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The Impact of Price Adjustment Costs on Price Dispersion in E-Commerce

Abstract

We analyze price dispersion using panel data from a large price comparison site. We use past pricing behavior to instrument for potential endogeneity that might result from the selection of firms to certain product markets. We find that greater price adjustment costs result in greater price dispersion. Although the impact of price adjustment costs on price dispersion became weaker over time, the causal effect of price adjustment costs on price dispersion is still present at the end of the period. Our results are robust to many alternative empirical specifications. We also test a range of alternative explanations of price dispersion, such as search cost, service differentiation, obfuscation, vertical restraints, and market structure.

JEL-Codes: D400, L110.

Keywords: price dispersion, price adjustment costs, menu costs, e-commerce.

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1 Introduction

Direct menu costs, such as writing new price tags, may not play a substantial role in e-commerce, as firms can change prices with a few mouse clicks, and technology ensures the synchronization of prices on all platforms on which the firm operates. Some components of price adjustment costs (PACs), such as the managerial costs of deciding if, and by how much, to change prices, could be an important reason why firms ask for different prices. PAC arises from the costs of gathering information on competitors' prices and consumers' reactions to price changes, and the costs of deciding on the extent and timing of price changes.[1] For instance, Kauffman and Lee (2010) conclude that PAC are one reason for price dispersion (PD), even in the presence of the most advanced information technology. There is, however, little evidence on the empirical impact of PACs on PD.

Economists frequently focus on price dispersion (PD) because it "reflects the ignorance of the market" (Stigler, 1961). In efficient markets, PD should only be a disequilibrium phenomenon that vanishes over time, and in perfect markets, we expect a PD of zero. The question of whether online markets are more efficient than conventional markets is central in the analysis of e-commerce. For example, Gorodnichenko et al. (2018) show that even in e-commerce markets, PD does not vanish over time and it is important to identify why in order to understand PD in online markets. We show that PACs are, among others, one reason for diverse prices in e-commerce.

We analyze the effect of firms' PAC on PD using panel data from the dominant price comparison site in Austria, geizhals.at ("miser" or "skinflint"), and cover the universe of Austrian firms with an online shop. Firms post prices for goods in narrow categories. The price comparison site lists the prices along with product descriptions, availability, shipping costs, pay formalities, and so on, which substantially reduces

[1] We should note that some authors consider the managerial costs of price changes as components of menu costs (e.g., Blinder et al. (1998) or Levy et al. (1997)). However, it is more common to see PAC as the sum of direct menu costs and managerial costs. Costain and Nakov (2015) also argue that a firm pays a cost for managerial decisions when setting prices.

the search costs for consumers.[2] We analyze 241,606 products listed between July 1, 2006 and December 31, 2012.

We proxy PAC by the firms' price setting behavior using three different sets of proxies. First, following Nakamura and Steinsson (2008), we use the number and size of price changes. We expect that firms that change their prices less often will have a greater PAC than firms that change their prices more often. In addition, firms that change their prices less often might in consequence change their prices by more than firms that change their prices more often. Second, following Fisher and Konieczny (2000), we consider the synchronicity of price changes for multi-product firms. Firms that change the prices of their goods at the same time (or by the same amount) might have a greater PAC than firms that change the prices of their goods more discerningly. Third, we also use the rank of the prices to construct a proxy for PAC. If the rank of a firm's price in the distribution of all prices for this product varies little over time; for example, if it is consistently the third lowest price, we expect the firm to have low PAC as the firm succeeds in keeping the rank in the price listing.

E-commerce is an appropriate field to study PD and PACs. In this area, both should be negligibly small. The homogeneity of traded products and Bertrand competition should drive PD to zero. Consumers' low search costs should also support this effect. Due to low search costs, small price differences between retailers should strongly influence consumers' buying decisions. Hence, we expect PD to be small in e-commerce markets. Given the penetration of IT in this market, we also expect PAC to be small. If we find a causal effect of PAC on PD, even in markets where we do not expect a substantial connection between these two variable, it would be a valuable insight into the functions of markets.

Two sources of endogeneity might threaten the causal interpretation that PAC has a significant impact on PD in online markets. Firms might select themselves into markets according to the current PD; second, firms might adopt technologies such as price monitoring software according to the PD in the market. We address these

[2] Bodoh-Creed et al. (2017) argue that the increase in online trade might have increased search costs, as searches for a product require sophisticated techniques or costly information processing.

two potential sources of endogeneity using an instrumental variables approach in which we use the firm's listing decision for earlier versions of goods as an instrument for its current price setting behavior.

We obtain robust results that suggest that there is indeed a causal link from firms' heterogeneous price setting costs to PD. We find evidence for this causal link when controlling for other possible causes for PD, such as consumers' search costs, obfuscation, or vertical constraints. Our results show that prices are less flexible than the theoretical expectation of Jevons (1871)' "Law of one Price" predicts. Amongst other explanations, PAC acts as a substantial price rigidity, even in such competitive markets as e-commerce, where we would not expect PAC—and other reasons—to play an important role in the determination of PD.[3] However, our results demonstrate that over time, the influence of PAC on PD weakened. Technological advances in price setting, such as intelligent price setting algorithms, could contribute to more efficient markets in the future.

We contribute to the literature in several ways. First, we find that an increase in PAC should lead to more PD. Second, we provide and test several proxies for PAC in e-commerce (including evidence on synchronized price changes). Third, we offer a comprehensive set of control variables that control for most of the alternative theoretical explanations for PD. Fourth, we suggest an instrumental variable strategy to solve potential endogeneity biases arising from firms' potential selection into markets with a certain PD. Sixth, we illustrate that greater PAC leads not always to greater PD, and we exemplify that under certain conditions an increase in the level or the heterogeneity of PAC could also reduce PD.

2 PAC and other explanations for PD

Several studies show a comparable or smaller PD in online markets than in conventional markets (e.g., computer memory (Ellison and Ellison, 2009) or books (Clay

[3]From the viewpoint of economic policy, this might even have implications for aggregate price-level indicators and their ability to relay information from the micro- to the macro-economic level, where decisions about policy interventions are necessary. For instance, Midrigan (2011) discusses the implications of monetary policy shocks in a menu-costs model when prices are dispersed.

et al., 2001), see also Clemons et al. (2002)). Brynjolfsson and Smith (2000) find a lower PD for online channels when prices are weighted with market shares compared to conventional retail channels. Zhuang et al. (2018) document higher online PD than offline PD and state that heterogeneous retailers who compete for consumers with different perception of transaction risk explains this difference.

From a dynamic perspective, Pan et al. (2003) show a declining PD for 2000 and 2001 and an increase from 2001 to 2003. Baye et al. (2004b) analyze data from a price comparison site and find only limited evidence of shrinking PDs. Kaplan and Menzio (2015) analyze the structure of PD based on Nielsen's Scantrack Markets (mainly products bought in traditional brick and mortar stores) and find constant PD over time. Gorodnichenko et al. (2018) find similar, or even larger, PD in online shopping platforms than in brick-and-mortar stores. They estimate PD on the frequency and absolute size of regular price changes, as well as on the synchronization of posted price changes, which are common proxies for PAC. They estimate that the more frequent and the larger the price changes are, the more prices vary, but they find no effect of synchronized price changes on PD. Although Gorodnichenko et al. (2018) provide helpful insights into the firms' price setting behavior in e-commerce, they do not control for potential endogeneity issues or alternative explanatory approaches to explain PD.

Several theories might explain the existence of PD.

Price adjustment cost

Levy et al. (1997) report that menu costs are as large as 0.7% of revenue and Zbaracki et al. (2004) provide an estimate of about 1.2% of revenue. Zbaracki et al. (2004) show that PACs consists not only of the physical costs of price changes, but also include managerial costs to gather information, make decisions, and communicate. They stress that the managerial costs are six times greater than the direct costs of price changes are.

Chakrabarti and Scholnick (2007) find strong evidence that in e-commerce, the managerial costs component is an important reason for nominal price rigidities.

Bergen et al. (2003) argue that spill-over effects from high menu costs in the brick and mortar stores might also be relevant for the magnitude of the PAC in multichannel online shops. As different prices for different distribution channels might deter customers, high menu costs in the brick and mortar store could delay price changes in the online store.[4]

Businesses that have both online and offline stores are becoming more common. The increase in multichannel businesses could contribute to more online PD if price setting in offline distribution channels influences the price setting in the online channel (Bergen et al., 2003). Brynjolfsson and Smith (2000) find that even after controlling for shipping, handling costs, and taxes, online prices are lower than in conventional markets. They also find that online firms change prices by smaller amounts than do conventional firms. Bailey (1998) find that online firms increase prices more frequently than conventional firms do. These findings suggest lower PACs for online markets.

Kauffman and Lee (2010) present a survey on PACs and conclude that PAC are one reason for price rigidity, even in the presence of the most advanced information technology. However, their study provides hardly any empirical evidence on the impact of PACs on PD. Using a field experiment, Anderson et al. (2015) analyze the probability of prices changes depending on the size of the PACs, and find that the lower the PACs are, the higher is the probability of price changes.

There are surprisingly few theoretical models of the effect of PACs on PD. Sheshinski and Weiss (1977) present a model to explain the effect of inflation on firms' price setting. In this model, an increase in the costs of price adjustment leads to less frequent and larger price changes. Fishman (1992) provides a model in which search costs and PACs affect PD, and increased PD is one of the real effects of inflation. Benabou (1988, p. 364) gives an explicit result on the impact of PACs on PD, "As it becomes less costly to change prices, firms do it more frequently, thereby reducing (for any given maximum real price) the amount of PD and raising

[4] Dulleck et al. (2011) show that online stores that have a pick up facility generate more demand than do internet-only stores.

the average price in the market." Obviously, the underlying literature assumes a positive relationship between PAC and PD unambiguously.

Although we do not wish to question this common wisdom fundamentally, we want to make clear that this assumption does not hold in any case. We illustrate in the appendix that under certain, but not unusual conditions, an increase in PACs might also result in less PD. However, as these situations are (statistically) rarer, we expect PAC to have a positive impact on PD.

