefficient of variation of items that before the implementation of the new pricing strategy had a p5-p95 range inside of the minimum-recommended price range showed an increase of 1.5 percentage points relative to the other items, significant at the 5% level. The corresponding 3.3% increase in the ratio between the 95th and the 5th percentiles of the quarterly real price distribution is instead not significant. These results suggest that pricing for this category of products is becoming more flexible after the introduction of the new pricing strategy, probably because sales managers are now justified in practicing higher or lower prices than before.

We find interesting heterogeneous results across customer classes, trade segments, and destinations. In Appendix Fig. 18, we present the results of the regression in column 2 of Table 9 by customer class, trade segment, and destination. Our findings reveal that the significant reduction in price dispersion is driven by customers in the VIP and C classes, who are active in cargo and offshore operations in Norway, France, and South Africa.[37]

[36] The results presented in this section are robust to a series of test, including controlling for whether an item has minimum or recommended prices in the price lists, defining the price range as wider (p1–p99) or smaller (p10–p90), defining the Post$_q$ variable as equal to 1 starting from the first quarter of 2018, restricting the sample to the 383 item-destination-customer combinations that appear in at least two quarters and at least three times per quarter, changing the implied new pricing range from $\left(p_{min}, p_{rec}\right)$ to $\left(p_{min} 1.5 \times p_{rec}\right)$ and $\left(p_{min}, 2 \times p_{rec}\right)$. All tables are in the online appendix.

[37] Since the results of this section are based on quarterly data, for completeness, we replicate the analysis in Sect. 5.1 using the quarterly dataset and estimate (13) using as outcomes the log of the average quarterly real price. Appendix Table 35 confirms our results.

Table 9 Impact of the price lists on price dispersion

Dep. var.	100× (sd/p)		Log of p95/p5	
	(1)	(2)	(3)	(4)
Explanatory variables				
Post-March 2018× in price list	3.749	3.628	0.075	0.075
	(3.366)	(3.370)	(0.093)	(0.093)
Post-March 2018× in range		1.542**		0.033
		(0.727)		(0.020)
Post-March 2018× out of range		− 3.552***		− 0.109***
		(1.135)		(0.031)
Observations	6983	6983	6983	6983
Additional controls				
Item-destination-customer FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Transaction characteristics	Yes	Yes	Yes	Yes

Standard errors in parentheses. Sample: All item-destination-customer of products sold in 2015–2018 and sold continuatively in 2016–2018 in destinations where we observe above 500 transactions, excluded UAE and Australia. Restricted to item-destination-customers sold in at least two quarters and at least 2 times per quarter in both the period 2015–2017 and in 2018. Source: Viking Life-Saving Equipment A/S. Outcomes: quarterly coefficient of variation of real prices calculated as $100 \times (sd/p)$ and the log of the ratio between the 95th and the 5th percentile of the quarterly price distribution. OLS of the outcome on interactions of a dummy for post-March 2018 with a dummy for the item being in the price list in the destination responsible for the sale and (cols. 2, 4) with dummies for the price distribution being in the price strategy range ($p5_{pre} > p_{min}$, $p95_{pre} \leq p_{rec}$) and being outside of the price strategy range ($p5_{pre} \leq p_{min}$, $p95_{pre} > p_{rec}$). Other controls include: item-destination-customer fixed effects, year-quarter fixed effects, and transaction characteristics (average transactions where the item is sold in a bundle with other products, average transaction revenue in thousands of real March 2018 euro)

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

6 Conclusions

Using data from a Danish multinational, we study price dispersion in firm-to-firm trade. Our analysis reveals that a significant portion of the variation in prices for a given product is transaction-specific, even after controlling for a rich set of fixed effects. To examine the role of sales agents' negotiation freedom in influencing price dispersion, we investigate the impact of a centralization in pricing decisions through the implementation of a list of recommended and minimum prices. Our findings suggest that these prices are an effective tool in regulating price setting. Specifically, a stricter pricing range than what was previously applied by sales agents leads to a decrease in price dispersion.

We also document a a significant level of heterogeneity in the implementation of the new pricing strategy across destinations, which implies that some degree of decentralization is inherent to the company's organizational structure. These differences could depend on Viking's particular history in the various destinations, on area-specific features such as the prevalence of competitors or trade patterns, or on cultural differences that influence business practices. Investigating how cultural norms impact bargaining and price setting in firm-to-firm trade presents an intriguing avenue for future research.

Overall, we find a high degree of price discrimination across customers. Moreover, we find that VIP customers are less affected by the new pricing strategy. This can be attributed, in part, to the fact that the recommended prices in the price lists have been established near the prices paid by VIP customers. This outcome is not surprising, as sales agents have collected more data on the willingness of large repeat customers to pay and use this information when determining prices. Therefore, it is reasonable to expect that the implementation of price lists would have a relatively smaller effect on these customers.

Appendix 1: Model

We develop an algorithm that solves the pricing problem of the sales agent for an array of values for the observed and unobserved willingness to pay a_t and μ_t of the customer. In particular, we assume that the sales agent meets 100×100 times with a customer with heterogeneous a_t and μ_t. We draw 100 realizations of a_t from a normal distribution with mean 1 and standard deviation 1. For each a_t we draw 100 realizations of μ_t from a normal distribution with mean 0 and standard deviation 1. For each pair (a_t, μ_t) we solve the pricing problem as discussed above, dropping solutions with negative prices (due to negative realizations of a_t).

In our simulation, we evaluate the effects of various parameters on the performance outcome of the new pricing strategy. The baseline values of the parameters are as follows. We set the parameter controlling the penalty for deviating from the recommended price $\theta = 0.1$, and the penalty for setting a price below the minimum price $m = 0.5$. In our baseline specification, we set $\gamma = 1$, but also consider the effects of varying this parameter. Unless we consider the effects of varying the recommended price, we set the recommended price $p_R = \left(\frac{\gamma E[a_t]}{\gamma+1}\right)^{\frac{1}{\gamma}}$, as such value equal the expected optimal price in the absence of minimum or recommended price. In fact, the expected optimal price is $\left(\frac{\gamma E[a_t]}{\gamma+1}\right)^{\frac{1}{\gamma}}$, and $E[a_t] = 1$ in our simulation. Unless we vary the minimum price, we set it equal to 70% of the recommended price ($p_{min} = 0.7p_R$), which is in line with the Viking data (Figs. 3, 4, 5, 6, 7, 8, 9).

Complements and substitute items

In this section, we consider an extension to the baseline model where the sales agent sells two good, denoted by $i = 1, 2$. The two goods can be complements, substitutes, or unrelated. The goal of this exercise is to show whether price lists benefit more the firm if the two goods are complements or substitutes. For simplicity, we consider the case of linear demand, i.e., $\gamma = 1$. The demand for the two goods equal:

$$d_{1t} = a_{1t} + \mu_{1t} - p_{1t} + \beta p_{2t} \tag{14}$$

$$d_{2t} = a_{2t} + \mu_{2t} - p_{2t} + \beta p_{1t} \tag{15}$$

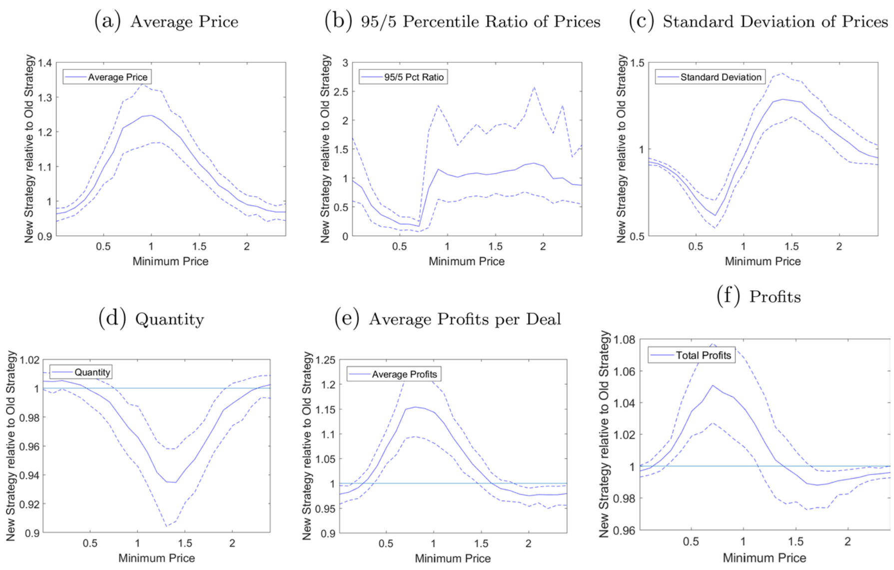


Fig. 3 Performance of price lists. Minimum price level. Notes: average price (**a**), 95/5 percentile ratio of prices (**b**), standard deviation of prices (**c**), average quantity (**d**), average profits per deal (**d**), and average profits (**e**) with price lists relative to decentralized pricing strategy and 95% CI resulting from model simulation for a range of values for the minimum price level. Details in "Appendix 1"

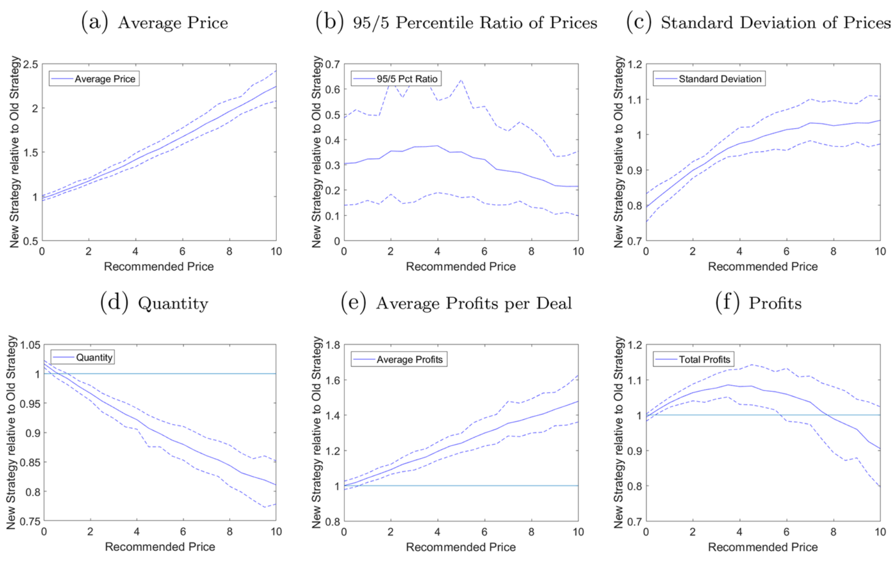


Fig. 4 Performance of new strategy relative to old strategy. Recommended price level. Notes: average price (**a**), 95/5 percentile ratio of prices (**b**), standard deviation of prices (**c**), average quantity (**d**), average profits per deal (**e**), and average profits (**e**) with price lists relative to decentralized pricing strategy and 95% CI resulting from model simulation for a range of values for the recommended price level. Details in "Appendix 1"

