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Dynamic pricing and exchange rate pass-through: Evidence from transaction-level data

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Non-technical summary

Research Question

The extent to which exchange rate movements are passed on to consumer prices plays a central role in international macroeconomics. Previous work on the micro determinants of exchange rate pass-through has so far focused mainly on time-invariant product and firm characteristics such as product quality. In contrast, evidence on the role of dynamic pricing (i.e. firms flexibly setting prices of goods and services, e.g. taking into account current market conditions) for pass-through remains rather limited.

Contribution

We explore how the heterogeneous response of consumer prices to exchange rate fluctuations can be explained by different forms of dynamic pricing. In particular, we study the role of clearance sales, seasonality of demand, and advance-purchase discounts. First, we provide a theoretical model that illustrates how foreign producers and domestic retailers adjust their prices to exchange rate fluctuations in these settings. Second, we investigate empirically how prices and exchange rate pass-through vary for the three forms of dynamic pricing. We do so by analyzing a unique German transaction-level data set of package tours at the daily frequency between 2012 and 2018.

Results

Overall, we find that the response of prices and pass-through with regard to dynamic pricing is in line with the model predictions. First, prices for last-minute bookings are on average 6.1% lower and pass-through is 6% higher than for the average trip. Second, prices during the high season are unambiguously higher, while exchange rate pass-through increases with the capacity costs of hotels. Third, advance-purchase discounts are predominantly granted during the high season and prices for high-season tours booked more than seven and a half months in advance are 3.7% lower. In contrast to last-minute bookings, however, pass-through decreases for advance-purchase discounts in the high season, as predicted by our theoretical model.

Nichttechnische Zusammenfassung

Fragestellung

Die Weitergabe von Wechselkursbewegungen in die Verbraucherpreise (Wechselkurstransmission) ist in der internationalen Makroökonomik von zentraler Bedeutung. Bestehende Arbeiten zu den Mikrodeterminanten der Wechselkurstransmission konzentrierten sich bisher hauptsächlich auf zeitinvariante Produkt- und Unternehmensmerkmale wie die Produktqualität. Im Gegensatz dazu wurde der Zusammenhang zwischen dynamischen Preisstrategien (d.h. Unternehmen legen Preise von Gütern und Dienstleistungen flexibel fest, beispielsweise unter Berücksichtigung vorherrschender Marktbedingungen) und der Wechselkurstransmission bislang kaum untersucht.

Beitrag

Wir analysieren, inwiefern die heterogene Weitergabe von Wechselkursbewegungen in die Verbraucherpreise durch verschiedene Formen dynamischer Preisstrategien erklärt werden kann. Insbesondere untersuchen wir die Auswirkungen von Last-Minute-Käufen, Saisonalität der Nachfrage und Preisnachlässe für Vorbestellungen. Zunächst entwickeln wir ein theoretisches Modell, das veranschaulicht, wie ausländische Produzenten und inländische Einzelhändler in diesen Fällen ihre Preise als Reaktion auf Wechselkursbewegungen anpassen. Im Anschluss daran untersuchen wir empirisch, wie Preise und Wechselkurstransmission für die drei Arten dynamischer Preisstrategien variieren. Grundlage hierfür bildet ein deutscher Transaktionsdatensatz von Pauschalreisen mit täglicher Frequenz im Zeitraum der Jahre 2012 und 2018.

Ergebnisse

Wir finden, dass die Reaktionen von Preisen und Wechselkurstransmission mit Blick auf dynamische Preisstrategien mit den Vorhersagen des Modells übereinstimmen. Erstens sind die Preise für Last-Minute-Buchungen im Durchschnitt 6,1% niedriger und die Wechselkurstransmission 6% höher als für die durchschnittliche Pauschalreise. Zweitens sind die Preise in der Hochsaison eindeutig höher, während die Wechselkurstransmission mit den Kapazitätskosten der Hotels zunimmt. Drittens werden Frühbucherrabatte vorwiegend in der Hochsaison gewährt, und die Preise für Pauschalreisen in der Hochsaison, die mehr als siebeneinhalb Monate im Voraus gebucht wurden, fallen 3,7% niedriger aus. Im Gegensatz zu Last-Minute-Buchungen verringert sich jedoch für Frühbucherrabatte – wie von unserem theoretischen Modell vorausgesagt – die Wechselkurstransmission in der Hochsaison.

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Abstract

Dynamic pricing is a widely employed pricing strategy for goods and services in which firms flexibly set prices, taking into account current market conditions. This paper studies theoretically and empirically the role of this pricing strategy in explaining the heterogeneous response of consumer prices to exchange rate fluctuations. We provide a theoretical model that illustrates how foreign producers and domestic retailers adjust prices to exchange rate fluctuations for three forms of dynamic pricing. Our model predicts that pass-through increases for clearance sales and with the capacity costs of producers in periods of high demand, while it decreases for advance purchases. We find robust empirical evidence for the model predictions using a unique German transaction-level data set of package tours at the daily frequency between 2012 and 2018 featuring rich variation of prices over time.

Keywords: exchange rate pass-through, dynamic pricing, heterogeneity, services trade, tourism

JEL codes: F14, F31

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1 Introduction

The extent to which exchange rate movements are passed on to consumer prices plays a central role in international macroeconomics. Exchange rate pass-through has implications for, inter alia, deviations from the law of one price, the international transmission of shocks, and the optimal conduct of monetary policy.[1] Thanks to the increasing availability of firm-level and product-level data, recent studies have started to investigate the micro determinants of exchange rate pass-through. This strand of the literature has highlighted factors such as exporter productivity (Berman, Martin, and Mayer, 2012; Li, Ma, and Xu, 2015), import shares (Amiti, Itskhoki, and Konings, 2014), multi-product firms (Chatterjee, Dix-Carneiro, and Vichyanond, 2013), retailer market share (Antoniades and Zaniboni, 2016), goods quality (Bernini and Tomasi, 2015; Chen and Juvenal, 2016; Auer, Chaney, and Sauré, 2018), the currency of invoicing (Gopinath, Itskhoki, and Rigobon, 2010), the frequency of price adjustment (Gopinath and Itskhoki, 2010), and the degree of competition in product markets (Auer and Schoenle, 2016; Amiti, Itskhoki, and Konings, 2019).