Search cost:

Search models stress the heterogeneity in customers' search costs. For example, Carlson and McAfee (1983) suggest consumers' search costs as a driving factor in PD. Kaplan et al. (2016) suggest that PD results from price discrimination between high-valuation customers, who prefer to make all of their purchases in the same store, and low-valuation buyers, who are willing to purchase different products from different e-shops. In Menzio and Trachter (2018), PD results from buyers who differ in their ability to shop at only one or different stores. Caglayan et al. (2008) analyze the PD in bazaars and supermarkets and find a lower PD in bazaars compared to supermarkets and attribute this to the easier comparability of prices in bazaars compared to supermarkets. Baylis and Perloff (2002) find evidence for the Salop-Stiglitz model search model, in which firms price discriminate across informed and uninformed consumers and thereby generate PD. Pan et al. (2001) argue that consumers search more when a product is more expensive (they speak also of consumer involvement); hence, PD for more expensive products should be greater than that for cheaper products. The authors also argue that products with greater demand should have less PD than products with less demand, as information, such as more consumer ratings, is more readily available.

In our estimations we control for both the products' absolute price as well as the demand for the product in order to control for search cost.

Various firm heterogeneities

Firms could follow different strategies in how they handle *inventories*. Some firms maintain stock to attract impatient customers and other firms might only order the product from the wholesaler upon receiving an order. Firms that keep stock might accept low, or even negative, markups to reduce their stock, such as towards the end of a product's life cycle. In that sense, Aguirregabiria (1999) discusses how inventory influences firms' markup behavior. Different markups might result in PD. Our data provide the status of a product's availability which we use as proxy for inventories in our estimations.

Betancourt and Gautschi (1993), Ratchford and Stoops (1988), and Pan et al. (2004) stress *service differentiation* as an explanation for PD. Pan et al. (2002) and Brynjolfsson and Smith (2000) explain the PD they observe in online markets by differences in firms' service quality. As potential buyers see different service qualities of a homogeneous product, firms could set their prices accordingly. We control for the varying service levels of online shops using changes in consumer ratings.

Brand loyalty could also be responsible for PD (Wernerfelt (1991)). In e-commerce this argument is closely connected to trust (Ribbink et al., 2004) and brand awareness (Chen and Hitt, 2001). Degeratu et al. (2000) argue that the less information consumers have about product attributes, the more important brand names become in online markets compared to offline markets. We use firm fixed effects to control for brand names and other unobserved firm heterogeneities in our panel estimations.

Obfuscation strategies ("bait and switch" strategies), different consumer perceptions of shipping costs or different local taxes could also cause PD (e.g., Pan et al. (2002) or Ellison and Ellison (2009)). We control for obfuscation strategies using the firms' shipping costs, which are listed separately from the prices.

Kauffman and Wood (2007) suggest that PD could result if some, but not all, firms agree on *price collusion*. Furthermore, time lags in price adjustment in a Bertrand Edgeworth competition could explain PD. Clemons et al. (2002) suggest *price discrimination* as a potential reason for PD. Other reasons why firms do not continuously change their prices are information-processing lags, customer acceptance, strategic recognition, or managerial inattention (Davis and Hamilton (2004), Ellison and Snyder (2011)).

Market heterogeneity

Carlton (1986) argues that firms in less concentrated markets tend to change their prices less frequently than do firms in highly competitive ones. Similarly, Haynes and Thompson (2008) and Nelson et al. (2007) stress market structure and find a strong positive relationship between the *number of sellers* and PD. Moreover, they argue that seller heterogeneity might be an important determinant of PD. However, a lack of data on e-seller attributes, especially cost differences, prevents them from further exploring this issue. Our data contain a broad variety of control variables, which allows us to pick up at the point of the limitations of their data. Barron et al. (2004) empirically estimate the relationship between seller density, average product price, and PD in the retail gasoline industry. We can control potential market structures with the change in the number of offering firms and the number of changes in price leadership.

Vertical restraints might be an additional cause for (the lack of) PD, which the existing literature did not discuss thus far. If manufacturers have a strong influence on the firms' prices, we expect prices to be more similar than when manufacturers do not have such influence. In our panel estimations, we use the change in the spread of the firms' concentration on branded products on the market as a proxy for these vertical restraints.

3 Data and Estimation Strategy

We use data on 241,606 products listed on the Austrian price comparison site www.geizhals.at between July 1, 2006 and December 31, 2012. The site is *the* main price comparison site in Austria and covers the universe of offering firms.

The data are ideal to study the relationship between firms' PAC and the PD of a product for several reasons. First, the website is the main price listing site and has close to all firms in the (Austrian) e-commerce market.[5] Compared to price search engines in other countries, prices listed in geizhals.at are not only a representative sample of offering firms, it is the whole population of e-commerce in Austria within the offered product categories. Second, the data provide very detailed characteristics of firms and products, including product availability, shipping costs, pay formalities, and customer ratings. Third, our dataset includes data from 1,113 firms. These firms can change their prices at any time directly in the geizhals.at system. Firms pay for each referral request from the price search engine to its web-shop (pay-per-click model). A legal contract between geizhals.at and the online-shop guarantees that the price listed in the price search engine has to be equal to the price shown in the online shop. Fourth, the dataset includes product and firm characteristics together with consumers' behavior over a long period. Thus, the dataset also offers reliable and robust instruments to identify causal inference.

We analyze PD in a panel dataset for product i at time t.[6] The products are mainly consumer articles listed on the price search engine, which we can classify into a hierarchical system of categories, subcategories, and subsubcategories.[7] Time t refers to quarters over a period of more than 6 years. The panel is unbalanced, with 31,730 products in 2006 and 88,948 products by the end of 2012.

Measures of PD

Prior studies used several measures of PD: the coefficient of variation (e.g., Baye et al. (2004a) or Sorenson (2000)), the value of information (e.g., Baye et al. (2003) or Pan et al. (2004), and the difference between the best and the second lowest price (e.g., Baye et al. (2004a). The coefficient of variation (CoV) is the ratio of

[5] The actual sales for most of the shops are not available. However, the authors have anecdotal evidence from personal correspondence with the web-shop managers: "The first day we can get rid of geizhals.at will be the best day of my life" is one quote that alludes to the fact that geizhals.at does indeed bring orders, but at the same time, reduces the profit opportunities due to competition.

[6] We restricted our dataset to product markets with at least two suppliers. Moreover, to eliminate possible outliers due to input errors from e-tailers, we eliminate observations with (i) prices higher than €10,000 (these products are typically not traded via e-commerce), (ii) a difference between the mean price and the minimum price (value of information, VoI) of more than 500%, and (iii) a difference between the lowest and the second lowest price quote above 200%.

[7] Geizhals.at originally specialized in the "hardware," "software," "games," "video/foto/tv," "telephone," and "audio and hifi-systems" product categories. In the last years, they introduced the "household appliances," "sports and recreation equipment," and "drugstore items" product categories.

the standard deviation of the prices for a product i offered by firm j to its average price, $\bar{p}_{i,t}$, $CoV_{i,t} = \sqrt{\text{Var}(p_{i,j,t})}/\text{Mean}(p_{i,t})$. The VoI ($VoI$) measures the difference between the mean and the minimum price as a fraction of the minimum price, $VoI_{i,t} = [\text{Mean}(p_{i,j,t}) - \text{Min}(p_{i,j,t})]/\text{Min}(p_{i,j,t})$. The VoI indicates the customer's savings by buying at the minimum price instead at the mean price. Finally, we also use the difference between the best price and the second lowest price divided by the best price, $D\_1\_2_{i,t}$, as the third PD indicator.

In contrast to the CoV or the VoI, which incorporate more information on the distribution of prices, $D\_1\_2_{i,t}$ focuses only on the two lowest prices, which, arguably, is the relevant part of the price distribution for consumers. We thus expect a weaker association between PAC and $D\_1\_2_{i,t}$ than for the other two indicators. We measure all three of our indicators at the last day of a quarter t at noon. A quick descriptive glance over our measures for PD reveals an average increase of about 40% over our estimation period.[8]

Measures of PAC

Direct measures of PAC are not available. Instead, we use different interpretations of the firms' price setting behavior over a quarter to calculate several proxy variables for their PAC.

- We suspect that the duration between price changes and the size of the price changes indicate differences in firms' PACs (e.g., Nakamura and Steinsson (2008)). Firms that change their prices often perhaps have lower PACs in contrast to firms that change their prices infrequently.

  The indicator LENGHT$\Delta p_{j,t}$ is the average duration between the price changes of all offered products i for firm j in quarter t. Similarly, HEIGHT$\Delta p_{j,t}$ is the average of all price changes for all products offered by firm j in a quarter.[9] As both indicators are likely to interact with each other, we also calculate the

[8]Specifically, the changes in PD are: (1) the CoV increased by 31.17%, (2) the VoI increased by 43%, and D_1_2 grew by 53%.

[9]Note that for LENGHT$\Delta p_{j,t}$ and HEIGHT$\Delta p_{j,t}$, we calculated the daily averages of the firms' price changes and durations for all products. In a second step, we computed the average over all days for a given firm.

interaction term, $\mathrm{L} \times \mathrm{H}\Delta p_{j,t}$, as the average product of the duration between two price changes with the size of the price change.

- Firms might not focus on the prices themselves, but are perhaps more concerned with the position their prices have on the price listing site. If we assume that a firm aims to maintain a certain rank in the price listings, we can use the variance of the firms' ranking as another proxy for PAC. Under this assumption, a lower variance of the rank implies that the firm spends more effort on setting the prices to maintain a certain position. This implies that these firms have a lower PAC compared to firms whose prices change ranks more. Because the number of firms influences the variation of ranking, we normalize the ranks with the number of firms that offer the product. We calculate the proxy as $\mathrm{RANK}_{j,t} = \sum_i \sqrt{\mathrm{Var}(r_{i,j,t})}/I_j$, where r is the normalized rank and I_j is the number of listed products of firm j.