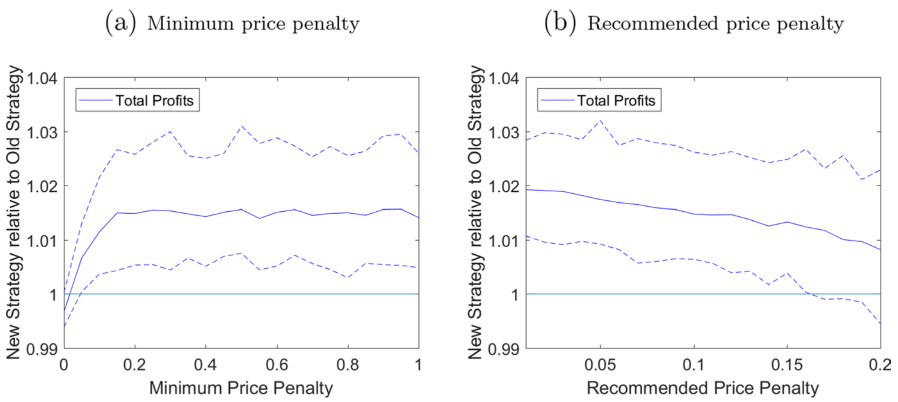


Fig. 5 Performance of price lists relative to decentralized strategy: profits. Notes: total profits with the price lists relative to the decentralized pricing strategy and 95% CI resulting from model simulation for a range of values for the minimum price penalty m (**a**) and the recommended price penalty θ (**b**)

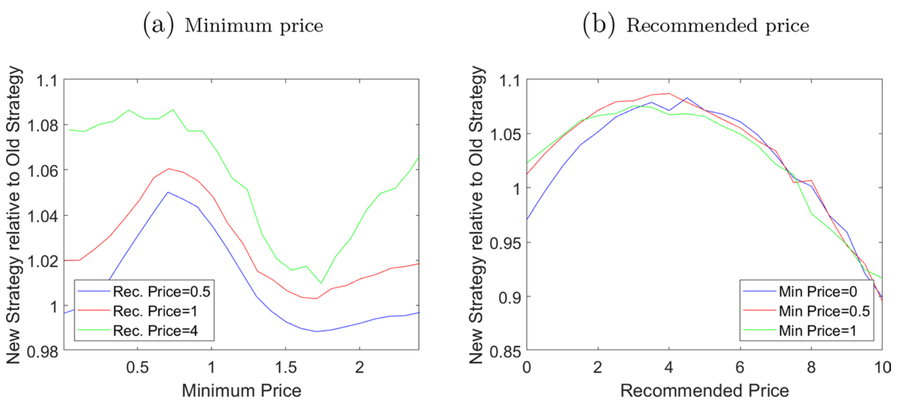


Fig. 6 Performance of price lists relative to decentralized strategy: profits. Different scenarios. Notes: average profits with the price lists relative to the decentralized pricing strategy across 100 iterations of the model simulation. **a** We vary the minimum price for set values of the recommended price (0.5, 1, 4). **b** We vary the recommended price for set values of the minimum price (0, 0.5, 1)

where β is a parameter that controls the degree of complementarity and substitutability of items. If $\beta = 0$, the two items are unrelated, and the optimal price and effects of price lists are identical to the baseline case. If $\beta > 0$, the two items are imperfect substitutes: An increase in the price of item 2 increases the demand for item 1 and vice versa. If $\beta < 0$, the two items are imperfect complements: An increase in the price of item 2 decreases the demand for item 1 and vice versa.

As in the baseline model, we assume that $E[\mu_{1t}] = E[\mu_{2t}] = 0$. The objective function of the sales agent without price lists equal:

$$E[\pi_t] = d_{1t}p_{1t} + d_{2t}p_{2t} = a_{1t}p_{1t} + a_{2t}p_{2t} - p_{1t}^2 - p_{2t}^2 + 2\beta p_{1t}p_{2t} \tag{16}$$

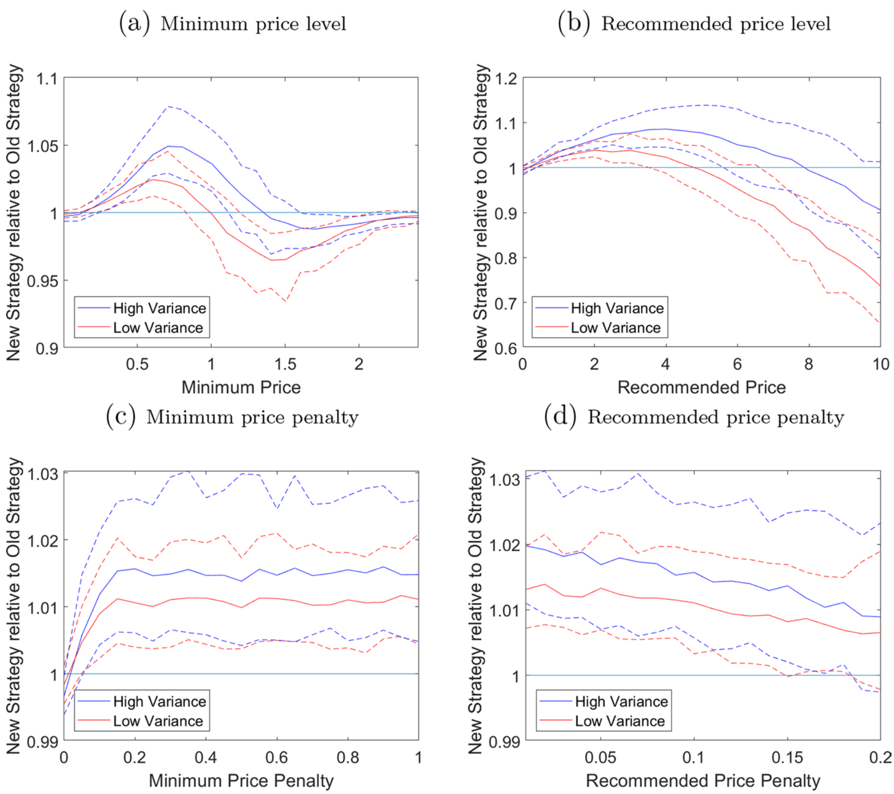


Fig. 7 Performance of price lists relative to decentralized strategy: profits. High and low variance of the unobserved component of the customer's willingness to pay. Notes: total profits with the price lists relative to the decentralized pricing strategy resulting from model simulation for a range of values for the minimum price level (**a**) and penalty (**c**), and the recommended price level (**b**) and penalty (**d**). Two cases with high and low variance of the unobserved component of the customer's willingness to pay. The standard deviation of the case with low variance is 75% of the case with high variance. Details in "Appendix 1"

The first order conditions with respect to the two prices yield the following system of equations:

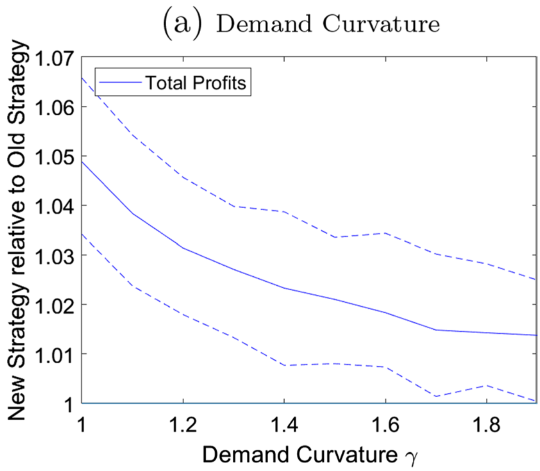
$$a_{1t} - 2p_{1t} + 2\beta p_{2t} = 0 \tag{17}$$

$$a_{2t} - 2p_{2t} + 2\beta p_{1t} = 0 \tag{18}$$

Solving the first order conditions yields the optimal price for the two items:

$$p_{1t} = \frac{a_{1t} + \beta a_{2t}}{2(1 - \beta^2)} \tag{19}$$

Fig. 8 Performance of price lists relative to decentralized strategy: profits. Notes: total profits with the price lists relative to the decentralized pricing strategy and 95% CI resulting from model simulation for a range of values for the demand curvature γ



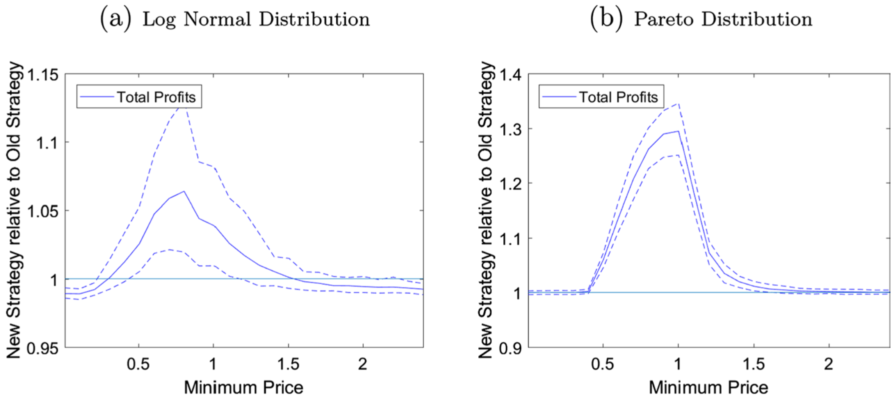


Fig. 9 Performance of price lists relative to decentralized strategy: profits. Notes: total profits with the price lists relative to the decentralized pricing strategy and 95% CI resulting from model simulation for a range of values for the minimum price under a log normal distribution of demand shifters (**a**) and a Pareto distribution (**b**)

$$p_{2t} = \frac{a_{2t} + \beta a_{1t}}{2(1 - \beta^2)} \tag{20}$$

To gather some intuition on the difference in pricing between substitutes and complements, consider the simple case of $a_{1_t} = a_{2_t} = a$. The price equals $p = \frac{a}{2(1-\beta)}$ and is increasing in β. When $\beta > 0$ and goods are substitutes, prices are higher than the case of unrelated products. This occurs because the firm internalizes the cannibalization effects across the imperfectly substitutable goods.[38] By increasing the price of

[38] For an analysis of cannibalization effects see Eckel and Neary (2010), Hottman et al. (2016), and Macedoni (2022).

an item, the firm increases the demand for the other item as it reduces the cannibalization effects. As a result, when the firm sells substitutes, it charges a higher price than the case of unrelated products. When $\beta < 0$ and goods are complements, prices are lower relative to the case of unrelated and substitutable products. This occurs because the firm internalizes the fact that reducing the price of an item increases the demand for the other item.