While previous work on the micro determinants of exchange rate pass-through has focused mainly on time-invariant product and firm characteristics, evidence on the role of dynamic pricing remains relatively limited. Dynamic pricing is a widely employed pricing strategy for goods and services in which firms flexibly set prices, taking into account current market conditions such as capacity utilization, customers' price sensitivity, and the state of demand. For example, prices of fashion goods usually decrease as the season progresses (Soysal and Krishnamurthi, 2012), Uber uses surge pricing, raising the price of a trip when demand exceeds supply within a fixed geographic area (Cramer and Krueger, 2016), and airline tickets are usually cheaper when bought well in advance (Stavins, 2001). Dynamic pricing policies have been employed for a long time in the transportation, hospitality, entertainment, and energy industries. More recently, the emergence of e-commerce and the increasing use of digital price tags have enabled dynamic pricing to become more ubiquitous across industries, most notably in the retail of goods (Bakos, 2001).

In this paper, we explore how the heterogeneous response of consumer prices to exchange rate fluctuations can be explained by different forms of dynamic pricing. In particular, we study the effects of (i) clearance sales, (ii) seasonality of demand, and (iii) advance-purchase discounts. First, we provide a theoretical model that illustrates how foreign producers and domestic retailers adjust their prices to exchange rate fluc-

[1] See Goldberg and Knetter (1997) and Burstein and Gopinath (2014) for a review of the literature, and Devereux and Engel (2003) and Corsetti and Pesenti (2005), among others, for an analysis of the implications of pass-through for optimal monetary policy.

tuations in these three settings. Second, we investigate empirically how prices and exchange rate pass-through vary in these cases. We do so by analyzing a unique German transaction-level data set of package tours at the daily frequency between 2012 and 2018 that provides rich variation of prices over time.

To guide our empirical analysis, we provide a theoretical model on the relationship between dynamic pricing and exchange rate pass-through. Building on Antoniades and Zaniboni (2016), we extend the model of international trade by Corsetti and Dedola (2005) to include heterogeneous retailers and a linear demand system (Melitz and Ottaviano, 2008).[2] In this framework, exchange rate pass-through depends on, inter alia, the price elasticity of demand, which we assume to vary across consumers. This consumer heterogeneity can be used by firms for price discrimination insofar as consumers can be segmented sufficiently well according to observable characteristics such as the time of purchase. In addition, we include the following two features. First, we allow the producer's marginal costs to vary with the state of demand. To increase capacity in periods of high demand (i.e. the high season), the producer incurs additional (capacity) costs, which increase prices during the high season above and beyond price effects stemming from higher demand.[3] Second, if total demand during the high season is uncertain, there is an incentive to acquire information concerning the state of demand in advance if expanding capacity at short notice is comparatively costly. By offering advance-purchase discounts, the producer obtains demand information which, in turn, allows capacity to be expanded at a lower cost.[4]

Overall, the outlined model delivers three main predictions on the relationship between dynamic pricing and exchange rate pass-through.[5] Specifically, exchange rate pass-through (i) increases for last-minute bookings given that firms' perceived demand elasticity is higher in this case since last-minute bookers, ceteris paribus, are characterized by lower product valuations, (ii) increases with capacity costs of hotels in holiday destination countries in the high season given that hotels' associated marginal costs are higher than in the low season, and (iii) is smaller for package tours that are booked well ahead of the departure date during the high season (i.e. early bookings) given that capacity-constrained hotels use advance-purchase discounts as an information acquisition device in the presence of uncertain demand.

[2] In this setting, the choice of a quadratic utility function is important for capturing the effect of consumer heterogeneity on pass-through (see Section 2).

[3] A review of the associated literature on peak-load pricing can be found in Crew, Fernando, and Kleindorfer (1995). Note that this feature of the model is also related to the recent literature relaxing the assumption of constant marginal costs in models of firm-level trade (Vannoorenberghe, 2012; Blum, Claro, and Horstmann, 2013; Soderbery, 2014; Berman, Berthou, and Héricourt, 2015; Almunia, Antràs, Lopez-Rodriguez, and Morales, 2018).

[4] This feature of the model is related to the literature on information acquisition (Section 2.2).

[5] The model is also consistent with the previous literature regarding the effect of producer, retailer, and product characteristics on pass-through (Section 2.3).

The model predictions are tested using a transaction-level data set of package tours purchased by German tourists.[6] The package tour market is well-suited to studying how dynamic pricing affects exchange rate pass-through into prices not least for the following reasons.[7] First, the separation between time of purchase and actual consumption introduces a trade-off for consumers between buying early and buying late that influences the way in which prices change over time (e.g. Nocke and Peitz, 2007; Möller and Watanabe, 2010). Second, tourism is characterized by a strong degree of seasonality, resulting in a peak-load pricing problem for hotels given labor adjustment costs and their fixed physical capacity in the short run (Baum and Lundtorp, 2001). Third, prices can be continuously adjusted at low cost in response to changes in demand and supply given the widespread use of online booking engines (Candela and Figini, 2012). Correspondingly, our transaction-level data set includes all the necessary features to identify the heterogeneous pass-through due to dynamic pricing. First, it records the booking day and the travel day for every transaction. Second, it contains the name of the hotel along with its location, province, and destination country. This allows us to complement the data set with information about hotel size and quality from TripAdvisor using webscraping techniques as proxies for the extent of their capacity costs. Third, our sample contains around 8.5 million observations, including 58 tour operators and 9,823 hotels in 86 countries. Finally, in a large number of robustness tests we ensure that factors such as compositional changes and unobserved heterogeneity related to our transaction-level package tour data set do not qualitatively affect our estimates of exchange rate pass-through.

Overall, the empirical results suggest that pass-through into package tour prices is incomplete and low, but similar in magnitude to estimates of exchange rate pass-through into retail prices (Antoniades and Zaniboni, 2016). In response to a 10% depreciation of the euro, package tour prices (in euro) increase by 1.5% after one year. More importantly, we find that the response of prices and pass-through with regard to dynamic pricing is in line with the model predictions. First, prices for last-minute bookings – i.e. those booked 14 days or less before departure – are on average 6.1% lower and pass-through is 6% higher than for the average trip. Evidence from traveler characteristics and their consumption choices are consistent with the notion that the demand elasticity of consumers increases as the departure date approaches.[8] Second, prices during the high season are unambiguously higher, while exchange rate pass-

[6] A package tour comprises transport and accommodation which are organized by a tour operator and is sold to a consumer either directly or by a travel agent.

[7] Other examples in the literature that focus on particular industries include Hellerstein (2008) for beer, Goldberg and Verboven (2001) and Auer, Chaney, and Sauré (2018) for cars, Nakamura and Zerom (2010) for coffee, and Chen and Juvenal (2016) for wine.