- Our third set of proxies is based on firms' synchronicity of price changes.[10] A large number of synchronous price changes, either with respect to the timing or to the amount, could indicate a high PAC. We define the indicator $\mathrm{ST}_{j,t,d}$ for the number of synchronous price changes normalized to the number of offered goods at day d as:

$$\mathrm{ST}_{j,t,d} = \begin{cases} 0 & \text{if } \sum_{i=1}^{I_{j,t,d}} \delta_{i,j,t,d} \leq 1, \\ \left(\sum_{i=1}^{I_{j,t,d}} \delta_{i,j,t,d}\right)/I_{j,t,d} & \text{in all other cases,} \end{cases} \tag{1}$$

where $\delta_{i,j,t,d}$ is a binary indicator of whether the price for product i changed on day d or not. $I_{j,t,d}$ denotes the total number of products firm j offered on day d.

The average synchronicity of price changes is

$$\mathrm{SYNC}^{T}_{j,t} = \frac{\sum_d ST_{j,t,d}}{D_j}, \tag{2}$$

[10] For the monopoly case, Sheshinski and Weiss (1992) show that a store tends to change the prices of different products in sync rather than adopting a staggered price policy. Furthermore, Fisher and Konieczny (2000) suggest different indices for price synchronization.

where D_j is the number of days on which firm j changed at least one price. A firm with a lower PAC will change their prices more asynchronously than a firm with a high PAC. We therefore expect $\text{SYNC}^T_{j,t}$ to be a good proxy for the firms' PAC.

By construction, $\text{SYNC}^T_{j,t}$ measures the degree of simultaneous price changes and ignores the amount by which the prices change. We argue that a firm has a lower PAC if it changes the price for each product individually than does a firm that changes all prices by a certain amount or proportion. To account for similar amounts of price changes, we use the coefficient of variation of the price changes as the percent of the original price, $\Delta p_{i,j,t,d}$, on day d:

$$\text{SH}_{j,t,d} = \begin{cases} \text{undefined} & \text{if } \sum_{i=1}^{I_{j,t,d}} \delta_{i,j,t,d} \leq 1, \\ \frac{\sqrt{\text{Var}(\Delta p_{i,j,t,d})}}{\text{Mean}(\Delta p_{i,j,t,d})} & \text{in all other cases.} \end{cases} \tag{3}$$

We calculate the average synchronicity of price changes in period t as the average of the daily $\text{SH}_{j,t,d}$:

$$\text{SH}_{j,t} = \frac{\sum_d \text{SH}_{j,t,d}}{D_j}. \tag{4}$$

This variable will be greater for firms with more variation in their price changes. For ease of interpretation, we prefer the proxy to have greater values when firms have similar price changes. We therefore transform the variable such that lower values indicate more varied price changes, which we interpret as a lower PAC, and that greater values indicate more similar price changes; that is, a greater PAC:

$$\text{SYNC}^H_{j,t} = |\text{SH}_{j,t} - \max(\text{SH}_{j,t})| + \min(\text{SH}_{j,t}). \tag{5}$$

The timing of price changes, $\text{SYNC}^T_{j,t}$, and the similarity of the amount of price changes, $\text{SYNC}^H_{j,t}$, might interact with each other. To account for this empirically, we calculate the interaction of the two indicators:

$$\text{SYNC}^I_{j,t} = \text{SYNC}^T_{j,t} \times \text{SYNC}^H_{j,t}. \tag{6}$$

We calculate the averages of each indicator at the product level i using the PAC values of all firms j that offered product i in quarter t. The proxies for the firms' PAC aggregated at the product level indicate whether the firms that offer a product have, on average, a lower or higher PAC than do firms that offer some other product.

Let $L_{i,j,t}$ indicate firm j's decision to offer product i (=dummy variable for the listing decision) and $J_{i,t}$ the total number of firms that offer product i. The average PAC proxy for product i in quarter t is then

$$\text{PAC}_{i,t} = \frac{\sum_j \text{PAC}_{j,t} L_{i,j,t}}{J_{i,t}}. \tag{7}$$

Table 1 provides the descriptions of our PAC and PD measures. As these indicators are dimensionless, we use z-transformed variables with a zero mean and a variance of one.

3.1 Hypotheses and Identification Strategy

We estimate the impact of PACs on PD with the following equation.

$$PD_{it} = \alpha + \beta PAC_{it} + \gamma X_{it} + \nu_i + \epsilon_{it}, \tag{8}$$

where PD_{it} indicates the PD for product i at time t. The variable PAC_{it} is one of our proxies for the PAC. The vector X_{it} contains product-specific and firm-specific characteristics, for which we control for alternative explanations of PD. The variable ϵ_{it} is an error term and ν_i are product-specific fixed effects.

Although we do not rule out that under certain conditions an increase in PAC can also result in less PD, in general, we expect that prices in markets in which the firm's PAC are greater will be more dispersed; that is, $\beta > 0$. This is because a higher PAC leads to a lower PD less often than it leads to a higher PD.[11] (See the appendix for more details on this hypothesis.)

The proxy for PAC in equation (8) is a composite of the firms' listing decisions $L_{i,j,t}$ and the costs of changing prices. Both components could be endogenous, as firms might select into markets with a certain PD and possibly change their price setting technology, and thus their PACs, depending on the market's PD.

To account for the endogeneity of the listing decision, we use an instrumental variable approach, where we instrument a firm's listing decision by its listing decision for an earlier variant of the product, $\hat{L}_{i,j,t}$. We use the product's predecessor for five product generations. For example, we instrument the listing decision $L_{i,j,t}$ on the xth day of product i's life cycle by the firm's listing decision on the xth day of the life cycle for the product offered five product generations earlier.We define products by their sub-subcategory in the hierarchical classification system of the price listing site.[12] We use the dates of the products' first appearance on the price listing site to date product generations. Because the PD of product i on day d was unknown five product generations ago, we argue that the exclusion restriction should not be violated.[13]

In the second case of the potential endogenous adaption of price setting technology, we argue that it is extremely unlikely that a market's PD determines the firm's PAC. A firm's choice of price setting technology typically depends on aspects besides the market's PD, such as the operating costs, number of products, compatibility with other software, costs to acquire information about competitors, and so on.

If the choice of technology decision depends on the ease of changing the prices of many products, it is even more unlikely that a market's PD will determine the choice

[11]In contrast to the consequences of the level of PACs, Section 5.2 and the Appendix discuss the impact of PAC heterogeneity, which is theoretically and empirically less clear-cut.

[12]The price listing site has a hierarchical classification of main categories (e.g., hardware), subcategories (e.g., input devices), and sub-subcategories (e.g., keyboards).

[13]Our argument for this instrument is similar to the argument in the shift-share approach common in the migration literature. See, for example, Card (2001).

of technology. Note that in this sample, a firm offers 2,564 products on average and there is considerable heterogeneity in PD for the average firm's product assortment.

4 Empirical Results

4.1 Main results

We present our main results in Table 2. Each number is a coefficient from a separate two-stage least squares (2SLS) panel-data regression of one of our PAC proxies on one of three PD indicators. For ease of comparison, we present the beta coefficients. We transformed all measures of PD, PAC, and all controls to variables of mean 0 and variance 1. In column (1), we tabulate the results using CoV as the PD indicator. Column (2) tabulates the results using VoI, and column (3) tabulates the results using the difference between the lowest and the second lowest price, D_1_2. We report the F-statistics from the first stages in column (4). These range from 791 to 73,891. Each row has the same first stage specification.

Due to the instrumentation strategy, we lose 886,733 observations (34%) or 76,558 products (24%) for which we cannot define the instrument. The main reasons for the sample losses are new firms entering the market, products listed at the beginning of our records that lack a defined predecessor good, and long running products that have a predecessor with a substantially shorter product life cycle. The selected and full sample do not differ significantly.

Comparing the fixed effects panel regressions with the IV panel regressions shows a clear tendency that the 2SLS coefficients are greater than those from regular OLS panel regressions. This implies that firms with high (low) PAC tend to list on product markets with low (high) PD. With our instrumentation strategy, we control for this endogeneity problem.

Almost all coefficients are statistically significant at conventional error levels, and 19 of the 21 coefficients are positive. The PAC based on the amount of price changes, HEIGHT$\Delta p_{j,t}$, cannot explain any variation in PD if we measure it using

VoI or D_1_2. However, its coefficient is statistically different from zero if we use the CoV to measure PD.

The results for the PD measure that focuses on only the two lowest prices, D_1_2, are overall weaker than those for either CoV or VoI. This is not surprising, as the D_1_2 indicator disregards any other information on the distribution of prices besides the difference between the two lowest prices (this number is small if the two lowest prices are close, even when the other prices have a large variance). The estimated coefficients are negative in only two instances; in both cases, we measure PD by the difference in the two lowest prices.

Hence, in the following interpretations, we focus primarily on the results from the VoI and CoV measures of PD. Overall, we interpret these results as evidence of the substantial role of PAC in PD, even in markets where we would not expect that PAC is important.

If we compare the sizes of the estimated effects, we see that the effect of PAC on PD is greatest when we use the duration between price changes as the proxy for PAC. A look at our synchronization-based PAC measures reveals somewhat smaller but similar explanatory power than the length between the price changes, especially in the interaction between the timing and height of the price changes. The effect is smallest when we use firms' variances in price ranking in the listings as a proxy for PAC. If we see our results as a test to identify the best proxy variables for PAC, we recommend the average duration between two price changes $\text{LENGHT}\Delta p_{j,t}$, which is easy to calculate, or the more complex synchronicity measure $\text{SYNC}^{I}_{j,t}$. Measures based on the price rankings are perhaps a worse approximation of the true underlying PAC.

4.2 Alternative theories to explain PD

All of our regressions include a set of explanatory variables to control for other potential sources of PD. The control variables are product-level characteristics, and we aggregate firm characteristics for all firms that offer the product. We tabulate the estimated beta coefficients for these variables in Table 3. These estimates use

CoV as the measure of PD. The coefficients vary little if we use one of the other two PD measures.

Section 2 also provides the background of and relevant literature on these alternative explanations.