Next, we consider how pricing changes when we introduce price lists. In particular, let p_{R1} and p_{R2} denote the recommended price for the two items, and p_{min1} and p_{min2} the minimum prices. The objective function of the sales agent equals:

$$E[\pi_t] = d_{1t}p_{1t} + d_{2t}p_{2t} - m\mathbb{1}_{p_{1t}<p_{min1}} - m\mathbb{1}_{p_{2t}<p_{min2}} - \theta(p_{1t} - p_{R1})^2 - \theta(p_{2t} - p_{R2})^2 \tag{21}$$

The first order condition of the sales agent problem yield the following optimal prices:

$$p^*_{1t} = \frac{(2+\theta)(a_{1t} + \theta p_{R1}) + 2\beta(a_{2t} + \theta p_{R2})}{(2+\theta)^2 - 4\beta^2} \tag{22}$$

$$p^*_{2t} = \frac{(2+\theta)(a_{2t} + \theta p_{R2}) + 2\beta(a_{1t} + \theta p_{R1})}{(2+\theta)^2 - 4\beta^2} \tag{23}$$

As in the baseline model, if the optimal prices are below the minimum price, the sales agent compares the expected profits from charging the prices defined in (22) and (23) and pay the minimum penalty price or charge the minimum price and avoid paying m. Hence, the offered prices equal:

$$(p_{1t}, p_{2t}) = \begin{cases} (p^*_{1t}, p_{min2}) & \text{if } E[\pi_t(p^*_{1t}, p^*_{2t})] < E[\pi_t(p^*_{1t}, p_{min2})] \\ (p_{min1}, p^*_{2t}) & \text{if } E[\pi_t(p^*_{1t}, p^*_{2t})] < E[\pi_t(p_{min1}, p_{2t})] \\ (p_{min1}, p_{min2}) & \text{if } E[\pi_t(p^*_{1t}, p^*_{2t})] < E[\pi_t(p_{min1}, p_{min2})] \\ (p^*_{1t}, p^*_{2t}) & \text{otherwise} \end{cases} \tag{24}$$

The quantities exchanged and the profits of the firm are analogous to the baseline model. Namely,

$$d_{1t} = \max\{a_{1t} + \mu_{1t} - p_{1t} + \beta p_{2t}; 0\} \tag{25}$$

$$d_{2t} = \max\{a_{2t} + \mu_{2t} - p_{2t} + \beta p_{1t}; 0\} \tag{26}$$

$$\pi_t = d_{1t}p_{1t} + d_{2t}p_{2t} \tag{27}$$

To verify the effects of price lists under different values of β, we apply the same simulation algorithm of the baseline model. We assume that the observed and unobserved demand shifters are *i.i.d.*, i.e., there is no correlation between the demand shifters of the two goods. Furthermore, we impose symmetry between the two items: $E[a_{1t}] = E[a_{2t}] = 1$ and the standard deviation of the two shifters are also identical.

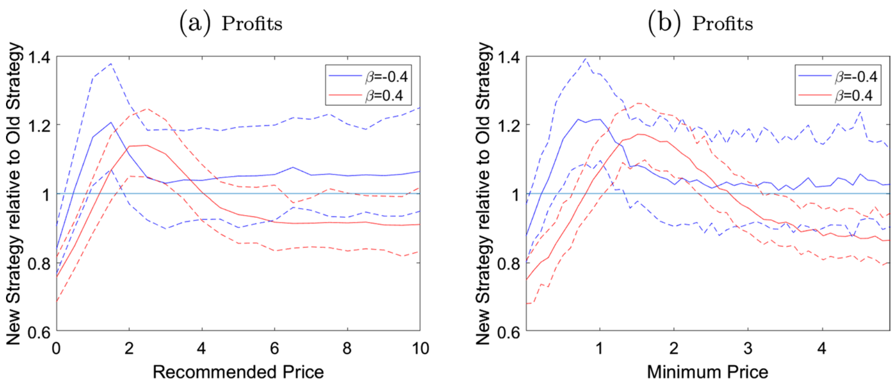


Fig. 10 Performance of new strategy relative to old strategy. Notes: profits with price lists relative to decentralized pricing strategy and 95% CI resulting from model simulation for a range of values for the recommended price (**a**) and minimum price (**b**). The two demand shifters follow a Normal distribution. When $\beta = 0.4$, the two items are substitutes and when $\beta = -0.4$, the two items are complements

Furthermore, $p_{min1} = p_{min2}$ and $p_{R1} = p_{R2}$. The values for the parameters are identical to the baseline simulation algorithm.

Figure 10 shows the results from the simulation. The result indicates that the optimal recommended price and minimum price is smaller for complement goods than for substitute goods. This is intuitive and it reflects the difference in the optimal price in the presence of full information for the two goods. Furthermore, the figure shows that the implementation of the optimal price list tends to have a larger effect for complement goods than for substitutes. This is likely driven by the fact that without price lists, sales agents tend to charge too low prices for complement goods than for substitute goods. Since the price lists manage to increase the average price charged, their effect is magnified for complements relative to substitutes.

Appendix 2: Data and descriptive statistics

Data details The dataset comprises 166,183 observations, where each observation corresponds to an item sold in a transaction to a customer. This includes 74,940 transactions involving 7271 unique items sold to 6244 different customers. Of the 74,940 transactions, 2355 included items recorded in different dates, and 92 span 2 years.

To avoid including item-destinations that are being discontinued or have just been put for sale at the time of the implementation of the pricing strategy, we restrict the dataset to all products sold every year in the period 2016–2018. We do not include 2015 in this restriction because of the relatively large product turnover between 2015 and 2018, which would end up restricting our dataset unnecessarily. This step reduces our dataset by 22,807 observations, equivalent to 5432 item-destinations.

To avoid that our results depend on sales from small or recently entered destinations, we drop the destinations for which we observe fewer than 500 transactions in the period 2015–2018. Specifically, we drop all 1,468 observations from Belgium, China, Croatia, Greece, South Korea, and Thailand. We drop the observations of United Arab Emirates (1608) and Australia (1655) because of a mismatch in the currency in the price lists. We drop 65 item-destinations (2055 observations) for which the recommended price in the price list is lower than the minimum price.

Finally, in order to control for item-destination-customer fixed effects in our regressions, we drop 32,305 singleton observations. This leaves us with 104,285 observations of transactions of 4057 item-destinations and 19,065 item-destination-customers (Tables 10, 11, 12, 13, Figs. 11, 12, 13, 14).

Table 10 Summary statistics

Panel A				
Year	Sales (000 Euro)	# Transactions	# Customers	# Products
2015	15,810	17,894	2546	3554
2016	14,386	18,151	2953	3911
2017	18,204	18,912	3087	3755
2018	19,792	20,075	3299	3772
Panel B: customer and product churning				
Year	# New customers	# Lost customers	# New products	# Discontinued products
2015	–	1028	–	1157
2016	1435	1267	1514	1551
2017	1401	1241	1395	1464
2018	1453	–	1481	–

Sample: All transactions in the period 2015–2018. Source: Viking Life-Saving Equipment A/S. New Customers/Products: Customers/Products absent in previous year. Lost Customers/Discontinued Products: Customer or Products absent in following year

Table 11 Sales, customers and items by destination (2018)

Country	Sales (000 Euro)	# Customers	# Items
USA	2785	200	483
DEU	1714	278	1347
DNK	1644	165	551
NoR	1636	434	461
FRA	1338	72	443
ZAF	1327	407	541
NLD	1127	143	392
GBR	903	123	287
FIN	893	157	288
SGP	854	137	221
TUR	751	139	247
ARE	658	79	159
MEX	587	72	210
ITA	577	125	198
AUS	513	102	198
EST	466	101	246
HKG	402	42	81
ISL	391	253	241
PAN	303	41	95
ESP	247	105	275
SWE	201	50	145
BEL	138	14	72
GRC	125	15	46
THA	103	42	76
HRV	56	22	67
KOR	48	6	6
CHN	9	14	8

Table 12 Customer class—descriptive statistics

Class	Share of total sales	Average sales	# Customers
VIP	24	39,165	122
A	23	15,620	287
B	25	6795	734
C	26	2437	2126
Unassigned	2	–	–

Data for 2018. The results are similar for the previous years. Viking does not record a customer identification for one-time customers, which are recorded under the Unassigned category

Table 13 Customer segment—descriptive statistics

Class	Share of total sales	Average sales	# Customers
Cargo	48	7849	1203
Defense	3	12,762	39
Fire	3	4491	150
Fishing	4	1833	475
Offshore	18	9474	382
Passenger	12	10,152	237
Yachting	2	2138	148
Not Assigned	10	2957	665