[8] In Section 4.4, we provide complementary evidence which suggests that during periods associated with lower demand elasticities – such as school holidays in Germany – package tour prices are higher and pass-through is lower.

through increases with the capacity costs of hotels. Third, advance-purchase discounts are predominantly granted during the high season and prices for high-season trips booked more than seven and a half months in advance are 3.7% lower. In contrast to last-minute bookings, pass-through decreases for advance purchases in the high season. Moreover, this effect is more pronounced for hotels with higher capacity costs. Altogether, the empirical evidence is consistent with the idea that hotels use advance-purchase discounts to plan their capacity for the high season.

In addition to the main results concerning dynamic pricing, our theoretical model also nests predictions regarding factors which have previously been highlighted in the literature as playing a role for exchange rate pass-through. We empirically test these partly in the main empirical analysis on dynamic pricing and partly in extensions in Section 4.4. First, pricing-to-market increases with producer (hotel) productivity (Berman, Martin, and Mayer, 2012; Chatterjee, Dix-Carneiro, and Vichyanond, 2013; Li, Ma, and Xu, 2015). Second, higher-quality producers (hotels) price more to market than lower-quality producers (Bernini and Tomasi, 2015; Chen and Juvenal, 2016; Auer, Chaney, and Sauré, 2018). Third, higher foreign wages are associated with higher exchange rate pass-through (Antoniades and Zaniboni, 2016). Finally, pass-through declines with the importance of distribution costs (e.g. Goldberg and Campa, 2010; Berman, Martin, and Mayer, 2012; Li, Ma, and Xu, 2015), in particular, retailers' (tour operators') distribution costs (Antoniades and Zaniboni, 2016; Hong and Li, 2017), and transport costs (Chen and Juvenal, 2016).

In addition, this paper is the first to focus in detail on exchange rate pass-through into services prices at the micro level. While there is a burgeoning literature examining services trade using firm-level data (e.g. Breinlich and Criscuolo, 2011; Ariu, 2016), commonly used data sets from the balance of payment statistics typically only record transaction values which – in the absence of quantity information – do not allow for the analysis of firms' price setting behavior. Overall, our results indicate that the general economic principles governing exchange rate pass-through into goods' prices – particularly regarding firm productivity, product quality, and distribution costs – also apply to services trade.

The remainder of the paper is structured as follows. The next section presents the theoretical framework detailing the three main predictions related to dynamic pricing and exchange rate pass-through. Section 3 contains information on the transaction-level data set used for the empirical investigation. The main results from our empirical analysis are discussed in Section 4 and a comprehensive assessment of their robustness is provided in Section 5. Section 6 offers some concluding remarks.

2 Theoretical framework

In this section, we present a stylized model of international trade to analyze the effect of dynamic pricing on exchange rate pass-through into consumer prices. In the literature, heterogeneous exchange rate pass-through can emerge in the context of models with local additive distribution costs (Corsetti and Dedola, 2005), linear consumer demand (Melitz and Ottaviano, 2008), and imperfect competition (Atkeson and Burstein, 2008). Building on Antoniades and Zaniboni (2016), we extend the model of international trade by Corsetti and Dedola (2005) to include heterogeneous retailers. This additional layer in the structure of the model gives rise to a double-marginalization problem (e.g. Spengler, 1950). As a consequence, characteristics of the retailer can influence consumer prices above and beyond the presence of fixed distribution costs (e.g. Berman, Martin, and Mayer, 2012).[9] On the consumer side, we model preference with a quadratic utility function in line with Melitz and Ottaviano (2008).[10] In particular, we rely on a variant introduced by Di Comite, Thisse, and Vandenbussche (2014) in which the quality dimension of products is explicitly included.[11]

2.1 Clearance sales and capacity costs

The world economy consists of two countries, an exporting (foreign) country denoted by F and an importing (domestic) country denoted by D. Goods are produced in F, exported to D, and finally distributed to consumers by heterogeneous retailers (in our case tour operators). Producers (in our case hotels) and retailers are independent and possess monopoly power such that prices are set as markups over marginal costs.[12]

Assume that there is a representative consumer in country D who derives utility from the consumption of a continuum of product varieties and the numeraire:

$$U(C_r) = q_0 + \int_{i\in\Phi} \alpha(i)q_r(i)di - \frac{1}{2}\int_{i\in\Phi} \beta(i)[q_r(i)]^2 di - \frac{\gamma}{2}\left[\int_{i\in\Phi} q_r(i)di\right]^2, \quad (1)$$

where Φ denotes the set of available varieties, q_0 consumption of the numeraire, and $q_r(\varphi)$ consumption of variety φ at retailer r.

[9] This modeling choice is motivated, first, by the literature highlighting the importance of retailers in determining pass-through into consumer prices (e.g. Nakamura, 2008; Nakamura and Zerom, 2010) and, second, by our analysis of package tours which – similar to the vast majority of consumer goods – are not purchased directly from producers.

[10] In models of pass-through involving a double-marginalization problem and CES demand, the elasticity of substitution of consumer demand does not directly affect exchange rate pass-through (Antoniades and Zaniboni, 2016).

[11] This aspect is not crucial for our main predictions, but it plays an important role for explicitly capturing the effect of product quality on pass-through. Alternatively, using the Melitz and Ottaviano (2008) version of the quadratic utility delivers similar predictions for product quality under the additional assumption that high-performance firms also produce high-quality goods. A theoretical model with CES demand and in which higher-quality goods are assumed to have higher (per unit) distribution costs yields the same prediction (Chen and Juvenal, 2016). See also Auer, Chaney, and Sauré (2018) for an alternative modeling approach.

[12] In the outlined model, we abstract from travel agencies linking tour operators and hotels. We assume instead that the costs incurred by travel agencies for product distribution are part of the tour operators' total distribution costs, which are specified below.