Search costs

Search Costs: Search models argue that consumers invest more effort in searching if the expected gain from this search is sufficiently large. Hence, we expect a lower PD for expensive goods, as the relative gains are potentially larger than for cheaper products. Since we use *product-specific fixed effects* in the panel estimation, we cannot estimate this association directly. The coefficient on the deviation from the average price, however, is not statistically significant. However, the estimations based on pooled cross sections results in significantly lower PD for more expensive products.

Inventories

Customers might make a tradeoff between product availability and price. A market in which firms differentiate using a combination of these two dimension is thus likely to have a greater PD. At the same time, availability is a good predictor of firms' inventories.[14] Especially at the end of a product life cycle, firms might accept even negative markups to sell their stock.

Note that if all firms do (or do not) have the product available, then inventories cannot explain PD. Hence, we are interested in the heterogeneous product availability across offering firms. Therefore, we use the variance of firms' availability, where 1 indicates that the product is readily available and 0 otherwise, as an indicator of the heterogeneity in inventories.[15]

[14] Firms could have different business models: some firms could buy larger quantities and store the products, which provides the advantage of lower wholesale prices at the expense of higher storage costs. They also bear a greater entrepreneurial risk if demand for this product is low. In the alternative business model, the retailer orders the products from the supplier when a customer places an order. This second option reduces storage costs and lowers the entrepreneurial risk, but at the cost of higher wholesale prices.

[15] We calculated our control as the variance of a Bernoulli distributed random variable $p(1-p)$ (with p indicating the probability of product availability).

The estimated coefficient indicates a significant positive effect of an increase in the heterogeneity in availability, suggesting that a more disperse composition of firms with regard to inventories will increase PD.

Service differentiation

PD could arise when firms use different strategies or differ in their ability to generate *brand loyalty*. We include the average customer valuation of firms as a control variable. This variable ranges from 1 to 5, where 5 indicates the least satisfaction.[16] The estimated coefficients for this indicator are negative and indicate that markets served by firms with fewer satisfied customers have less PD.

More generally, the dispersion of firms' customer evaluations is an indicator of service differentiation among the firms. Hence, we also include the standard deviation of the firms' evaluation. The estimates indicate that the more varied the customers' views of the firms' service in the market is, the greater the PD will be.

Prices in the firms' brick and mortar channel might also be relevant for the PD in online shops. For example, high PACs in the offline business might reduce price flexibility in the online outlet if different prices in different channels might deter customers. If such spill-overs exist, we would expect that markets that have more firms offering customers the option to pick up a product purchased online from one of their stores have a greater PD. The results confirm this hypothesis, as markets with more heterogeneity in the firms' *Pick-Up-Possibilities* increase the market's PD.[17] Comparing the beta coefficient with the other explanations for PD suggests that the differing pick up options is among the most important factors in explaining PD.

Obfuscation

Firms might deliberately obfuscate parts of the price to tempt impatient customers into purchasing the product. We include the standard deviation of the firms' ship-

[16] The ratings on the price comparison site is the average of all ratings over the last 12 months.

[17] As the share would be non-informative, we calculated our control as the variance of a Bernoulli distributed random variable $p(1-p)$ with p indicating the probability that the shop has a pick-up option.

ping costs as an indicator for how pronounced obfuscation is in a market. If obfuscation strategies work, we expect a greater variance of shipping costs to increase net PD. We do observe this phenomenon in our data, the estimated coefficient of the standard deviation of shipping costs is positive and suggests that PD is indeed greater when firms use obfuscation strategies.

Vertical restraints

Manufacturers with a strong influence on the retailers' price setting (upstream market power) may focus on maintaining a single high price for the product for all of its retailers.[18] When manufacturers exploit their upstream market power to maintain uniform prices in downstream markets, these vertical restraints could lead to lower PD in retailing. In markets which are characterized by strong vertical restraints, we therefore expect a lower PD than in markets without vertical constraints.

To account for differences in such restraints across product markets, we distinguish between branded and unbranded products. We argue that vertical constraints are more likely to exist for branded products than for unbranded products. We construct an indicator for market heterogeneity and calculate the average of the firms' share of branded products of all of their offered products as a proxy for the ties that a retailer might have with an upstream manufacturer. The positive and significant sign of *Percentage Big Brand Std.* supports our expectation.

Our estimation approach, which uses product fixed-effects, does not allow us to create a direct control for branded products. The estimation results using the pooled cross-section data without product fixed effects, in which we include a dummy for branded products, indicate that branded products have significantly lower PD than unbranded products do.

Market structure

PD might be a consequence of market structure which we control for using the following indicators:

[18] Manufacturers typically want to maintain high prices since it provides greater profits for both the retailer and the manufacturer, and do so through tactics such as more promotion.

Average size of the firms: To approximate the average firm size, we use the total number of clicks a firm obtains for all of its products listed on the price search engine in the respective quarter.[19] The greater this number is, the more products the firm offers, and thus the larger the firm is. Our control variable *Clicks on Firm Avg.* is the average of the total number of clicks of all offering firms of a market. In our context, we interpret it as a proxy for firm size. As markets with larger firms tend to be more concentrated, we would expect a lower PD in these markets.[20] The negative coefficient in our estimations confirms this expectation.[21]

Heterogeneity in firm sizes: The variable *Clicks on Firm Std.* calculates the standard deviation of the total number of clicks of all offering firms and in our context, can be a proxy for heterogeneity in firm sizes. We expect greater PD as the heterogeneity in the firms in the market increases (in terms of size as total number of clicks) (e.g., cost differences due to different economies of scale). The positive sign on the estimation results confirms our expectation that offers from more heterogeneous firms result in higher PD. Note that our indicators for the average firm size and the heterogeneity in firm size are the most important factors explaining PD.

Strength of Demand: We measure the strength in demand by the number of clicks from an Austrian IP address on the product (*Austrian Clicks on Product*). The greater the demand for a product is, the more interesting the product will be for retailers. Hence, an increase in the demand for a product should stimulate additional market entries and therefore fiercer competition, resulting in a lower PD. Our results support this hypothesis.

Number of competitors: As we discussed in Section 2, it is not clear if and how the number of competitors affects PD. In our data, markets with a higher *No. of Offering Firms* have a greater PD than do markets in which fewer firms are offering

[19]Clicks are the referrals from the price listing site to the firm's homepage. They are the basis for the fee that the firm pays for the listing.

[20]In our data, the correlation between *Clicks on Firm Avg.* and the number of offering firms is -0.4016.

[21]This suggests that retailers in markets with few firms tend to be more homogeneous. This might indicate more competitive pressure, that brings prices closer to marginal costs, and thus reduces PD. The lack of theoretical and empirical evidence in this context opens an avenue for further research.

the product. This corresponds with the empirical literature on PD in online markets (e.g., Haynes and Thompson (2008) or Nelson et al. (2007)).[22]

Strength of Competition: We obtain an alternative indicator for the market structure by examining which firm has the lowest price. We count how often the firm that offers the lowest price changes, and interpret a greater number of price leader changes as an indicator of a competitive market that pushes the prices closer to marginal cost. Our results indicate that markets in which the price leader changes more often have a lower PD than markets with fewer price leader changes do.

Seasonality

We also control for seasonal effects using binary indicators for the quarter. These results show that the lowest PD occurs in the first quarter of a year, most likely due to the seasonal pattern of clearance sales throughout the year.

5 Robustness

We provide several robustness checks to assess the robustness of our results. First, we show the stability of our results when we stratify the sample by product characteristics. Here, we use different levels of demand for the product, branded versus unbranded products, and product type (e.g., hardware vs. software). Second, we provide the results when we use the standard deviation of the firms' PAC instead of the average PAC as an alternative measure of PAC heterogeneity in a market. Third, we estimate our specifications for different periods and split the data into an earlier period (2006–2009) and a later period (2009–2012).

5.1 Varying product characteristics

Tables 4 and 5 present the estimation results when we stratify the sample according to certain product characteristics.

[22] We confirm these results also using a pooled cross-sectional analysis. Although some of the results for the effect of market structure on PD are relatively small, more competition and more homogeneous firms lower PD.

High versus low demand: Price setting could be more important for products with greater demand. We expect a stronger association between PAC and PD in markets with greater demand compared to those with relatively low demand. We proxy the products' overall demand by the total sum of clicks over our complete observation period.

Columns (1) and (2) of Table 4 present the estimation results where we distinguish between products with clicks below and above the median number of total clicks. As expected, these estimates confirm our results in markets for high demand products, as the results consistently suggest a greater PD when PACs are greater. In contrast, in markets with low demand, several PAC indicators are not statistically significant (however, the statistically significant proxies at conventional error levels all point to the same positive association between PAC and PD).

The results also suggest that price setting for products with high demand is more important to firms than that for products with low demand. This is not surprising given that price setting for low demand products loses importance. It might well be that some of the offers are historical relicts that the firms no longer actively maintain (note that the listing itself produces no costs for the firm).

Branded versus unbranded products: Columns (3) and (4) of Table 4 present the estimates of the impact of PAC on PD for branded and unbranded products. We interpret products with a brand as indicative of vertical constraints between an upstream manufacturer and downstream retailers. Markets with stronger vertical constraints are likely to have less PD, as the upstream firm has an interest in maintaining a single price for its product across retailers. A descriptive comparison of the PD indicators confirms this expectation.[23]

Even in markets in which vertical constraints exist with a higher probability, we can confirm our results for the PAC measures: all but one PAC coefficient are positive and statistically significant. Only for the sub-sample of non-branded products do we obtain a negative association between the rank measure RANK and PD. Again, the RANK measure is perhaps not a good proxy for the true PAC.

[23]The respective PD measures for branded (non-branded) products are CoV=0.110 (0.129), VoI=0.178 (0.220), and D_1_2=0.0688 (0.153).

Different product types: Table 5 presents the estimation results when we split the sample into sub-samples along the main product categories that the price comparison site uses. Overall, our main results are robust to this stratification. Most of the coefficients are positive and statistically significant at the 5% level. However, some categories contain only few products, such as Health and Beauty. The site operators added these product categories to the price listing over time. Especially in these smaller product categories, the estimated coefficients lack precision. We obtain several negative coefficients for the perhaps less reliable proxies, such as HEIGHTΔp and RANK.