Data for 2018. The results are similar for the previous years

Table 14 Price dispersion measures—2017

Sample	Mean	Median	P1	P5	P10	P25	P75	P90	P95	P99	# Products
Coefficient of variation of prices											
All items	0.22	0.20	0.04	0.06	0.08	0.13	0.34	0.52	0.69	1.43	641
Item-Dest	0.15	0.14	0.02	0.05	0.07	0.10	0.21	0.35	0.48	0.97	896
Item-Dest.-Cust	0.10	0.06	0.00	0.00	0.00	0.03	0.10	0.19	0.26	0.78	333
Item-Dest.-Cust. (SP)	0.10	0.05	0.00	0.00	0.01	0.03	0.13	0.19	0.21	0.25	68
Standard deviation of log prices											
All items	0.20	0.19	0.04	0.06	0.13	0.29	0.41	0.49	1.20	2.08	641
Item-Dest	0.13	0.14	0.02	0.05	0.10	0.20	0.28	0.35	0.67	1.71	896
Item-Dest.-Cust	0.09	0.06	0.00	0.00	0.03	0.10	0.18	0.24	0.60	1.54	333
Item-Dest.-Cust. (SP)	0.09	0.05	0.00	0.00	0.03	0.12	0.17	0.18	0.25	1.36	68
95/5 percentile ratio											
All items	2.08	1.80	1.09	1.21	1.30	1.47	2.53	3.54	4.93	19.46	641
Item-Dest	1.71	1.53	1.05	1.17	1.24	1.35	1.83	2.57	3.30	7.19	896
Item-Dest.-Cust	1.54	1.20	1.00	1.00	1.00	1.08	1.40	1.72	2.13	4.63	333
Item-Dest.-Cust. (SP)	1.36	1.17	1.00	1.01	1.04	1.10	1.42	1.69	1.75	1.95	68

Sample: All transactions in the year 2017, samples restricted to products that have at least 10 observations in 2017. Source: Viking Life-Saving Equipment A/S. Mean is the sales-weighted average. Product definition: All items, items by destination, item by destination by customer. Item-Dest.-Cust. (SP) denotes the sample in which products are defined as item-destination-customer and restricted to only the transactions in which such products are sold as single products in one order. Measures of price dispersion: coefficient of variation of prices of a product in a year (σ/p); standard deviation of log prices of a product in a year; ratio of 95th percentile to 5th percentile of the price of a product in a year

Fig. 11 Minimum and recommended prices, by customer class. Notes: for each customer class: OLS of log of real prices over month dummies, item-destination-customer fixed effects and transaction characteristics. Sample includes all items included in the price lists with both recommended and minimum prices. In blue the estimated constant plus the coefficients of the time dummies, 95% confidence interval. Minimum prices (in red) and recommended prices (in green) net of fixed effects

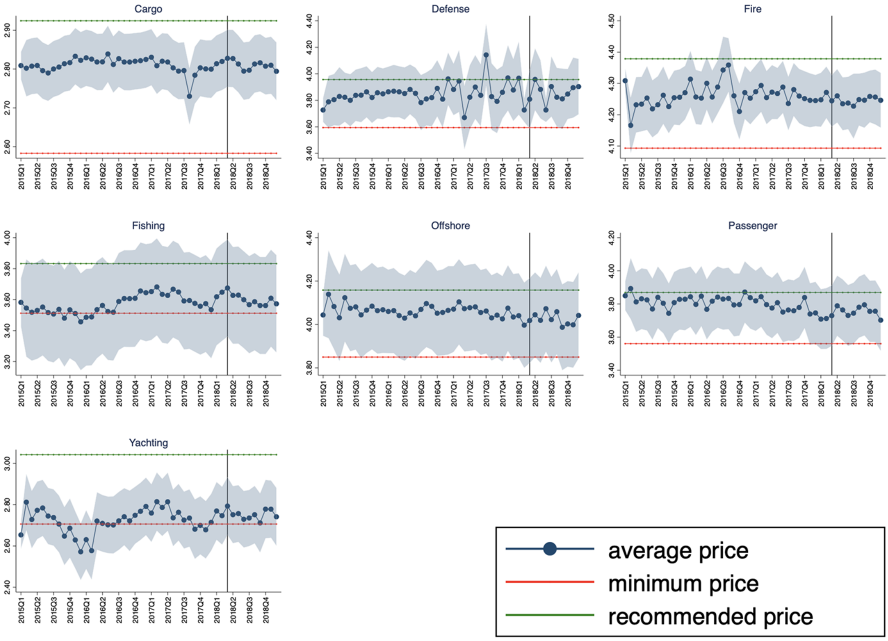


Fig. 12 Minimum and recommended prices, by trade segment. Notes: for each trade segment: OLS of log of real prices over month dummies, item-destination-customer fixed effects and transaction characteristics. Sample includes all items included in the price lists with both recommended and minimum prices. In blue the estimated constant plus the coefficients of the time dummies, 95% confidence interval. Minimum prices (in red) and recommended prices (in green) net of fixed effects (colour figure online)

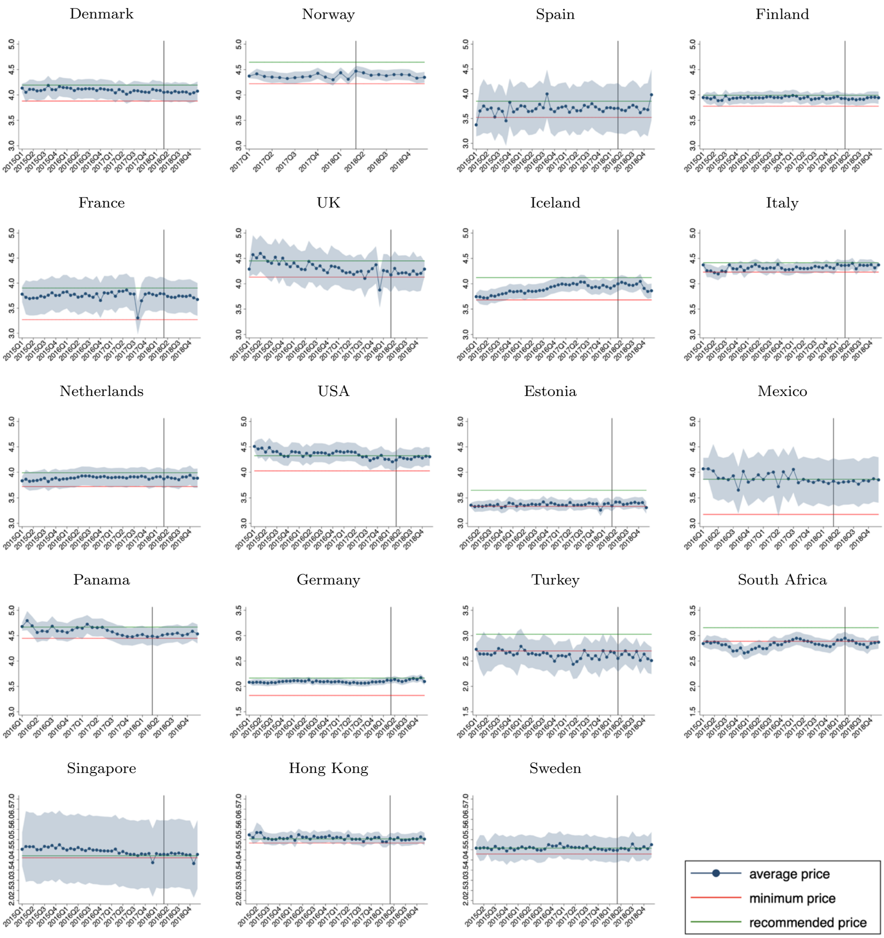


Fig. 13 Minimum and recommended prices, by destinations (all countries). Notes: sample: all transactions in the period 2015–2018 of products sold continuatively in 2016–2018 in sales destinations where we observe above 500 transactions over the period, excluding UAE and Australia. We exclude products in sale organizations where the minimum price is assigned to be above the recommended price. Source: Viking Life-Saving Equipment A/S. For each destination: OLS of log of real prices over month dummies, item-customer fixed effects and transaction characteristics, including a dummy for if the product is sold in a bundle with other products, and the revenue of the sale in thousands of real March 2018 euros. Sample includes all items included in the price lists with both recommended and minimum prices. In blue, the estimated constant plus the coefficients of the time dummies, 95% CI. Minimum prices (in red) and recommended prices (in green) net of fixed effects. Black vertical lines: the official implementation of the new pricing strategy (colour figure online)

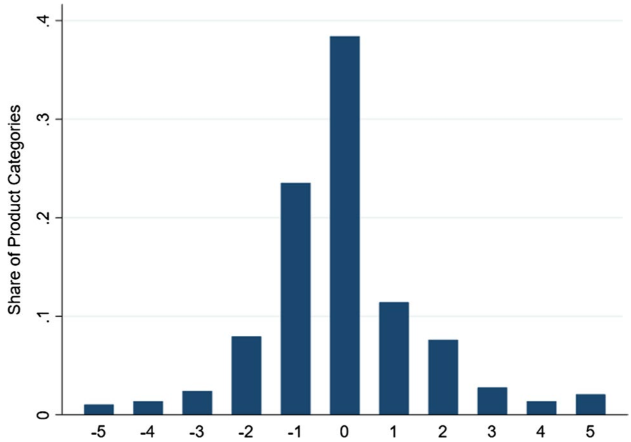


Fig. 14 Distribution of net product introduction by product category. Notes: data for 2016. The figure plots the share of product categories such that their net product introduction, defined as the difference between number of new products and number of dropped products, equals the value in the horizontal axis. The bin denoted by 5 reports the share of product categories with a net product introduction equal or larger than 5 and bin denoted by −5 reports the share of product categories with a net product introduction equal or smaller than −5 (colour figure online)

Appendix 3: Price dispersion in firm-to-firm trade

Price dispersion

See Tables 14, 15, 16, 17, 18, 19 and Fig. 15.