The standard quadratic utility function assumes that the preference parameters are constant across varieties. In contrast, the variant introduced by Di Comite, Thisse, and Vandenbussche (2014) shown in Equation (1) allows for asymmetric preferences (i.e. the parameters $\alpha(\varphi)$ and $\beta(\varphi)$ can vary across varieties). While $\alpha(\varphi) > 0$ captures the preference for the differentiated good with respect to the numeraire, $\beta(\varphi) > 0$ determines the intensity of the consumer's love for variety.[13] The degree of substitutability between any pair of varieties in Φ is governed by $\gamma > 0$ which takes on two values, γ_1 and γ_2, with $\gamma_1 < \gamma_2$. Differences in the degree of substitutability reflect consumer heterogeneity which firms can use for price discrimination insofar consumers can be segmented sufficiently well according to observable characteristics such as the time of purchase.[14]

For a given retail (consumer) price of variety φ at retailer r, $p_r^c(\varphi)$, the consumer's linear demand can then be derived as:

$$q_r(\varphi) = \tilde{\alpha}(\varphi) - \tilde{\beta}(\varphi)p_r^c(\varphi), \tag{2}$$

where $\tilde{\alpha}(\varphi) \equiv \frac{\alpha(\varphi)}{\beta(\varphi)} - \frac{\gamma(\mathbb{A}-\mathbb{P})}{\beta(\varphi)(1+\gamma\mathbb{N})}$ and $\tilde{\beta}(\varphi) \equiv \frac{1}{\beta(\varphi)}$.[15] Market aggregates are defined as $\mathbb{N} \equiv \int_{i\in\Phi} \frac{1}{\beta(i)}di$, $\mathbb{A} \equiv \int_{i\in\Phi} \frac{\alpha(i)}{\beta(i)}di$, and $\mathbb{P} \equiv \int_{i\in\Phi} \frac{p_r^c(i)}{\beta(i)}di$.

For retailer r, distribution requires η_r units of labor in country D per unit sold such that total distribution costs are given by $w\eta_r$.[16] Furthermore, exporting entails additive trade (transport) costs, $\tau > 0$, to be paid in the domestic (country D) currency.[17] Overall, retailer's profits, $\Pi_r(\varphi)$, thus read:

$$\Pi_r(\varphi) = q_r(\varphi)\left[p_r^c(\varphi) - \frac{p_r(\varphi)}{\varepsilon} - \tau - w\eta_r\right], \tag{3}$$

where $p_r(\varphi)$ denotes the producer price and ε the nominal exchange rate between countries D and F. The retailer sets the price $p_r^c(\varphi)$ in order to maximize Equation (3) subject to Equation (2). The resulting profit-maximizing consumer price as a function

[13] As highlighted by Di Comite, Thisse, and Vandenbussche (2014), $\alpha(\varphi)$ corresponds to the consumer's willingness to pay for the first unit of variety φ in the absence of substitutable varieties. A higher $\alpha(\varphi)$ is associated with an increasing willingness-to-pay for variety φ regardless of the quantity consumed and can thus be interpreted as a measure of product quality.

[14] Classic dynamic pricing models (e.g. Gallego and Van Ryzin, 1994; Bitran and Mondschein, 1997; Sweeting, 2012) typically assume a single seller facing stochastically arriving consumers who can decide whether to purchase the product or exit the market. While potential consumers are homogeneous ex ante, their individual product valuation is drawn from a time-invariant probability distribution such that they are heterogeneous ex post. In this setup, it is optimal for the seller of perishable goods to lower prices over time and consumers with comparatively low product valuations tend to purchase later. In general, a lower product valuation corresponds to a larger price elasticity of demand since the latter gives rise to a larger price-dependent adjustment in the quantity demanded. As a shortcut in our theoretical model, consumers buying shortly before actual consumption are therefore characterized by a higher value for γ. For a general overview of the literature on price discrimination, see Varian (1989) and Stole (2007), among others.

[15] The expression can be obtained by maximizing Equation (1) subject to the budget constraint $q_0 + \int_{i\in\Phi} p_r^c(i)q_r(i)di \leq y$ with respect to q_0 and $q_r(\varphi)$, where y denotes available income.

[16] Distribution costs are not modeled explicitly but are instead assumed to fall with retailer size due to economies of scale (e.g. Antoniades and Zaniboni, 2016).

[17] It could be argued that transport costs are paid in US dollars since this is the dominant currency in which fuel is traded on the world market. However, assuming that transport costs are paid in a third-country currency such as the US dollar does not have a bearing on the theoretical model results.

of the producer price is given by:

$$p_r^c(\varphi) = \frac{1}{2}\left[\frac{p_r(\varphi)}{\varepsilon} + \tau + w\eta_r + \frac{\tilde{\alpha}(\varphi)}{\tilde{\beta}(\varphi)}\right]. \tag{4}$$

Producing one unit of variety φ requires $1/m(\varphi)$ units of labor (i.e. $m(\cdot)$ measures the efficiency with which variety φ can be produced) such that labor costs amount to $w_F/m(\varphi)$, with w_F being the wage paid in country F. Let Ω denote (country-specific) fixed costs incurred in the production process, which are the same for all producers and varieties. The producer incurs additional costs in order to increase capacity in periods of high world demand (in our case the high season H) which are external to the model. These costs are denoted by ξ^H and are strictly positive during H (and zero otherwise).[18]

Producer profits are then given by:

$$\Pi_p(\varphi) = q_r(\varphi)\left[p_r(\varphi) - \frac{w_F}{m(\varphi)} - \xi^H\right] - \Omega. \tag{5}$$

The producer sets the price for each variety and retailer in order to maximize Equation (5) subject to Equations (2) and (4). Finally, substituting the resulting profit-maximizing producer price into the profit-maximizing consumer price yields:

$$p_r^c(\varphi) = \frac{1}{4}\left[\frac{1}{\varepsilon}\left(\frac{w_F}{m(\varphi)} + \xi^H\right) + \frac{3\tilde{\alpha}(\varphi)}{\tilde{\beta}(\varphi)} + \tau + w\eta_r\right]. \tag{6}$$

Pass-through of exchange rate fluctuations into consumer prices can be analyzed using the corresponding elasticity:[19]

$$e_{p_r^c(\varphi),\varepsilon} \equiv \left|\frac{\partial p_r^c(\varphi)}{\partial \varepsilon}\frac{\varepsilon}{p_r^c(\varphi)}\right| = \frac{\frac{w_F}{m(\varphi)} + \xi^H}{\frac{w_F}{m(\varphi)} + \xi^H + \varepsilon\left(\frac{3\tilde{\alpha}(\varphi)}{\tilde{\beta}(\varphi)} + \tau + w\eta_r\right)}. \tag{7}$$

The model leads to testable predictions on the role of dynamic pricing for exchange rate pass-through into consumer prices. In particular, two novel predictions can be inferred from Equation (7):

> ***Prediction 1:*** The elasticity of the consumer price to a change in the exchange rate, $e_{p_r^c(\varphi),\varepsilon}$, increases with the degree of product substitutability γ which enters the demand shifter $\tilde{\alpha}(\varphi)$. It then follows that exchange rate pass-through increases for clearance sales in the presence of γ_2 consumers with higher demand elasticities.[20]

[18]This model feature is inspired by the literature on peak-load pricing where marginal costs are comparatively low when there is excess capacity and high when additional capacity is needed in order to accommodate demand (e.g. Steiner, 1957; Williamson, 1966).