5.2 PAC Heterogeneity

In our estimations above, we characterized each market by the average of firms' PACs. To our knowledge, there is no theoretical model that links the variance in price setting costs to the PD in the market. In the appendix, we illustrate the implications of an increase in the heterogeneity in PACs on PD. Figure 2 (Panels C and D) plots the resulting PD for various levels of heterogeneity in PACs. This simple illustration suggests that an increase in the heterogeneity in PACs may not only increase PD, but may also decrease PD in certain situations. The falling segments of the functions plotted in Panels C and D of Figure 2 illustrate this finding. An increase in PAC heterogeneity means that some firms react slower, while others are faster in their price-setting. In some situations, this behavior might result in more similar prices (lower PD); while in others, the price gap between firms might widen. Hence, whether more PAC heterogeneity increases or decreases PD remains an empirical question.

To analyze this relationship empirically, we modify the aggregation from the firm level to the market level, as in Equation (7), by using the standard deviation of the firms' PAC:

$$\mathrm{STD(PAC)}_{i,t} = \sqrt{\frac{\sum_j (\mathrm{PAC}_{j,t} L_{i,j,t} - \mathrm{Mean}(\mathrm{PAC}_{j,t} L_{i,j,t}))^2}{J_{i,t}}}. \tag{9}$$

Table 6 replicates Table 2 using this alternative measure of the differences in firms' PACs. In particular, we find similar results compared to an increase in the level of PACs and a tendency for more heterogeneity in PACs to result in more PD.

Overall, the results are less clear than above. For CoV and VoI, some of our PAC measures are not statistically significant, and for two PAC measures, we observe a switch in signs. Similarly to Table 2, our extreme measure for PD $D\_1\_2_{i,t}$ behaves differently, as 5 of our PAC measures show a negative sign. However, note that we use the heterogeneity among all firms to explain the price difference for the two firms with the lowest prices. Hence, it is not surprising that this PD measure yields different results.

We illustrate in the appendix that under some circumstances, there is a higher probability that an increase in the heterogeneity in PACs could also lead to a fall in PD. However, in such an unusual case, we would assume a switch in signs for all of our PAC proxies. By and large, however, we find that a rise in PAC heterogeneity causally increases PD.

5.3 Time Split

Our main results in Table 2 are based on a sample from the third quarter of 2006 to the end of 2012. During this period, online markets emerged and consolidated in Austria, while the technology of e-commerce shops changed fundamentally at the same time. At the start of this period, firms used software in which someone had to enter price changes manually. Over the period, modern shop software, which allows automatic price setting algorithms, became commercially available.[24] In that sense, the firms' price setting behavior shifted from idiosyncratic decisions for each product to automated price changes. Of course, this might have lowered the PAC dramatically over the period, and we would expect a lower association between PAC and PD towards the end of the period.

The results in Table 7 aim to address this argument. Column (1) tabulates the estimated impact of PAC proxies on PD for the period of Q3 2006 to Q3 2009.

[24] Anecdotal evidence from managers suggests that important products (e.g., expensive products or products with a high markup) are still managed individually and prices are changed manually.

Column (2) presents the estimation results for the period Q4 2006 to Q4 2012. The estimated coefficients for the first period demonstrate a robust positive effect of PAC on PD. In contrast, the results in column (2) are much smaller. Moreover, we also obtain negative effects. We suppose the change in the technology is the reason for a less pronounced relationship between PAC and PD in the later period.[25]

6 Conclusions

Using panel data from a price comparison website, we use several indicators of firms' price adjustment costs (PACs) to analyze its effect on price dispersion (PD). The proxies for PAC are either proxies adopted from prior studies or are alternative indicators that are likely to capture firms' costs to set prices. To avoid the biases arising from selective market entry, we use an instrumental variables approach, in which we derive the instruments from firms' price setting behavior related to earlier generations of the product we analyze.

In general, we find considerable PD. Our estimation results suggest that PACs are a relevant cause for this PD. The estimated impact of our PAC measures is robust to several alternative empirical strategies. In particular, we stratify the sample according to several product characteristics, including high-demand versus low-demand products, and consistently find that a greater PAC leads to more PD.

Our results also show that during the sample period, 2006–2012, the influence of PAC on PD weakened. We interpret this finding as stemming from the increased use of specialized price monitoring and price setting software (Kephart et al., 2000).

In all of our specifications, we control for a rich set of alternative theories that could influence the PD. Our results are consistent with an interpretation that consumers are likely to search more for more expensive products, which will lower PD in these markets. PD is also greater for products offered by firms with greater heterogeneity in their inventories, for non-branded products, and in markets in which firms

[25]For instance, Calzolari et al. (2018) stress that even small retailers can now afford algorithmic pricing and that this may have consequences on markup and PD. Artificial intelligence programs are the next technology to automated price setting. The authors show that these programs have the potential for autonomous price collusion with obvious consequences for PD.

obfuscate prices. In addition, we find less PD for products with greater demand and for products which are offered by a smaller number of retailers.

Finally, we highlight that the link between the differences in firms' PACs and PD is not straightforward. Theoretically, in some situations, an increase in costs, or the heterogeneity in costs, may result in less PD, and vice versa.

The results imply that even when the search costs for consumers are comparably low and firms can change prices with one click, PACs may contribute to considerable PD.

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Appendix

We show that in some situations an increase in PAC or an increase in the variance of PAC might decrease PD. Surprisingly the economic literature does not offer a theoretical model of how a greater PAC affects PD. Sheshinski and Weiss (1977) and Fishman (1992) discuss the relationship between PAC and PD, but do not offer a model of how changes in PAC impacts PD. Benabou (1988, p. 364) argues that if price changes are less costly, firms change prices more often and therefore reduce PD. There is, however, no treatment on how an increase in the level or the heterogeneity in PACs might affect PD. The typical assumption is that a higher PAC or variation in PAC will lead to greater PD.

We do not aim to create a full model to analyze the effect of the heterogeneity in PAC on PD, but to illustrate (i) the effects of increasing average PAC as well as (ii) the implication of more variance in PAC for PD. We show that in certain cases, an increase in PACs might even result in less PD. However, in most cases, we find that increasing the PAC will lead to more PD. We use a very simple illustration to show this result. As a firm changes its prices only if the costs of doing so are less than the (expected) benefits of changing the price, greater costs, or more variance, will lead to more staggered price changes; that is, more PD at a particular point in time. A small exogenous change in the economic environment (e.g., a change in the factor or wholesale prices) could lead some firms to adjust their prices, while others keep their prices unchanged.

To illustrate the relationship between PAC and PD, we assume that for each firm there exists an Optimal Price Path (OPP), $OPP_j(t)$, which reflects the firms targeted price over time t. We could interpret the OPP as the sequence of optimal responses to exogenous shocks in the absence of PACs. This path is determined by the overall economic environment of the firm; that is, the factor costs, price elasticity of demand or market structure (e.g., we expect that optimal prices are greater in Cournot competition compared to Bertrand competition). All factors that imply PD for heterogeneous firms (e.g., horizontal product differentiation, different brand loyalty, different service characteristics, ...) could result in idiosyncratic OPPs.

In our illustration, we focus on a market with two firms that offer an identical good, but which differ in their PACs. This implies that the $OPP(t)$ is identical for both firms (different price paths do not change our results; however, the illustration would be more complex). The $OPP(t)$ could, in general, have any functional form. For illustration purposes, we assume a continuous and non-negative version, as in Figure 1. Firm 1 has a constant PAC of $(1-h)C$. Firm 2's PAC is greater, at $(1+h)C$. The parameter h $(0 < h < 1)$ captures the heterogeneity in PAC and a change in h results in a mean-preserving change in PACs.

A firm will change its price only if the benefit of doing so will exceed the cost of price adjustment. We normalize the amount of sold goods to one, which reduces the benefit of a price change to the absolute difference in prices.[26] In this case, firms adjust prices only if the difference between the actual and the optimal price is greater than the firms' PACs. Over time, when the difference between the actual price and the OPP equals the firm's PAC, the firm changes the price to the new

[26]With this assumption, we do not need to model the cost, demand, and competition structure explicitly, which would inflate our simple illustration. Sheshinski and Weiss (1977) use a similar approach, in which inflation generates an aspired price path for firms.

optimal price at time t.[27] Consequently, the actual prices are at all times the initial price plus or minus a multiple of the firms' PACs. The firm with the lower PAC adapts faster to the OPP.

For simplicity, we assume that both firms start with their optimal prices at $t = 0$, $OPP(t = 0) = p_1^0 = p_2^0$. For all $t > 0$ and $OPP(t) \geq p_1^0 = p_2^0$, we can state the prices as

$$\begin{aligned} p_1(t) &= p_1^0 + k_1(t)(1-h)C, \text{ and} \\ p_2(t) &= p_2^0 + k_2(t)(1+h)C. \end{aligned} \tag{10}$$

If $OPP(t) < p_1^0 = p_2^0$, then the prices are $p_1 = p_1^0 - k_1(t)(1-h)C$ and $p_2 = p_2^0 - k_2(t)(1+h)C$. The factors $k_1(t)$ and $k_2(t)$ denote the multiple of PACs and are the result of whether the OPP is falling or rising over time. $k_1(t)$ is either the floor function of $(|OPP(t)-p_1^0|)/((1-h)C)$ in case of (steadily) rising prices, or the ceiling function of $(|OPP(t) - p_1^0|)/((1-h)C)$ if the OPP is continuously falling. The argument of the floor (ceiling) function is the rounded difference in the optimal and actual prices in terms of multiples of PACs (rounded down to the next integer value for the floor function and rounded up for the ceiling function).

For short episodes of rising and falling OPPs, whether the floor or ceiling functions should be used is path-dependent. We verify our results for all possible combinations of the floor and ceiling functions in our illustration.

Figure 1 (Panel A) shows an arbitrary OPP and the sequence of firms' prices for (arbitrary) parameter values of $C = 3.5$ and $h = 0.1$. At time $t = 0$, both firms set optimal prices $p_1^0 = p_2^0 = 3$. Assume that the absolute difference between the two actual prices is our measure of PD, $PD(t) = |p_1 - p_2| = |p_1^0 - p_2^0 + k_1(t) * (1+h)C - k_2(t) * (1-h) * C|$.