Table 15 Price dispersion measures—2016

Sample	Mean	Median	P1	P5	P10	P25	P75	P90	P95	P99	# Products
Coefficient of variation of prices											
All items	0.41	0.19	0.02	0.07	0.08	0.13	0.34	0.52	0.68	1.30	732
Item-Dest	0.17	0.14	0.01	0.05	0.07	0.10	0.21	0.35	0.47	0.93	960
Item-Dest.-Cust	0.06	0.05	0.00	0.00	0.00	0.01	0.12	0.20	0.36	0.70	330
Item-Dest.-Cust. (SP)	0.08	0.06	0.00	0.00	0.00	0.01	0.14	0.19	0.22	0.29	63
Standard deviation of log prices											
All items	0.23	0.18	0.03	0.07	0.12	0.29	0.39	0.47	0.62	2.06	732
Item-Dest	0.15	0.14	0.01	0.05	0.10	0.19	0.28	0.35	0.52	1.60	960
Item-Dest.-Cust	0.06	0.05	0.00	0.00	0.01	0.11	0.21	0.27	0.48	1.23	330
Item-Dest.-Cust. (SP)	0.07	0.06	0.00	0.00	0.01	0.13	0.20	0.22	0.23	1.32	63
95/5 Percentile ratio											
All items	2.06	1.74	1.07	1.19	1.29	1.43	2.37	3.59	4.76	8.54	732
Item-Dest	1.60	1.51	1.01	1.15	1.22	1.34	1.81	2.42	3.02	5.33	960
Item-Dest.-Cust	1.23	1.18	1.00	1.00	1.00	1.03	1.46	1.80	2.26	4.08	330
Item-Dest.-Cust. (SP)	1.32	1.19	1.00	1.00	1.00	1.03	1.51	1.67	1.96	2.24	63

Sample: All transactions in the year 2016, samples restricted to products that have at least 10 observations in 2017. Source: Viking Life-Saving Equipment A/S. Mean is the sales-weighted average. Product definition: All items, items by destination, item by destination by customer. Item-Dest.-Cust. (SP) denotes the sample in which products are defined as item-destination-customer and restricted to only the transactions in which such products are sold as single products in one order. Measures of price dispersion: coefficient of variation of prices of a product in a year (σ/p); standard deviation of log prices of a product in a year; ratio of 95th percentile to 5th percentile of the price of a product in a year

Table 16 Price dispersion measures—2015

Sample	Mean	Median	P1	P5	P10	P25	P75	P90	P95	P99	# Products
Coefficient of variation of prices											
All items	0.27	0.17	0.03	0.06	0.08	0.11	0.27	0.47	0.68	1.75	800
Item-Dest	0.17	0.14	0.02	0.05	0.06	0.09	0.21	0.33	0.46	1.10	1001
Item-Dest.-Cust	0.11	0.07	0.00	0.00	0.00	0.04	0.12	0.22	0.31	0.71	461
Item-Dest.-Cust. (SP)	0.08	0.06	0.00	0.00	0.00	0.01	0.11	0.24	0.29	1.41	65
Standard deviation of log prices											
All items	0.22	0.16	0.03	0.06	0.11	0.24	0.36	0.49	0.82	2.20	800
Item-Dest	0.15	0.14	0.02	0.05	0.09	0.19	0.29	0.38	0.69	1.69	1001
Item-Dest.-Cust	0.10	0.07	0.00	0.00	0.04	0.12	0.21	0.27	0.45	1.60	461
Item-Dest.-Cust. (SP)	0.08	0.06	0.00	0.00	0.01	0.11	0.19	0.26	0.60	1.33	65
95/5 Percentile ratio											
All items	2.20	1.65	1.07	1.19	1.27	1.40	2.13	3.09	4.52	15.69	800
Item-Dest	1.69	1.48	1.04	1.15	1.21	1.32	1.79	2.43	3.14	9.48	1001
Item-Dest.-Cust	1.60	1.25	1.00	1.00	1.00	1.10	1.45	1.90	2.37	4.07	461
Item-Dest.-Cust. (SP)	1.33	1.19	1.00	1.00	1.00	1.03	1.42	1.89	2.46	13.45	65

Sample: All transactions in the year 2017, samples restricted to products that have at least 10 observations in 2015. Source: Viking Life-Saving Equipment A/S. Mean is the sales-weighted average. Product definition: All items, items by destination, item by destination by customer. Item-Dest.-Cust. (SP) denotes the sample in which products are defined as item-destination-customer and restricted to only the transactions in which such products are sold as single products in one order. Measures of price dispersion: coefficient of variation of prices of a product in a year (σ/p); standard deviation of log prices of a product in a year; ratio of 95th percentile to 5th percentile of the price of a product in a year

Table 17 Price dispersion measures—top products and customers (2018)

Sample	Mean	Median	P1	P5	P10	P25	P75	P90	P95	P99	# Products
Coefficient of variation											
Top 1% of products	0.20	0.19	0.06	0.06	0.09	0.14	0.25	0.44	0.44	0.51	25
Top 1% of customers	0.20	0.14	0.00	0.03	0.03	0.08	0.32	0.54	0.64	0.97	44
Standard deviation											
Top 1% of products	0.18	0.17	0.05	0.06	0.08	0.14	0.21	0.30	0.32	0.33	25
Top 1% of customers	0.18	0.14	0.00	0.03	0.03	0.08	0.28	0.38	0.47	0.68	44
95/5 Percentile ratio											
Top 1% of products	1.77	1.74	1.15	1.24	1.36	1.53	1.96	2.62	2.77	2.89	25
Top 1% of customers	1.77	1.58	1.00	1.07	1.09	1.28	2.32	3.39	4.82	6.87	44

Sample: All transactions in the year 2018, sample restricted to products that have at least 10 observations in 2018. Samples restricted to (a) the top 1% of items sold by revenue, (b) items sold to the top 1% of customers by revenue. Mean is the sales-weighted average. Source: Viking Life-Saving Equipment A/S. Product definition: All items. Measures of price dispersion: coefficient of variation of prices of a product in a year (σ/p); standard deviation of log prices of a product in a year; ratio of 95th percentile to 5th percentile of the price of a product in a year

Table 18 Standard deviation in the residual

Fixed effect	Standard deviation	Observations
Item	0.30	48,286
Item, Dest., Cust., Time	0.25	48,286
Item-Dest.-Cust., Time	0.18	48,286
Item-Dest.-Cust.-Time	0.13	48,286

Sample: All transactions such that for each Item-Dest.-Cust.-Time tuple there are at least two observations. Source: Viking Life-Saving Equipment A/S. Product definition: All items. We compute the standard deviation of the residuals from Eq. (7), in which we regress $\ln p_{jdcto}$ on various combinations of fixed effects. We restrict the sample so that we have the same number of observations across specifications

Table 19 Standard Deviation in the Residual

Fixed effect	Local	DKK	EUR
Item	0.31	0.21	0.29
Item, Dest., Cust., time	0.26	0.19	0.25
Item-Dest.-Cust., time	0.18	0.16	0.18
Item-Dest.-Cust.-time	0.13	0.11	0.15

Sample: (Local): All transactions invoiced in local currency. (DKK): All transactions invoiced in Danish kroners. (EUR): All transactions invoiced in euro. Source: Viking Life-Saving Equipment A/S. Product definition: All items. We compute the standard deviation of the residuals from Eq. (7), in which we regress $\ln p_{jdcto}$ on various combinations of fixed effects

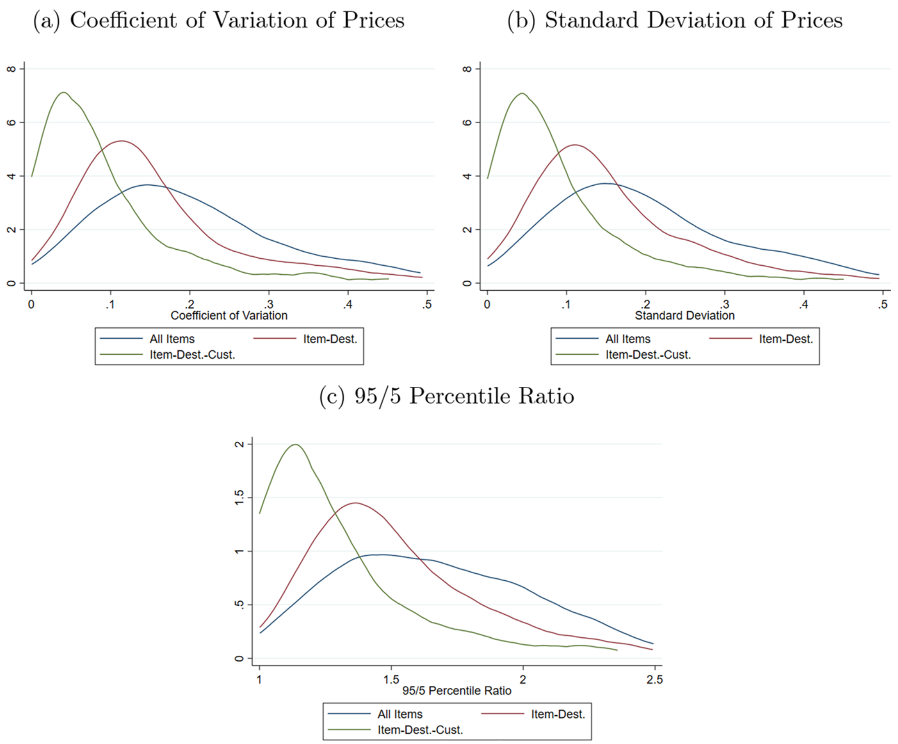


Fig. 15 Distribution of price dispersion measures (2018). Kernel density plots for the coefficient of variation, standard deviation, and 95/5 percentile ratio shown in Table 1. The distributions are truncated to the right for exposition purposes. Sample: all transactions in the year 2018, samples restricted to products that have at least 10 observations in 2018. Source: Viking Life-Saving Equipment A/S. Mean is the sales-weighted average. Product definition: All items, items by destination, item by destination by customer

Price variance

See Tables 20, 21, 22 and 23.