[19]To be consistent with the definition of the exchange rate in the remainder of the article, we consider the absolute value in Equation (7). Hence, an increase in ε corresponds to a depreciation of the home currency (i.e. the euro).

[20]γ is larger for consumers purchasing close to the consumption date as they perceive any pair of varieties in Φ to be closer substitutes. The prediction then follows from the observation that $\tilde{\alpha}(\cdot)\big|_{\gamma=\gamma_2} - \tilde{\alpha}(\cdot)\big|_{\gamma=\gamma_1} < 0$ as by definition $\mathbb{A} - \mathbb{P} > 0$. Note that in models without a double-marginalization structure, pass-through also decreases with the elasticity of substitution of consumer demand across sectors and products (e.g. Berman, Martin, and Mayer, 2012).

The intuition behind this prediction is as follows. Leisure travelers prefer not to buy very close to the departure date because, for example, their preferred package tour might then no longer be available. Consumers with higher demand elasticities are willing to compromise on this dimension if sufficient price discounts are granted. Tour operators and hotels use this knowledge to identify those consumers and to segment the market accordingly. Hence, tour operators and hotels reduce markups for last-minute bookings, i.e. the consumer price decreases. At the same time, prices adjust relatively more in response to exchange rate movements, i.e. pass-through increases.[21]

> ***Prediction 2:*** The elasticity of the consumer price to a change in the exchange rate, $e_{p_r^c(\varphi),\varepsilon}$, increases in the high season H with the capacity costs of producers ξ^H.[22]

Intuitively, tourism demand for holidays shows a strong seasonal pattern. For instance, demand is high during certain months due to attractive weather conditions in the holiday destination country (high season), while it is low in the remaining months (low season). In the high season, hotels have to hire additional temporary staff at above-average costs in order to accommodate the larger number of guests, resulting in higher marginal costs. As a consequence, prices rise in the high season with capacity costs and price adjustments to exchange rate fluctuations are higher, i.e. pass-through increases.

2.2 Advance-purchase discounts and information acquisition

Another dimension of the intertemporal pricing policy of firms relates to advance-purchase discounts, which are typically granted for different economic reasons compared to clearance sales. In this regard, consumer heterogeneity and demand uncertainty are thought to be important for rationalizing the existence of advance-purchase discounts (e.g. Möller and Watanabe, 2010). In the following, we extend the baseline model to examine the impact of advance-purchase discounts on exchange rate pass-through.

In general, consumers tend to face uncertainty about their valuation of a certain product when consumption lies ahead in the future. Apart from not buying too late, e.g. for rationing reasons (Prediction 1), consumers may prefer to purchase a good (i.e. book a package tour) not too far in advance of consumption (i.e. the actual holiday) since the longer consumers wait, the more likely it is that uncertainty concerning their product

[21] While hotels absorb exchange rate fluctuations in their markups (which depend on consumer characteristics), this effect is directly offset by tour operators in the process of converting the producer price into domestic currency. As a consequence, the absolute consumer price change in response to exchange rate movements does not depend on consumer characteristics (i.e. it is the same for last-minute bookings and other bookings) which, together with lower consumer prices for last-minute bookings, increases pass-through.

[22] The prediction follows from the observation that capacity costs by definition only materialize in periods of higher demand (i.e. the high season) and that, by assumption, $\varepsilon\big(\frac{3\tilde{\alpha}(\varphi)}{\tilde{\beta}(\varphi)} + \tau + w\eta_r\big) > 0$.

valuation will resolve.[23] We assume that there are two types of consumers, denoted by L ("late booking") and E ("early booking"), respectively, who differ with respect to their preference to buy close to the consumption date. Let $\theta \in (0,1)$ denote the fraction of L consumers in the population with a comparatively strong preference to buy close to the consumption date while, conversely, $1-\theta$ denotes the fraction of E consumers with a stronger preference to buy early. Even though θ is assumed to be common knowledge to the market, the producer cannot identify individual L and E consumers, respectively.

In this setup, the producer does not precisely know demand for variety φ in the high season. However, by offering a price discount for a particular variety when the purchase occurs early (i.e. an advance-purchase discount), the producer acquires information concerning total demand.[24] Specifically, assume for simplicity that a fixed $\iota^H \in (0,1)$ represents the advance-purchase discount in the high season H (and zero otherwise). This information acquisition allows production to be planned more efficiently and the producer can expand capacity for all sales in the high season in advance at a lower cost, i.e. the producer incurs lower capacity costs, $\xi^{H,\iota} < \xi^H$.[25]

For a given discount ι^H in the high season and taking into account both types of consumers in the population, the elasticity of the consumer price with respect to the exchange rate can be derived as:

$$e_{p_r^c(\varphi),\varepsilon} \equiv \left| \frac{\partial p_r^c(\varphi)}{\partial \varepsilon} \frac{\varepsilon}{p_r^c(\varphi)} \right| = \frac{\frac{w_F}{m(\varphi)} + \xi^{H,\iota}}{\frac{w_F}{m(\varphi)} + \xi^{H,\iota} + \frac{2-\tilde{\theta}}{\tilde{\theta}}\left(\tau\varepsilon + \varepsilon w \eta_r\right) + \frac{2+\tilde{\theta}}{\tilde{\theta}} \frac{\tilde{\alpha}(\varphi)\varepsilon}{\tilde{\beta}(\varphi)}}, \tag{8}$$

where $\tilde{\theta} \equiv \frac{\theta(1-\iota^H)+(1-\theta)(1-\iota^H)^2}{\theta+(1-\theta)(1-\iota^H)^2}$. Details on the derivation can be found in the Appendix (Section A.2.1). Note that Equation (7) is nested and can be obtained by setting $\iota^H = 0$. Equation (8) delivers an additional testable prediction:

> ***Prediction 3:*** The elasticity of the consumer price to a change in the exchange rate, $e_{p_r^c(\varphi),\varepsilon}$, decreases for advance purchases in the high season.[26]

The intuition behind this result is the following. While leisure travelers, ceteris paribus, prefer not to buy very close to the departure date (Prediction 1), they also do not like to book very far in advance as, for example, package tours better matching their

[23] For instance, Nocke, Peitz, and Rosar (2011) show that it can be optimal for a monopolist to use advance-purchase discounts in order to discriminate between consumers who differ with respect to their expected product valuations.