Figure 1 compares the price setting of firms with lower (Panel A) and greater average PACs (Panel B). Each price change changes the PD, but the direction of the change depends on the firms' relative prices and the $OPP(t)$. In this illustration, the mean PAC increased by 80%. A comparison of the PDs in Panels A and B shows ambiguous effects of a greater PAC: in some cases, the increase will lead to more PD, but in other cases, the PD is lower. These periods are shaded in gray.

Change in the level of PAC: Here, we investigate the conditions under which higher PACs result in less (more) PD. As the functions $k_1(t)$ and $k_2(t)$ are non-continuous (and hence is PD), the formal conditions under which an increase in PAC results in more PD are unwieldy, even in this very simple illustration.

Assume that both firms start with identical prices at $t = 0$. An increase in the PAC in the firms' price setting functions will always lead to more PD, if for neither firm the price is an exact multiple of the firms' PAC. When a price is an exact multiple of PAC, firms will adjust their prices discontinuously. This result holds for all combinations of floor and ceiling functions, although the discontinuities might occur at different levels of PAC. Figure 2 (Panel A) presents a graphical illustration of the application of the floor function for both firms, and hence the assumption of long-run upward trend in the $OPP(t)$.

[27] The OPP represents the sequence of optimal responses to unexpected exogenous shocks. It is not possible for firms to adopt forward looking behavior in price setting to address future price shocks.

When firms have different prices at $t = 0$, $p_1^0 \neq p_2^0$, we observe a (continuous) decrease in PD for certain parameter values when PACs are increasing.[28] Figure 2 (Panel B) illustrates this case. Generally, the greater the differences in the starting prices relative to C are, the larger the parameter space in which PD is decreasing when C increases. Note, however, that the greater the difference in starting prices is, the more unrealistic are the parameter constellations for real markets.

Change in the heterogeneity in PACs: An even less clear case arises when we consider the impact of firms' heterogeneity in PAC on PD. For both identical and different start prices, we find parameter constellations in which PD decreases when PAC increases. Even in the case in which the firms have different PACs, we observe constellations where the PD is zero.[29]

Figure 2 (Panels C and D) illustrates the effect of an increase in the heterogeneity in PACs on PD. Note that the question of whether an increase in the heterogeneity in PACs has a positive or negative effect on PD is essentially an empirical one. An increase in the heterogeneity in PACs also implies a change in the average PAC, which we ruled out here by the definition of PAC. Although we might expect a positive effect of PAC heterogeneity on PD, the connection is much less clear than the effect of an increase in the level of PACs is.

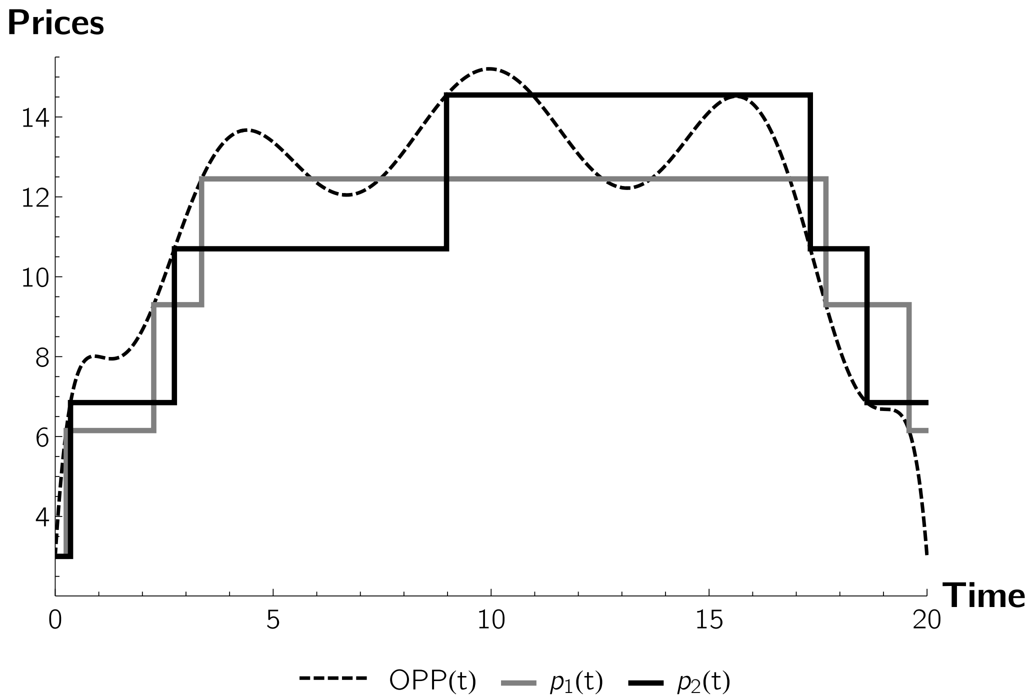
[28] The exact parameter constellations for a continuously falling PD when PAC are increasing are: $\Big[C < (p_1^0 - p_2^0)/(-Fm + Fp + (Fm + Fp)h)\Big]$ AND $\Big[\Big[p_1^0 > p_2^0$ AND $\big[(Fm = Fp)$ OR $\big[Fm > Fp$ AND $(2Fm)/(Fm + Fp) < (1 + h)\big]\big]\Big]$ OR $\Big[p_1^0 < p_2^0$ AND $(2Fm)/(Fm + Fp) > (1 + h)$ AND $Fm > Fp\Big]\Big]$, with $Fm = \text{Floor}(OPP(t)/(C(1-h)))$ and $Fp = \text{Floor}(OPP(t)/(C(1+h)))$. For other combinations of the floor and ceiling functions, we can derive similar conditions. Note that some combinations of floor and ceiling functions show a larger parameter space for falling PD functions. As this appendix is mainly for illustrative purposes, we do not elaborate on these conditions.

[29] In the case of identical starting prices, the conditions for a decreasing PD are $\Big[Fm = Fp\Big]$ OR $\Big[Fm > Fp$ AND $(2Fm)/(Fm + Fp) <$ AND $(1 + h)\Big]$. Again, we have discontinuities (kinks or upward or downward jumps) when a price is an exact multiple of the PAC. For situations with different starting prices, the conditions are more complicated: $\Big[\Big[Fm = Fp\Big]$ AND $\Big[\Big[p_1^0 <= p_2^0\Big]$ OR $\Big[p_1^0 > p_2^0$ AND $C > (p_1^0 - p_2^0)/(-Fm + Fp + (Fm + Fp)h)\Big]\Big]\Big]$ OR $\Big[\Big[Fm > Fp\Big]$ AND $\Big[\Big[1 + h < (2Fm)/(Fm + Fp)$ AND $p_1^0 < p_2^0$ AND $C < (p_1^0 - p_2^0)/(-Fm + Fp + (Fm + Fp)h)\Big]$ OR $\Big[1 + h = (2Fm)/(Fm + Fp)$ AND $p_1^0 < p_2^0\Big]$ OR $\Big[p_2^0 > 0$ AND $(2Fm)/(Fm + Fp) < 1 + h$ AND $[(p_1^0 <= p_2^0)$ OR $[p_1^0 > p_2^0$ AND $C > (p_1^0 - p_2^0)/(-Fm + Fp + (Fm + Fp)h)]]\Big]\Big]\Big]$. Again, we assume a continuously increasing $OPP(t)$; that is, we apply floor functions. For other combinations of floor and ceiling functions, we can derive similar conditions.

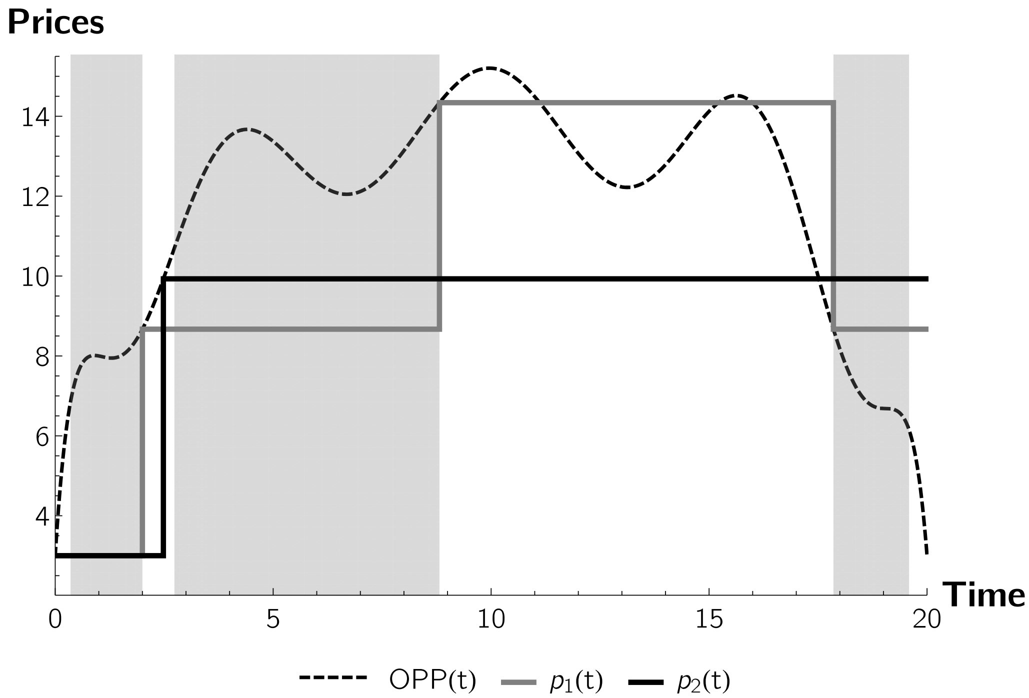
Figures and Tables

Figure 1: Illustration of low and high PAC on PD.