Table 20 Variance decomposition

	(Customer-destination)	(Time)	(Category)	(Transaction)
% of log price variance	0.183***	0.005***	0.011***	0.800***
	(0.001)	(0.000)	(0.001)	(0.001)
Observations	164,479	164,479	164,479	164,479

Standard errors in parentheses. Sample: All transactions in the period 2015–2018. Source: Viking Life-Saving Equipment A/S. The % of log price variance are the coefficients from OLS of the estimated fixed effects and residual of a specification of Eq. (8) with customer-destination, time, and product category FE on $\ln\left(\frac{p_{jdctoh}}{\bar{p}_j}\right)$. Product definition: item

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 21 Variance Decomposition

	(Customer-destination)	(Destination-time)	(Category)	(Transaction)
% of log price variance	0.182***	0.029***	0.011***	0.777***
	(0.001)	(0.000)	(0.001)	(0.001)
Observations	164,462	164,462	164,462	164,462

Standard errors in parentheses. Sample: All transactions in the period 2015–2018. Source: Viking Life-Saving Equipment A/S. The % of log price variance are the coefficients from OLS of the estimated fixed effects and residual of a specification of Eq. (8) with customer-destination, destination-time, and product category FE on $\ln\left(\frac{p_{jdctoh}}{\bar{p}_j}\right)$. Product definition: item

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

Table 22 Variance decomposition

	(Customer-destination-time)	(Category)	(Transaction)
% of log price variance	0.329***	0.014***	0.656***
	(0.001)	(0.001)	(0.001)
Observations	152,346	152,346	152,346

Standard errors in parentheses. Sample: All transactions in the period 2015–2018. Source: Viking Life-Saving Equipment A/S. The % of log price variance are the coefficients from OLS of the estimated fixed effects and residual of a specification of Eq. (8) with customer-destination-time, and product category FE on $\ln\left(\frac{p_{jdctoh}}{\bar{p}_j}\right)$. Product definition: item

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

Table 23 Variance decomposition

	(Customer-destination-time)	(Category-time)	(Transaction)
% of log price variance	0.327***	0.079***	0.593***
	(0.001)	(0.001)	(0.001)
Observations	150,095	150,095	150,095

Standard errors in parentheses. Sample: All transactions in the period 2015–2018. Source: Viking Life-Saving Equipment A/S. The % of log price variance are the coefficients from OLS of the estimated fixed effects and residual of a specification of Eq. (8) with customer-destination-time, and product category-time FE on $\ln\left(\frac{p_{jdctoh}}{\bar{p}_j}\right)$. Product definition: item

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

Table 24 Variance of prices in the residual—sales-weighted average

	(1)	(2)	(3)	(4)
% of log price variance	0.740***	0.740***	0.728***	0.646***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	164,576	164,479	164,462	152,346
Additional controls				
Customer FE	Yes	No	No	No
Destination FE	Yes	No	No	No
Time FE	Yes	Yes	No	No
Category FE	Yes	Yes	Yes	Yes
Customer-destination FE	No	Yes	Yes	No
Destination-time FE	No	No	Yes	No
Customer-destination-time FE	No	No	No	Yes

Standard errors in parentheses. Sample: All transactions in the period 2015–2018. Source: Viking Life-Saving Equipment A/S. The % of log price variance are the coefficients from OLS of the residual of different specifications of Eq. (8) on $\ln\left(\frac{p_{jdctoh}}{\bar{p}_j}\right)$ where $\bar{p}_j$ is the sales-weighted average of $\ln p_{jdctoh}$. Equation (8) ran with different combinations of fixed effects: (1) baseline customer, destination, time, and product category, (2) customer-destination, time, and product category, (3) customer-destination, destination-time and product category, (4) customer-destination-time and product category. The number of observations varies across the three columns as more singleton observations are dropped with interacted fixed effects. Product definition: item

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Robustness

In this section, we summarize the results from a robustness analysis of the results in Sect. 4.2. First, we use alternative measures of price dispersion, and we report the results in the “Appendix”. For each measure of price dispersion, we report the explanatory power of the fixed effects for all specifications described in Table 4. First, we consider the deviation of log prices from the sales-weighted average price (Table 24). In this case, the variance left in the residual is 74% in the first and second specification, and 65% in the specification with customer-destination-time fixed effects, which is similar to the baseline results. Second, we consider price deviations from their geometric average (Table 25). The variance left in the residual is 76% in the first and second specifications, and 58% in the last.

To further refine the analysis, we define a product as an item-destination (Table 26), and find that the percentage of the variance left in the residual is similar to the baseline case. Finally, we define a product as an item-customer-destination to further examine the sources of deviations within the same customer relationship (Table 27). In this case, the percentage of the variance left in the residual increases to 98% in the first two specifications and 80% in the third (Table 28).

As a robustness exercise, we repeat the baseline variance decomposition by customer class and segment in Tables 29 and 30 of the “Appendix”. The main pattern persists: The largest portion of the variance is explained by transaction-specific shocks. Furthermore, we find that these shocks are more relevant for the larger VIP and Class A customers (87% and 84%) than the smaller Class C customers (71%).

Table 25 Variance of prices in the residual—geometric average

	(1)	(2)	(3)	(4)
% of log price variance	0.763***	0.761***	0.733***	0.582***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	164,576	164,479	164,462	152,346
Additional controls				
Customer FE	Yes	No	No	No
Destination FE	Yes	No	No	No
Time FE	Yes	Yes	No	No
Category FE	Yes	Yes	Yes	Yes
Customer-destination FE	No	Yes	Yes	No
Destination-time FE	No	No	Yes	No
Customer-destination-time FE	No	No	No	Yes

Standard errors in parentheses. Sample: All transactions in the period 2015–2018. Source: Viking Life-Saving Equipment A/S. The % of log price variance are the coefficients from OLS of the residual of different specifications of Eq. (8) on $\ln\left(p_{jdctoh}\right) - \bar{p}_j$ where $\bar{p}_j$ is the average of $\ln p_{jdctoh}$. Equation (8) ran with different combinations of fixed effects: (1) baseline customer, destination, time, and product category, (2) customer-destination, time, and product category, (3) customer-destination, destination-time and product category, (4) customer-destination-time and product category. The number of observations varies across the three columns as more singleton observations are dropped with interacted fixed effects. Product definition: item

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 26 Variance of prices in the residual—product: item-destination

	(1)	(2)	(3)	(4)
% of log price variance	0.860***	0.858***	0.823***	0.641***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	164,576	164,479	164,462	152,346
Additional controls				
Customer FE	Yes	No	No	No
Destination FE	Yes	No	No	No
Time FE	Yes	Yes	No	No
Category FE	Yes	Yes	Yes	Yes
Customer-destination FE	No	Yes	Yes	No
Destination-time FE	No	No	Yes	No
Customer-destination-time FE	No	No	No	Yes

Standard errors in parentheses. Sample: All transactions in the period 2015–2018. Source: Viking Life-Saving Equipment A/S. The % of log price variance are the coefficients from OLS of the residual of different specifications of Eq. (8) on $\ln\left(\frac{p_{jdctoh}}{\bar{p}_j}\right)$. Equation (8) ran with different combinations of fixed effects: (1) baseline customer, destination, time, and product category, (2) customer-destination, time, and product category, (3) customer-destination, destination-time and product category, (4) customer-destination-time and product category. The number of observations varies across the three columns as more singleton observations are dropped with interacted fixed effects. Product definition: item-destination

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 27 Variance of prices in the residual—product: item-customer-destination

	(1)	(2)	(3)	(4)
% of log price variance	0.976***	0.976***	0.935***	0.805***
	(0.000)	(0.000)	(0.001)	(0.001)
Observations	164,576	164,479	164,462	152,346
Additional controls				
Customer FE	Yes	No	No	No
Destination FE	Yes	No	No	No
Time FE	Yes	Yes	No	No
Category FE	Yes	Yes	Yes	Yes
Customer-destination FE	No	Yes	Yes	No
Destination-time FE	No	No	Yes	No
Customer-destination-time FE	No	No	No	Yes

Standard errors in parentheses. Sample: All transactions in the period 2015–2018. Source: Viking Life-Saving Equipment A/S. The % of log price variance are the coefficients from OLS of the residual of different specifications of Eq. (8) on $\ln\left(\frac{p_{jdctoh}}{\bar{p}_j}\right)$. Equation (8) ran with different combinations of fixed effects: (1) baseline customer, destination, time, and product category, (2) customer-destination, time, and product category, (3) customer-destination, destination-time and product category, (4) customer-destination-time and product category. The number of observations varies across the three columns as more singleton observations are dropped with interacted fixed effects. Product definition: item-customer-destination

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

Table 28 Variance of prices in the residual—price demeaned with item FE

	(1)	(2)	(3)	(4)
% of log price variance	0.759***	0.757***	0.728***	0.577***
	(0.001)	(0.001)	(0.001)	(0.001)
# Observations	161,840	161,747	161,728	149,790
Additional controls				
Customer FE	Yes	No	No	No
Destination FE	Yes	No	No	No
Time FE	Yes	Yes	No	No
Category FE	Yes	Yes	Yes	Yes
Customer-destination FE	No	Yes	Yes	No
Destination-time FE	No	No	Yes	No
Customer-destination-time FE	No	No	No	Yes

Standard errors in parentheses. Sample: All transactions in the period 2015–2018. Source: Viking Life-Saving Equipment A/S. The % of log price variance are the coefficients from OLS of the residual of different specifications of Eq. (8) on the residual of a regression of $\ln p_{jdctoh}$ on item j fixed effect. Equation (8) ran with different combinations of fixed effects: (1) baseline customer, destination, time, and product category, (2) customer-destination, time, and product category, (3) customer-destination, destination-time and product category, (4) customer-destination-time and product category. The number of observations varies across the three columns as more singleton observations are dropped with interacted fixed effects. Product definition: item

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

Table 29 Variance decomposition by customer class

	(Customer)	(Destination)	(Time)	(Category)	(Transaction)
Class VIP	0.082***	0.014***	0.005***	0.029***	0.870***
	(0.002)	(0.001)	(0.000)	(0.001)	(0.002)
Class A	0.126***	0.001	0.007***	0.029***	0.837***
	(0.003)	(0.002)	(0.001)	(0.001)	(0.003)
Class B	0.138***	0.051***	0.008***	0.038***	0.766***
	(0.003)	(0.003)	(0.000)	(0.001)	(0.002)
Class C	0.174***	0.086***	0.012***	0.017***	0.711***
	(0.002)	(0.003)	(0.000)	(0.001)	(0.002)