[24] For the literature on information acquisition, see Crémer and Khalil (1992), Lewis and Sappington (1994), Boyacı and Özer (2010), and Prasad, Stecke, and Zhao (2011), among others.

[25] In the following, we assume that the resulting gain from lower capacity costs for all sales in the high season outweighs the revenue losses associated with granting the advance-purchase discount, ι^H, to the fraction of E consumers $(1-\theta)$ in the population.

[26] The prediction follows from the assumption that $\xi^{H,\iota} < \xi^H$ and the definition of $\tilde{\theta}$, which is equal to one when there is no discount and smaller than one in the presence of discounts.

preferences might become available in the meantime. Therefore, hotels do not know the precise level of demand during the high season. Since increasing capacity at short notice is comparatively costly, information about the level of demand is valuable to hotels. In order to acquire information regarding total demand, hotels grant advance-purchase discounts during the high season. As a consequence, hotels lower their prices for early bookings, also leading to a decrease in consumer prices. At the same time, prices adjust relatively less in response to exchange rate movements, i.e. pass-through decreases.[27]

2.3 Additional predictions

Apart from the three main predictions, the model is also consistent with previous theoretical and empirical results on the relationship between producer, retailer, and product characteristics on exchange rate pass-through. More specifically, in Equation (7) pass-through (i) decreases with producer productivity $m(\cdot)$ (e.g. Berman, Martin, and Mayer, 2012), (ii) decreases with product quality as $\tilde{\alpha}(\cdot)$ is larger for varieties of higher quality (e.g. Bernini and Tomasi, 2015), (iii) increases with foreign wages w_F (e.g. Antoniades and Zaniboni, 2016), (iv) decreases with the retailers' distribution costs η_r (e.g. Hong and Li, 2017), and (v) decreases with transport costs τ (e.g. Chen and Juvenal, 2016).

3 Data and descriptive statistics

3.1 Transaction-level data

We analyze transaction data for package tours purchased by German tourists compiled by Amadeus Leisure IT GmbH, an IT provider for the travel and tourism industry.[28] The data are collected at the daily frequency between 2012 and 2018 and record both booking date and departure date, allowing for the calculation of the booking lead time (i.e. the difference between departure date and booking date). For a comprehensive list of definitions and data sources, see Table A1 in the Appendix. In addition, the data set includes the total expense of each package tour in euro, the number of travelers, and the duration of the trip, which we use to obtain the price per person per day

[27] All components of the producer price (i.e. marginal costs and markup) are affected by the advance-purchase discount. Therefore, the absolute consumer price change in response to exchange rate movements also depends on the advance-purchase discount.

[28] According to the economic newspaper "WirtschaftsWoche" (issue 27/2018), Amadeus has a global market share of 43%. See Henn, Islam, Schwind, and Wieland (forthcoming) for an application of this data in the statistical measurement of aggregate price dynamics. Pursuant to Eurostat (2013), a "package (tour) comprises at least the components transportation and accommodation and is provided at an inclusive price". In general, travel expenditures account for roughly 25% of Germany's services imports. According to the German Travel Association ("Deutscher Reiseverband"), around half of German travel expenses are on package tours.

for each tour.[29] Importantly, the data set contains identifiers for both tour operators and hotels, as well as the name of the hotel, its location, province, and country. We augment the data set with additional hotel information collected from TripAdvisor using web-scraping techniques. We match the hotels in the transaction data set with the ones from TripAdvisor by name and hotel location. For the empirical analysis, we use the number of rooms as a proxy for hotel productivity, and the average customer ratings as a measure of hotel quality. Finally, a range of additional information – such as the age of travelers – is provided for a subset of the transactions.

Note that we confine our analysis to a subset of the raw data. First, we exclude from the sample all euro area countries and all countries whose currencies are pegged to the euro. Second, we disregard package tours that were cancelled before the day of departure. Third, we drop outliers defined by the 1st and 99th percentile of the distribution of prices. Finally, to ensure that changes in pass-through are not driven by the entry and exit of tour operators in our sample over time, we restrict our analysis to a balanced sample of tour operators between 2012 and 2018.[30]

3.2 Macroeconomic data

Exchange rate data are taken from Thomson Reuters and Investing and represent closing prices. Data for non-trading days correspond to values for the last trading day. Exchange rates are defined in euro per unit of foreign currency such that an increase in the exchange rate variable denotes a depreciation of the euro. For the purpose of the estimation, twelve 30-day averages of the daily exchange rate were computed covering the 360 days preceding a transaction. The monthly index of consumer prices of holiday destination countries is taken from the IMF, Eurostat, and various national sources. Monthly personal travel expenditures are taken from the German balance of payment statistics to measure time-varying demand for travel services in Germany. The price level of real GDP expressed in purchasing power parity (PPP) is from the Penn World Tables. Bilateral distances are taken from the Centre d'Études Prospectives et d'Informations Internationales (CEPII). Seasonality in the demand for tourism services in holiday destination countries is measured by the total number of tourist arrivals, for which data are collected from Haver Analytics, the IMF, Eurostat, and various national sources. The high season is defined as the six months with the largest average number of tourist arrivals between 2012 and 2018.[31]

[29] Similar to other studies in the literature, information on the currency of invoicing between tour operators and hotels is not available in the data set.

[30] In Section 5, we also consider a balanced sample of hotels and tour operators.

[31] Note that the observed number of tourist arrivals is ultimately an equilibrium outcome which is influenced by, inter alia, the pricing decisions of firms. In Section 5, we show that our results are robust to a range of alternative definitions of the high season.

3.3 Descriptive statistics

Our data set contains 58 tour operators and 9,823 hotels in 86 countries. In 2012, there were 5,114 hotels in 68 countries, while this number slightly increased to 6,536 hotels in 72 countries in 2018. Between 2012 and 2018, the average tour operators sold package tours to 1,224 hotels in 21 countries, while the average hotel accommodated guests from 7 distinct tour operators. As detailed in Table 1, the average package tour was booked for two travelers, had a duration of ten days, and costs 2,099 euro in total, corresponding to an average price of 90 euro per person per day. The average hotel was relatively large in size with a capacity of 380 rooms and was comparatively good in quality with a TripAdvisor traveler rating of 4.2 on a scale from 1 (worst) to 5 (best). The price level of German holiday destinations is on average substantially lower than the reference country, corresponding to around 42% of the US price level in 2011.