Panel A - Low Price Adjustment Cost



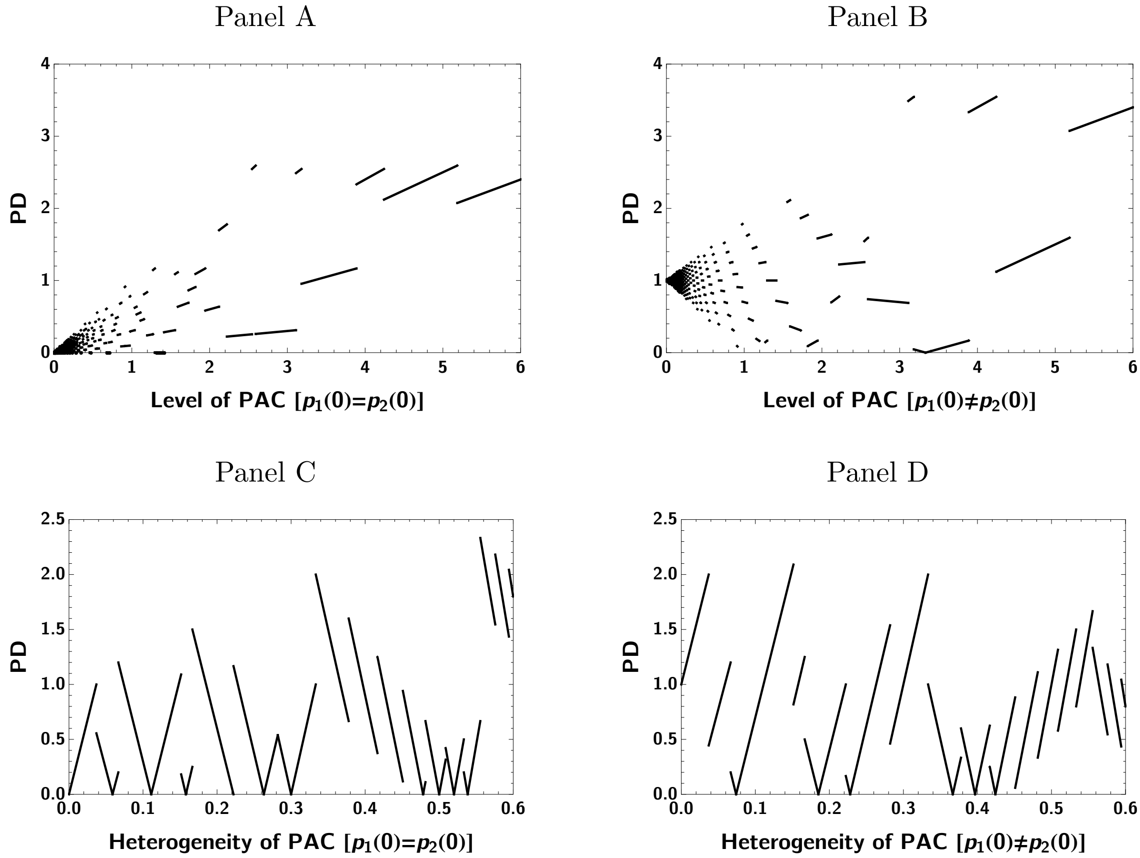
Panel B - High Price Adjustment Cost



Note: $OPP(t)$ shows the optimal price path both firms would followed if no PAC would be incurred.

The figure compares two scenarios with different PACs (low PAC in Panel A and high PAC in Panel B). The shaded areas show time periods where we observe lower PD in the case of higher average PAC for both firms. We chose the following parameterization for the price paths: $p_1^0 = p_2^0 = OPP(0) = 3$, $h = 0.1$, Panel A's $C = 3.5$, Panel B's $C = 6.3$.

Figure 2: Effects of PAC average and PAC heterogeneity on PD.



Note: The figure illustrates the effects of changes in the PAC average and PAC heterogeneity on PD. For all graphs Floor Functions have been used to calculate the multiple of PAC (hence a monotoneous increase of OPP(t) has been assumed). The four figures show that under certain parameter constellations an increase in average PAC or PAC heterogeneity can decrease PD. For example, in Panel A, an increase in PAC from 3.18 increases PD from 0.33 to 2.57, and an incrase at 3.21 reduces PD from 2.62 to 0.94. Parametrization: Panel A [$OPP(t) = 14$, $h = 0.1$, $p_1(0) = p_2(0) = 2$], Panel B [$OPP(t) = 14$, $h = 0.1$, $p_1(0) = 1.5$, $p_2(0) = 2.5$], Panel C [$OPP(t) = 14$, $C = 1.5$, $p_1(0) = p_2(0) = 2$], Panel D [$OPP(t) = 14$, $C = 1.5$, $p_1(0) = 1.5, p_2(0) = 2.5$].

Table 1: Descriptive Statistics of our main variables.

	Mean	Standard Deviation	Minium	Maximum
Price Dispersion Indicators				
Coefficient of Variation, CoV	0.120	0.121	0	4.240
Value of Information, VoI	0.200	0.309	0	5.000
Difference lowest two prices, D_1_2	0.113	0.212	0	2.000
Price Adjustment Costs Indicators				
LENGTHΔp	52.63	50.56	2.234	1.132
HEIGHTΔp	0.101	0.0474	0.0067	1.826
L $\times$ HΔp	10.99	16.90	0.0962	1.190
RANK	0.07	0.0125	0.00186	0.176
SYNC^T	0.0801	0.0468	0.0001	0.834
SYNC^H	2,516	211.1	-72.77	7,816
SYNC^I	201.1	118.5	-6.141	2,105
E-tailer characteristics				
Firm Evaluation Avg. (1=good,5=bad)	1.638	0.371	1	5
Firm Evaluation Std.	0.387	0.278	0	2
Pick-Up-Possibility Std.	0.320	0.201	0	0.500
Percentage Big Brand Std.	0.113	0.0614	0	0.500
Shipping Costs Std.	3.284	4.020	0	47.86
Clicks on Firm Avg.	149,535	170,399	79	914,418
Clicks on Firm Std.	192,839	188,771	0	723,752
Product characteristics				
Availability Std.	0.0682	0.0287	0	0.0995
No. of Price Leader Changes	5.516	7.887	0	82
No. of Offering Firms	10.36	10.74	2	87
Price in Euro	288.3	699.4	0.710	9,999
Austrian Clicks on Product	88.94	584.7	0	146,137

Note: Descriptive statistics for the variables of our main regressions are shown. The observational unit refers to products i which are observed over time t: We have 1,698,370 observations for 241,606 products. E-tailer and product characteristics are calculated using the average (Avg.) or the standard deviation (Std.) of the offering firms on market i. For the regressions these variables are transformed into z-scores (mean of 0 and variance of 1).

Table 2: Estimated effect of price adjustment costs on price dispersion.

	CoV (1)	VoI (2)	D_1_2 (3)	First Stage F-statistic
LENGTHΔp	0.0653***	0.0759***	0.0642***	3,503.5
	(0.00599)	(0.00704)	(0.00726)	
HEIGHTΔp	0.0171***	0.00803	0.00935	2,547.7
	(0.00543)	(0.00500)	(0.00687)	
L $\times$ HΔp	0.0396***	0.0419***	0.0269***	791.4
	(0.00444)	(0.00472)	(0.00542)	
RANK	0.00545**	0.00446*	−0.0352***	73,891.9
	(0.00268)	(0.00249)	(0.00300)	
SYNC^T	0.0267***	0.0419***	−0.0131*	13,603.0
	(0.00640)	(0.00604)	(0.00698)	
SYNC^H	0.0119***	0.00702***	0.0152***	30,903.8
	(0.000892)	(0.000670)	(0.00133)	
SYNC^I	0.0518***	0.0543***	0.0181***	17,181.0
	(0.00563)	(0.00528)	(0.00622)	
Controls	yes	yes	yes	
Product fixed effects	yes	yes	yes	

Note: 1,698,370 observations on 241,606 products. Coefficients for the controls of column (1) are tabulated in Table 3. All variables are transformed into z-scores (mean of 0 and variance of 1). Hence, each number is a beta coefficient from a separate 2SLS-panel regression where the F-statistics from the first stages are presented in column (4). Price dispersions are measured by the coefficient of variation (column (1)), the value of information (column (2)), and the difference between the lowest and the second lowest price (D_1_2, column (3)). Price adjustment costs are proxied by the firms' price setting behavior and are based on the firms' price changes, the variance of the rank of their prices, and on the synchronicity of their price changes. All regressions include the same set of covariates, the estimated coefficients are presented below in Table 3. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Estimated coefficients for price dispersion, measured by CoV (2SLS), by proxy for PAC.