Standard errors in parentheses. Sample: All transactions in the period 2015–2018 by customer class. Source: Viking Life-Saving Equipment A/S. The % of log price variance are the coefficients from OLS of the estimated fixed effects and residual of a specification of Eq. (8) with customer-time, destination-time and product category FE on $\ln\left(\frac{p_{jdctoh}}{\bar{p}_j}\right)$. Product definition: item. Number of Observations: 31,432 for VIP, 21,530 for Class A, 38,759 for Class B, and 63,923 for Class C

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 30 Variance decomposition by customer segment

	(Customer)	(Destination)	(Time)	(Category)	(Transaction)
Cargo	0.106***	0.034***	0.003***	0.018***	0.838***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Defence	0.144***	0.000**	0.028***	0.303***	0.525***
	(0.016)	(0.000)	(0.006)	(0.018)	(0.016)
Fire	0.328***	0.018	0.015***	0.097***	0.542***
	(0.014)	(0.011)	(0.002)	(0.005)	(0.008)
Fishing	0.460***	− 0.121***	0.033***	0.086***	0.542***
	(0.008)	(0.005)	(0.002)	(0.004)	(0.005)
Offshore	0.173***	0.087***	0.011***	0.080***	0.649***
	(0.005)	(0.005)	(0.001)	(0.003)	(0.004)
Passenger	0.127***	0.021***	0.019***	0.093***	0.741***
	(0.004)	(0.003)	(0.001)	(0.003)	(0.004)
Yachting	0.136***	− 0.000**	0.037***	0.259***	0.568***
	(0.006)	(0.000)	(0.003)	(0.007)	(0.007)

Standard errors in parentheses. Sample: All transactions in the period 2015–2018 by customer segment. Source: Viking Life-Saving Equipment A/S. The % of log price variance are the coefficients from OLS of the estimated fixed effects and residual of a specification of Eq. (8) with customer-time, destination-time and product category FE on $\ln\left(\frac{p_{jdctoh}}{\bar{p}_j}\right)$. Product definition: item. Number of Observations: 95,548 for Cargo, 1002 for Defense, 4259 for Fire, 12,150 for Fishing, 12,383 for Offshore, 10,700 for Passenger, 5731 for Yachting

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

This result is not surprising as it indicates a larger willingness of sales agents to accommodate requests of larger clients (for discounts or for urgent deliveries that may raise the price). The explanatory power of transaction shocks also varies across segments: For cargo, passenger, and offshore, it attains the largest values of 84%, 74%, and 65%, while for the other segments it is around 55%.

Transaction- and customer-specific characteristics

See Tables 31, 32 and 33.

Table 31 Prices and transaction characteristics

	(8-dig)	(8-dig)	(6-dig)	(6-dig)	(4-dig)	(4-dig)
Avg. price in cat	0.183***	0.304***	0.328***	0.308***	0.324***	0.303***
	(0.044)	(0.048)	(0.041)	(0.040)	(0.040)	(0.040)
Avg. price outside cat	− 0.443***	− 0.412***	− 0.426***	− 0.432***	− 0.514***	− 0.517***
	(0.059)	(0.050)	(0.047)	(0.044)	(0.026)	(0.026)
Log(quantity)		− 0.046***		− 0.045***		− 0.044***
		(0.007)		(0.007)		(0.007)
Log(1+ trans. value -j)		0.002		0.002		0.002
		(0.002)		(0.002)		(0.002)
Log(# prod. in trans.)		− 0.042***		− 0.037***		− 0.036***
		(0.004)		(0.004)		(0.004)
Local currency		− 0.041		− 0.032		− 0.035
		(0.025)		(0.024)		(0.024)
R^2	0.35	0.31	0.30	0.31	0.32	0.33
Observations	101,322	164,576	164,576	164,576	164,576	164,576
Additional controls						
Customer FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Product-category FE	Yes	Yes	Yes	Yes	Yes	Yes
Cust.-Dest.-Time-Cat. FE	No	No	No	No	No	No

Cluster-robust standard errors in parentheses. Cluster: destination country. Sample: All transactions in the period 2015–2018. Source: Viking Life-Saving Equipment A/S. Results from OLS of Eq. (9) of $\ln\left(\frac{p_{jdctoh}}{\bar{p}_j}\right)$ on transaction characteristics described in the main text. Customer, Destination, Category, and Time fixed effects in (1)-(6). Product definition: item. Viking identifies a product category with an 8-digit code (results shown in columns denoted by 8-dig). In this table, we also consider more aggregate definitions of product category at the 6-digit and 4-digit level (results shown in columns denoted by 6-dig and 4-dig)

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

Table 32 Prices and transaction characteristics

	(Trans.)	(Trans.)	(Month)	(Month)	(Quarter)	(Quarter)
Log(# Prod. in Trans.)	− 0.027***	− 0.042***	− 0.021***	− 0.016***	− 0.023***	− 0.018***
	(0.005)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)
Log(quantity)		− 0.046***		− 0.044***		− 0.044***
		(0.007)		(0.007)		(0.007)
Log(1+ Trans. Value -j)		0.002		− 0.007**		− 0.007***
		(0.002)		(0.002)		(0.002)
Local currency		− 0.041		− 0.047**		− 0.048**
		(0.025)		(0.021)		(0.021)
Avg. price in cat		0.304***		0.309***		0.309***
		(0.048)		(0.049)		(0.049)
Avg. price outside cat		− 0.412***		− 0.405***		− 0.405***
		(0.050)		(0.051)		(0.051)
R^2	0.20	0.31	0.20	0.30	0.20	0.30
Observations	164,576	164,576	164,576	164,576	164,576	164,576
Additional controls						
Customer FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Product-category FE	Yes	Yes	Yes	Yes	Yes	Yes

Cluster-robust standard errors in parentheses. Cluster: destination country. Sample: All transactions in the period 2015–2018. Source: Viking Life-Saving Equipment A/S. Results from OLS of Eq. (9) of $\ln\left(\frac{p_{jdctoh}}{\bar{p}_j}\right)$ on transaction characteristics described in the main text. Customer, Destination, Category, and Time fixed effects in all columns. In the columns labeled (Trans.), we use the number of products in the transaction, in the columns labeled (Month), we consider the number of products sold to a customer-destination in a month, and in the columns labeled (Quarter), we consider the number of products sold to a customer-destination in a quarter. Product definition: item

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

Table 33 Prices and customer characteristics

Dep. var.	Log of demeaned price			
	(1)	(2)	(3)	(4)
Cargo	− 0.002		− 0.003	0.042**
	(0.017)		(0.018)	(0.018)
Defence	− 0.052		− 0.053	− 0.009
	(0.043)		(0.044)	(0.039)
Fire	− 0.033		− 0.034	− 0.025
	(0.030)		(0.030)	(0.030)
Fishing	0.025		0.024	0.043
	(0.024)		(0.024)	(0.028)
Offshore	0.024		0.022	0.044***
	(0.017)		(0.017)	(0.016)
Passenger	0.018		0.018	0.057**
	(0.016)		(0.018)	(0.021)
Class VIP		0.013	0.010	0.053***
		(0.010)	(0.011)	(0.014)
Class A		− 0.018	− 0.020	0.007
		(0.024)	(0.025)	(0.019)
Class B		0.015	0.013	0.017
		(0.020)	(0.021)	(0.012)
Log(tot. sales)				− 0.008
				(0.005)
Log(tot. # products)				− 0.024**
				(0.009)
Log(# orders)				− 0.003
				(0.005)
Employee resp				− 0.028
				(0.017)
New customer				− 0.002
				(0.015)
Lost customer				− 0.003
				(0.012)
R^2	0.10	0.10	0.10	0.11
Observations	143,188	143,188	143,188	69,550
Additional controls				
Destination FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Product-category FE	Yes	Yes	Yes	Yes

Cluster-robust standard errors in parentheses. Cluster: destination country. Sample: All transactions in the period 2015–2018 by customer segment. Source: Viking Life-Saving Equipment A/S. We drop the dummy for class C and segment Yachting. Results from OLS of Eq. (10) of $\left(\frac{p_{jdctoh}}{\bar{p}_j}\right)$ on customer characteristics described in the main text. All columns include destination, time, and category fixed effects. Product definition: item. Column (4) includes only observations from 2016 and 2017

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

Evaluating the new price lists

See Tables 34, 35 and Figs. 16, 17, 18.

Table 34 Average characteristics of the product-sale organization units, by treatment

	Not in price list		In price list		In price list: p(min)		In price list: no p(min)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Real price[a]	125	356	85	203	84	205	109	136
Real revenue per transaction[a]	345	888	317	1167	315	1189	361	550
Overall real revenue per transaction[a]	1950	5640	1086	3375	1069	3373	1426	3406
Share of transactions with multiple products	0.686		0.744		0.748		0.651	0.477
Times sold per unit	63	113	210	272	208	274	248	232
Total quantity sold per unit	984	2194	1226	2868	1234	2931	1064	921
Number of different customers per unit	21	37	45	42	43	39	87	72
Share of sales to A customers	0.186		0.126		0.119		0.272	
Share of sales to B customers	0.314		0.226		0.225		0.235	
Share of sales to C customers	0.315		0.367		0.367		0.358	
Share of sales to VIP customers	0.165		0.212		0.217		0.114	
Share of sales to unclassified customers	0.021		0.070		0.072		0.022	
Share of sales in cargo	0.533		0.608		0.620		0.381	
Share of sales in defense	0.004		0.006		0.006		0.009	
Share of sales in fire	0.054		0.026		0.025		0.044	
Share of sales in fishing	0.047		0.070		0.068		0.105	
Share of sales in offshore	0.099		0.050		0.047		0.106	
Share of sales in passenger	0.122		0.053		0.054		0.050	
Share of sales in yachting	0.048		0.037		0.038		0.013	
No. item-destinations	686		3371		3138		233	
No. transactions	4347		99,938		95,204		4734	
No. item-destination-customers	1165		17,900		16,847		1053	

Sample: All transactions in the period 2015–2018 of products sold continuatively in 2016–2018 in sales organizations where we observe above 500 transactions over the period, excluded UAE and Australia. We exclude products in sale organizations where the minimum price is assigned to be above the recommended price. Source: Viking Life-Saving Equipment A/S