Table 1: Summary statistics.

	Observations	Mean	Standard deviation	10th percentile	90th percentile
expense	8,499,445	2,098.7	1,445.9	767.0	3,808.0
travelers	8,499,445	2.4	1.1	1.0	4.0
duration	8,499,445	10.3	4.2	7.0	14.0
price	8,499,445	89.7	41.4	47.9	141.3
lead time	8,499,445	97.7	83.0	11.0	223.0
rooms	7,806,767	380.3	211.2	144.0	658.0
rating	8,368,207	4.2	0.4	3.5	4.5
price level	8,381,666	0.42	0.14	0.18	0.57

Notes: Definitions and data sources can be found in Table A1 in the Appendix.

Table 2 shows that while proximate destinations such as Turkey, Egypt, and Tunisia are the most popular, more distant countries like the Dominican Republic, the United Arab Emirates, and the Maldives also attract a sizeable share of German package tourists traveling outside the euro area.[32] As one would expect, the average price per person per day varies systematically with distance and price level of the destination country. Note also that the top ten holiday destinations are served by a large number of tour operators and feature between 109 and 2,359 hotels.

[32] The regional concentration of trade in our data set is a also common feature of other studies. For example, the United States accounts for 30.8% of exports in Chen and Juvenal (2016), while the euro area constitutes 56% of import value in Antoniades and Zaniboni (2016). Omitting individual countries among the top destinations from our data set leaves the coefficients by and large unaffected in terms of sign and significance.

Table 2: Summary statistics on top holiday destinations 2012-2018.

Country	% of value	*price*	*price level*	*distance*	Hotels	Tour operators
Turkey	43.7	79.7	0.48	2,168	2,359	51
Egypt	20.2	79.0	0.25	2,957	536	51
Dominican Republic	6.9	129.8	0.49	7,710	175	43
United Arab Emirates	4.6	134.8	0.59	4,824	522	46
Tunisia	4.3	66.9	0.36	1,729	315	47
Maldives	3.9	200.1	0.65	7,886	133	39
Thailand	2.7	105.4	0.41	8,878	874	40
Cuba	2.4	133.0	N/A	8,098	186	38
Mexico	2.4	145.2	0.55	9,476	238	37
Mauritius	2.0	173.6	0.49	9,224	109	38

Notes: The table shows the ten most popular holiday destinations ranked by their share in total expenditure and shows unweighted averages of variables. The last two columns report the number of hotels and tour operators.

Table 3 provides descriptive statistics by booking lead time. Package tours that are booked close to the departure date represent a large share of the sample. More than half of the package tours in the sample are booked less than three months in advance and around a quarter have a booking lead time of less than a month. In general, the number of monthly bookings decreases with booking lead time. At the same time, the data set still contains a fair number of package tours that are booked well in advance. For instance, more than 7% of observations have a booking lead time of nine months or more.

Table 3: Summary statistics by booking lead time.

lead time (in months)	*price*	% of bookings	Cum. % of bookings
1	82.8	26.5	26.5
2	90.0	18.1	44.6
3	92.8	12.0	56.6
4	93.1	9.5	66.1
5	92.7	8.4	74.5
6	93.2	7.1	81.6
7	93.4	6.1	87.8
8	92.9	4.8	92.5
9	93.3	3.4	95.9
10	92.6	2.0	98.0
11	90.9	1.2	99.2
12	86.0	0.8	100.0

Notes: Average price and (cumulated) share of bookings by booking lead time in months.

Overall, booking lead time has a noticeable effect on package tour prices.[33] While the average price per person per day is around 93 euro for package tours booked between three and ten months in advance, the price falls to 90 euro (83 euro) for a booking lead time of two months (less than one month).[34] Similarly, early bookers also seem to benefit from lower prices. Package tours booked 11 months (12 months or more) before the departure date cost only 91 euro (86 euro) per person per day.

[33] Note that here we only report unconditional averages and do not control for potential composition effects. However, the overall pattern is confirmed using within estimations in Section 4.

[34] Prices fall monotonically for more fine-grained bins when the booking lead time decreases. For example, package tours booked two weeks (less than one week) in advance have an average price of 82 euro (80 euro).

Table 4: Seasonality of international tourist arrivals and German package tour prices.

Country	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Price difference [%]
Turkey													29.3
Egypt													10.7
Dominican Republic													14.5
United Arab Emirates													13.8
Tunisia													20.3
Maldives													12.1
Thailand													20.9
Cuba													16.0
Mexico													12.9
Mauritius													8.6

Notes: The table shows the seasonal classification of the top ten holiday destinations (from external data sources) together with the price difference of German package tour prices (from the package tour data set) defined as the difference between average prices in the high season and the low season relative to average prices in the low season. Gray-shaded cells indicate the high season.

Table 4 illustrates the seasonality of international tourist arrivals (from external data sources) and German package tour prices for the top ten holiday destinations (from the package tour data set). For Mediterranean countries, the high season – defined as the six months with the largest number of international tourist arrivals – is usually from late spring to early fall, reflecting attractive weather conditions and the incidence of school holidays in neighboring countries, among other factors. In contrast, in more distant destinations and those located in the southern hemisphere, the high season is more focused around the winter months. Irrespective of the country, German package tour prices increase during the high season of the holiday destination country, with price differences varying between 8.6% and 29.3%.

4 Empirical analysis

To test the three main predictions of our theoretical model (Section 2), we estimate standard pass-through regressions (e.g. Gopinath, Itskhoki, and Rigobon, 2010). Specifically, we employ the following transaction-level model:[35]

$$\ln p_k = \sum_{m=1}^{12} \beta_{1,m} \ln NER_{k,m} + \sum_{m=1}^{12} \beta_{2,m} \ln NER_{k,m} \times X_k + \beta_3 X_k + \beta_4 D_k + \varepsilon_k, \quad (9)$$

where k references a single transaction, p_k is the price per person per day expressed in euro, $NER_{k,m}$ is a 30-day average of the nominal exchange rate between Germany and the holiday destination country (euro per unit of foreign currency) associated with transaction k and time lag m,[36] X_k is a particular characteristic of transaction k, D_k represents a set of control variables, and ε_k is an idiosyncratic error term.[37] The sum

[35] Bonadio, Fischer, and Sauré (forthcoming) use a similar transaction-level model to study the speed of exchange rate pass-through at the daily frequency.