Included PAC (see Table 2)	LENGTHΔp (1)	HEIGHTΔp (2)	L $\times$ HΔp (3)	RANK (4)	SYNC^T (5)	SYNC^H (6)	SYNC^I (7)
Evaluation Avg.	-0.0356***	-0.0332***	-0.0349***	-0.0314***	-0.0286***	-0.0299***	-0.0253***
	(0.00176)	(0.00181)	(0.00176)	(0.00169)	(0.00184)	(0.00169)	(0.00184)
Evaluation Std.	0.0541***	0.0520***	0.0545***	0.0510***	0.0499***	0.0518***	0.0494***
	(0.00138)	(0.00138)	(0.00140)	(0.00133)	(0.00137)	(0.00133)	(0.00135)
Pick-Up-Possibility Std.	0.0759***	0.0747***	0.0738***	0.0746***	0.0739***	0.0748***	0.0729***
	(0.00132)	(0.00132)	(0.00133)	(0.00132)	(0.00134)	(0.00132)	(0.00133)
Percentage Big Brand Std.	0.0268***	0.0289***	0.0284***	0.0302***	0.0311***	0.0297***	0.0323***
	(0.00162)	(0.00161)	(0.00160)	(0.00159)	(0.00162)	(0.00159)	(0.00162)
Shipping Costs Std.	0.0169***	0.0153***	0.0158***	0.0147***	0.0140***	0.0150***	0.0130***
	(0.000743)	(0.000727)	(0.000727)	(0.000736)	(0.000752)	(0.000724)	(0.000745)
Clicks on Firm Avg.	-0.200***	-0.210***	-0.208***	-0.215***	-0.221***	-0.214***	-0.227***
	(0.00344)	(0.00348)	(0.00328)	(0.00325)	(0.00359)	(0.00322)	(0.00352)
Clicks on Firm Std.	0.237***	0.248***	0.241***	0.248***	0.248***	0.248***	0.249***
	(0.00352)	(0.00345)	(0.00349)	(0.00344)	(0.00346)	(0.00345)	(0.00346)
Availability Std.	0.0241***	0.0248***	0.0253***	0.0250***	0.0256***	0.0253***	0.0267***
	(0.00124)	(0.00124)	(0.00124)	(0.00124)	(0.00125)	(0.00124)	(0.00125)
No. of Price Leader Changes	-0.0139***	-0.0149***	-0.0148***	-0.0154***	-0.0174***	-0.0150***	-0.0195***
	(0.000967)	(0.000964)	(0.000963)	(0.000965)	(0.00109)	(0.000962)	(0.00106)
No. of Offering Firms	0.0698***	0.0634***	0.0645***	0.0621***	0.0575***	0.0626***	0.0521***
	(0.00267)	(0.00261)	(0.00261)	(0.00263)	(0.00289)	(0.00261)	(0.00284)
Price in Euro	0.0297	0.0245	0.0268	0.0243	0.0228	0.0247	0.0212
	(0.0184)	(0.0184)	(0.0184)	(0.0184)	(0.0184)	(0.0184)	(0.0185)
Austrian Clicks on Product	-0.00525***	-0.00559***	-0.00542***	-0.00556***	-0.00519***	-0.00555***	-0.00480***
	(0.00104)	(0.00106)	(0.00105)	(0.00105)	(0.00104)	(0.00105)	(0.00102)
Quarter Dummies	yes	yes	yes	yes	yes	yes	yes
Product fixed effects	yes	yes	yes	yes	yes	yes	yes
Observations	1,698,370	1,698,370	1,698,370	1,698,370	1,698,370	1,698,370	1,698,370
R-squared	0.039	0.040	0.039	0.039	0.039	0.040	0.038
Number of products	241,606	241,606	241,606	241,606	241,606	241,606	241,606

Note: 1,698,370 observations on 241,606 products. Dependent variable is price dispersion CoV. Each column includes the set of controls for one regression including a different measure of PAC, these coefficients are tabulated in Table 2. All variables are transformed into z-scores (mean of 0 and variance of 1). Hence, each number is a beta coefficient from a separate 2SLS-panel regression. E-tailer and product characteristics are calculated using the average (Avg.) or the standard deviation (Std.) of the offering firms on market i. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Robustness - Type of Product (Demand & Brand).

Dependent: PD CoV	DEMAND		TYPE OF PRODUCT	
	LOW	HIGH	BRANDED	NO-Name
	(1)	(2)	(3)	(4)
Variables for price adjustment cost				
LENGTHΔp	0.0289***	0.105***	0.0354***	0.0679***
	(0.00895)	(0.00796)	(0.00930)	(0.00742)
HEIGHTΔp	0.00911	0.0305***	0.00588	0.0228***
	(0.00724)	(0.00823)	(0.00959)	(0.00656)
L $\times$ HΔp	0.0137**	0.0812***	0.0783***	0.0325***
	(0.00555)	(0.00808)	(0.0172)	(0.00455)
RANK	0.000716	0.0139***	0.0272***	-0.0247***
	(0.00342)	(0.00418)	(0.00377)	(0.00386)
SYNC^T	0.0266***	0.0272***	0.0236***	0.0141
	(0.00810)	(0.0101)	(0.00879)	(0.00975)
SYNC^H	0.0141***	0.000221	0.0185***	0.00989***
	(0.000980)	(0.00208)	(0.00303)	(0.000945)
SYNC^I	0.0626***	0.0356***	0.0344***	0.0504***
	(0.00663)	(0.00964)	(0.00868)	(0.00772)
Controls	yes	yes	yes	yes
Product fixed effects	yes	yes	yes	yes
Number of Observations	747,514	950,856	813,921	884,449
Number of products	120,564	121,042	116,293	125,314

Note: Price dispersion CoV is used as dependent variable. The columns refer to different product types (high versus low demand products, branded versus no-name products). The rows show the coefficients for different PAC measures. All variables are transformed into z-scores (mean of 0 and variance of 1). Hence, each number is a beta coefficient from a separate 2SLS-panel regression including the set of controls. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Robustness - Product Main Categories.

Dependent: PD CoV	PRODUCT MAIN CATEGORIES									
	AUDIO	HEALTH AND BEAUTY	MOVIES	GAMES	HARDWARE	HOME AND LIVING	SOFTWARE	SPORTS	PHONE	VIDEO/TV/ CAMERAS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
LENGTHΔp	0.0210**	-0.00406	0.0709***	0.0667*	0.0959***	-0.000220	0.0493**	0.0243*	0.297***	0.0755***
	(0.00914)	(0.0485)	(0.0202)	(0.0401)	(0.0205)	(0.00670)	(0.0243)	(0.0128)	(0.0908)	(0.00993)
HEIGHTΔp	0.00921	-0.0865**	0.0351	-0.129**	0.0423***	-0.00803	-0.00448	-0.0226***	0.0754	0.0853***
	(0.0117)	(0.0347)	(0.0213)	(0.0590)	(0.0119)	(0.00552)	(0.0226)	(0.00838)	(0.0641)	(0.0134)
L $\times$ HΔp	0.0206**	-0.0745	0.0354**	0.0462*	0.0904***	0.00181	0.0979***	0.00602	0.353***	0.115***
	(0.0101)	(0.0475)	(0.0140)	(0.0274)	(0.0195)	(0.00192)	(0.0348)	(0.00420)	(0.108)	(0.0120)
RANK	0.00926	-0.0115	-0.0372***	-0.0760**	-0.0148***	0.0233***	-0.0128	0.0577***	0.0436	0.0936***
	(0.0132)	(0.0191)	(0.00687)	(0.0322)	(0.00525)	(0.00439)	(0.0101)	(0.00809)	(0.0342)	(0.0100)
SYNC^T	-0.00149	0.0800	-0.000618	-0.00971	-0.0168*	0.0125	-0.0951***	0.240***	0.00217	0.183***
	(0.0544)	(0.0570)	(0.0457)	(0.0846)	(0.00975)	(0.0141)	(0.0224)	(0.0451)	(0.0591)	(0.0170)
SYNC^H	0.00561	-0.0168***	0.00807***	0.00709*	0.0449***	-0.000279	0.0218***	-0.000671	0.0196*	0.0198***
	(0.0103)	(0.00514)	(0.00107)	(0.00388)	(0.0102)	(0.00295)	(0.00696)	(0.00459)	(0.0107)	(0.00627)
SYNC^I	0.00862	0.0449	0.100***	0.0550	-0.00894	0.0149	-0.0657***	0.169***	0.0270	0.194***
	(0.0521)	(0.0436)	(0.0149)	(0.0593)	(0.00986)	(0.0125)	(0.0204)	(0.0334)	(0.0617)	(0.0166)
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Product fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	67,517	21,203	242,697	60,758	649,611	202,681	58,515	53,707	49,102	234,119
Number of products	11,267	3,237	26,865	9,395	92,099	28,175	11,598	10,191	8,761	30,865

Note: Price dispersion CoV is used as dependent variable. The columns refer to different product categories offered at the website from geizhals.at. The rows show the coefficients for different PAC measures. All variables are transformed into z-scores (mean of 0 and variance of 1). Hence, each number is a beta coefficient from a separate 2SLS-panel regression including the set of controls. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Robustness - Alternative PAC Measures.

Dependent price dispersion	CoV (1)	VoI (2)	D_1_2 (3)
STD(LENGTHΔp)	0.0214***	0.0240***	-0.0252***
	(0.00328)	(0.00313)	(0.00415)
STD(HEIGHTΔp)	0.0658***	0.0837***	0.0459***
	(0.00462)	(0.00576)	(0.00560)
STD(L $\times$ HΔp)	0.0435***	0.0510***	0.0264***
	(0.00389)	(0.00455)	(0.00447)
STD(RANK)	-0.00141	-0.0199***	-0.0408***
	(0.00421)	(0.00392)	(0.00419)
STD(SYNC^T)	-0.00253	0.0163***	-0.0197***
	(0.00402)	(0.00384)	(0.00417)
STD(SYNC^H)	-0.0300***	-0.0212***	-0.0230***
	(0.00112)	(0.000926)	(0.00149)
STD(SYNC^I)	0.00305	0.0191***	-0.0115***
	(0.00393)	(0.00375)	(0.00408)
Controls	yes	yes	yes
Product fixed effects	yes	yes	yes

Note: 1,698,370 observations on 241,606 products. Columns refer to our measures for price dispersion used above. Rows show the coefficients for the markets' standard deviation of the offering firms' PAC measures as an indicator for the heterogeneity in PAC. All variables are transformed into z-scores (mean of 0 and variance of 1). Each number is a beta coefficient from a separate 2SLS-panel regression. All regressions include the same set of covariates. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Robustness - Time Split.

	PERIOD	
Dependent: PD CoV	QUARTER 1-13	QUARTER 14-26
	(1)	(2)
LENGTHΔp	0.0927***	0.0596***
	(0.00825)	(0.00666)
HEIGHTΔp	0.0533***	0.00835
	(0.00893)	(0.00588)
L $\times$ HΔp	0.176***	0.0238***
	(0.0157)	(0.00356)
RANK	0.0559***	-0.0393***
	(0.00361)	(0.00435)
SYNC^T	0.120***	-0.0676***
	(0.0101)	(0.00858)
SYNC^H	0.00820***	0.103***
	(0.000941)	(0.0159)
SYNC^I	0.125***	-0.0611***
	(0.00744)	(0.00859)
Controls	yes	yes
Product fixed effects	yes	yes
Observations	671,569	1,009,234
Number of products	120,130	170,372

Note: Price dispersion CoV is used as dependent variable. The columns refer to a time split between the first and the second half of our observation period. The rows show the coefficients for different PAC measures. All variables are transformed into z-scores (mean of 0 and variance of 1). Hence, each number is a beta coefficient from a separate 2SLS-panel regression including the set of controls. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.