[a] Real euros March 2018

Table 35 Impact of new pricing strategy on real prices

Dep. var.	Log of real prices		
	(1)	(2)	(3)
Explanatory variables			
Post-March 2018×in price list	0.023	0.025	0.024
	(0.047)	(0.047)	(0.047)
Post-March 2018× in range		0.007	
		(0.010)	
Post-March 2018× out of range		− 0.046***	
		(0.016)	
Post-March 2018×$p95 < p_{min}$			0.051***
			(0.013)
Post-March 2018×$p5 > p_{rec}$			− 0.079***
			(0.015)
Observations	6983	6983	6983
Additional controls			
Item-destination-customer FE	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes
Transaction characteristics	Yes	Yes	Yes

Standard errors in parentheses. Sample: All item-destination-customer of products sold in 2015–2018 and sold continuatively in 2016–2018 in destinations where we observe above 500 transactions, excluded UAE and Australia. Restricted to item-destination-customers sold in at least two quarters and at least 2 times per quarter in both the period 2015–2017 and in 2018. Source: Viking Life-Saving Equipment A/S. OLS of the log of quarterly average price in real March 2018 euros on interactions of a dummy for post March 2018 with a dummy for the item being in the price list in the destination responsible for the sale and (col. 2) with dummies for the price distribution being in the price strategy range ($p5_{pre} > p_{min}$, $p95_{pre} \leq p_{rec}$) and being outside of the price strategy range ($p5_{pre} \leq p_{min}$, $p95_{pre} > p_{rec}$), or (col. 3) dummies for the price distribution being mostly below the minimum price ($p95 < p_{min}$) and mostly above the recommended price ($p5 > p_{rec}$). Other controls include: item-destination-customer fixed effects, year-quarter fixed effects, and transaction characteristics (average transactions where the item is sold in a bundle with other products, average transaction revenue in thousands of real March 2018)

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

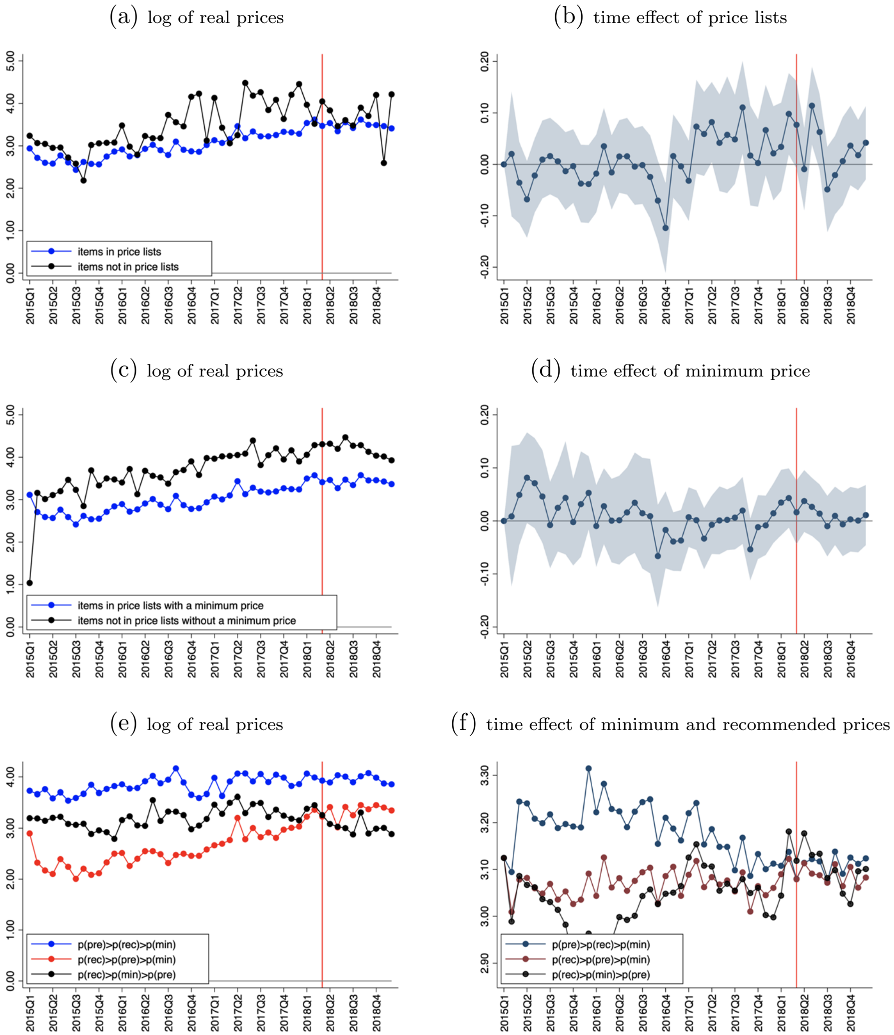


Fig. 16 Comparison of items in the price lists and off the price lists. Notes: sample: all transactions in the period 2015–2018 of products sold continuatively in 2016–2018 in destinations where we observe above 500 transactions, excluded UAE and Australia. We exclude observations where the minimum price is assigned to be above the recommended price. Source: Viking Life-Saving Equipment A/S. **a, c, e** Monthly average log of real prices for items in price lists and items off price lists (**a**), items in price lists with and without minimum price (**c**), items in price lists with average pre-2018 unit price below/above minimum and recommended prices. **b, d, f** OLS of log of real prices over month dummies interacted with a dummy for being in the price lists (**b**), or a dummy for having a minimum price (**d**), interacted with dummies for both recommended and minimum prices below the pre-2018 average unit price, recommended price above and minimum price below the pre-2018 average unit price, both recommended and minimum prices above the pre-2018 average unit price. Other controls include: item-destination-customer fixed effects, month fixed effects, and transaction characteristics (a dummy equal to one if the item is sold in a bundle with other products, the revenue of the transaction in thousands of real March 2018 euros). In the plot: coefficients of the month dummies interacted with a dummy for being in the price lists (**b**), or a dummy for having a minimum price (**d**), 95% confidence intervals. **d, f** Sample includes only items included in the price lists. Vertical red line at the official implementation of the new pricing strategy

Fig. 17 Impact of minimum price on log prices relative to the 2015–2017 average price, by customer class, trade segment and destination. Notes: estimates and 95% CIs for Eq. (12) by customer class (**a–c**), trade segment (**d–f**) and destination (**g–i**). Full result tables and average treatment across segment and destination are in the online appendix. Sample: All transactions in the period 2015–2018 of products sold continuatively in 2016–2018 in destinations where we observe above 500 transactions, excluded UAE and Australia. We exclude observations where the minimum price is assigned to be above the recommended price. We include only items included in price lists. Source: Viking Life-Saving Equipment A/S. Outcome: the log of the price in real March 2018 euros. OLS of the log of real prices on interactions of a dummy for post-March 2018 with dummies for having both recommended and minimum prices below the average unit price charged in 2015–2017 (**a, d, g**), recommended price above and minimum price below the average unit price (**b, e, h**), both recommended and minimum prices above the average unit price (**c, f, i**), and a dummy for having only minimum or recommended price (not shown). Other controls include: item-destination fixed effects, customer fixed effects, month fixed effects, and transaction characteristics (a dummy equal to one if the item is sold in a bundle with other products, the revenue of the transaction in thousands of real March 2018 euros)

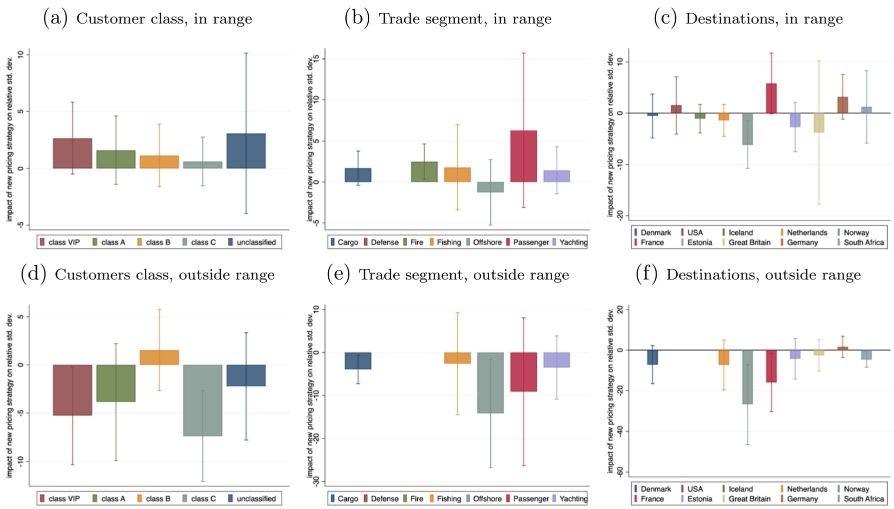


Fig. 18 Impact of new pricing strategy on price dispersion, by customer class, trade segment and destination. Notes: estimates and 95% CIs for Eq. (13) by customer class (**a–d**), trade segment (**b–e**) and destination (**c–f**). We include only destinations with at least 200 observations. Full result tables and average treatment across segment and destination are in the online appendix. Sample: All item-destination-customer of products sold continuatively in 2016–2018 in destinations where we observe above 500 transactions, excluded UAE and Australia. Restricted to item-destination-customers sold in at least two quarters and at least 2 times per quarter in both the period 2015–2017 and in 2018. Source: Viking Life-Saving Equipment A/S. OLS of quarterly coefficient of variation of real prices calculated as $100 \times (sd/p)$ on interactions of a dummy for post-March 2018 with a dummy for the item being in the price list and with dummies for the price distribution being in the price strategy range ($p5_{pre} > p_{min}$, $p95_{pre} \leq p_{rec}$) and being outside of the price strategy range ($p5_{pre} \leq p_{min}$, $p95_{pre} > p_{rec}$). Other controls include: item-destination-customer fixed effects, year-quarter fixed effects, and transaction characteristics (average transactions where the item is sold in a bundle with other products, average transaction revenue in thousands of real March 2018)

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Declarations

Conflict of interest None.

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