[36] In other words, an increase in $NER_{k,m}$ corresponds to a depreciation of the euro. For lag $m = 1$ ($m = 2$), we use the average daily nominal exchange rate between Germany and the holiday destination country over the past 30 days (31–60 days) from the day the transaction occurred, et cetera. Hence, the exchange rate variable varies at the daily level.

[37] For a detailed overview of data sources, see Table A1 in the Appendix.

of the coefficients on the nominal exchange rate, $\tilde{\beta}_1 \equiv \sum_{i=1}^{12} \beta_{1,i}$, measures the cumulative impact of changes in the exchange rate on the consumer price over a one year horizon. Given the high level of disaggregation of the data, exchange rate movements can be assumed to be exogenous to individual firms' pricing strategies. The statistic of interest is $\tilde{\beta}_2 \equiv \sum_{i=1}^{12} \beta_{2,i}$ which captures the effect of characteristic X on exchange rate pass-through. The vector of controls, D_k, comprises 12 lags of the monthly consumer price index of the holiday destination country,[38] 12 lags of monthly German demand conditions (using personal travel expenditure at the time of departure from the German balance of payment statistics),[39] as well as a comprehensive set of fixed effects. Generally, we perform within estimations and include tour operator $\times$ hotel $\times$ duration (in days) fixed effects to allow for hotel- and duration-specific marginal costs, tour operator $\times$ year fixed effects to capture shocks to marginal costs of individual tour operators, travel month $\times$ country fixed effects to control for country-specific seasonality patterns,[40] and booking lead time (in weeks) fixed effects to account for dynamic pricing of hotels and tour operators as a function of the difference between booking date and departure date. Finally, standard errors are clustered at the hotel level, allowing unobserved errors to be correlated across bookings and time.

To get a sense of the overall exchange rate pass-through into package tour prices, we initially estimate Equation (9) without including interactions. As expected, package tour prices systematically vary with the exchange rate. In response to a 10% depreciation of the euro, package tour prices (in euro) increase by 1.5% after one year, i.e. pass-through is around 15%.[41] Those results are similar in magnitude to estimates of exchange rate pass-through into retail prices (Antoniades and Zaniboni, 2016), while they fall in the mid-range of estimates from studies using prices of traded goods at the dock (e.g. Gopinath and Itskhoki, 2010) and prices of aggregate consumption baskets including both traded and non-traded goods (e.g. Goldberg and Campa, 2010).[42]

The subsequent sections are organized around the three main predictions summarized in Table 5.[43] First, we analyze the dynamic pricing behavior of hotels and tour operators linked to clearance sales and the heterogeneity of consumers (Section 4.1). Second,

[38] This is a commonly used proxy for the input costs of producers. In Section 5, we alternatively include month $\times$ year $\times$ country fixed effects, which control for time-varying factors at the country level such as input costs.

[39] One can assume that this measure more accurately captures demand for package tours in Germany than GDP. In the literature, the latter is often used as a proxy for demand conditions in the importing country. In addition, in Section 5 we additionally include month $\times$ year $\times$ country fixed effects, which effectively control for time-varying destination-specific tourism demand.

[40] That is to say, we include 12 dummy variables (one for January, February, et cetera) for each country. In Section 5, we also control for intra-country patterns of seasonality.

[41] Prices increase gradually over time and pass-through is higher when considering horizons longer than one year.

[42] Firm-level studies on export prices in the manufacturing sector – which do not include transportation and distribution costs – tend to find substantially larger pass-through (e.g. Berman, Martin, and Mayer, 2012; Amiti, Itskhoki, and Konings, 2014; Li, Ma, and Xu, 2015).

[43] In the following, we analyze the three main predictions individually. However, the empirical results remain qualitatively unchanged when testing them simultaneously.

Table 5: Summary of main model predictions.

		Price	Pass-through
Prediction 1	Clearance sales	−	+
Prediction 2	Capacity costs (high season)	+	+
Prediction 3	Advance purchases (high season)	−	−

we examine the effect of seasonality and capacity costs of hotels in holiday destination countries (Section 4.2). Third, we study a setting in which advance selling and capacity costs interact with hotels offering advance-purchase discounts for capacity planning during the high season (Section 4.3). Subsequently, we briefly summarize additional empirical tests of model features on the relationship between producer, retailer, and product characteristics on pass-through, the results of which are in line with the previous literature (Section 4.4).

4.1 Clearance sales and consumer heterogeneity (Prediction 1)

According to Prediction 1, the exchange rate elasticity increases (and the price decreases) for last-minute bookings since consumers booking close to the time of departure tend to have higher demand elasticities. To test Prediction 1, we estimate Equation (9) and include increasingly more fine-grained measures of last-minute bookings (Table 6).[44] To get an idea of how prices change as the departure date approaches, we initially omit booking lead time fixed effects in columns (1)-(2). According to column (1), package tours booked in the last 14 days prior to departure are on average 6.1% (i.e. $e^{-0.063}-1$) cheaper than the average package tour. Furthermore, column (2) shows that prices tend to decrease even further within this 14-day window. While prices for trips booked 11 to 14 days (8 to 10 days) in advance are 4.4% (5.7%) lower, prices drop by 6.9% (8.2%) for bookings with a lead time of 4 to 7 days (0 to 3 days). In column (3), we interact the dummy for last-minute bookings with the exchange rate.[45] Its coefficient is positive and significant, in direct support of Prediction 1, i.e. pass-through increases for last-minute bookings. The exchange rate elasticity is equal to 0.151 for the average package tour and increases to 0.160 for trips booked in the last 14 days of the departure date, which represents a 6% increase in pass-through. In addition, column (4) indicates that pass-through progressively increases as the departure date approaches. While the exchange rate elasticity for trips booked 11 to 14 days (8 to 10 days) in advance equals 0.153 (0.157), it increases to 0.163 (0.176) for bookings with a lead time of 4 to 7 days (0 to 3 days).

[44] The German Travel Association ("Deutscher Reiseverband") defines a travel offer to be last minute if the day of departure is within the next 14 days.

[45] The main effect of booking lead time drops out due to the presence of booking lead time fixed effects.

Table 6: Last-minute bookings.

	(1)	(2)	(3)	(4)
lead time (0–14 days)	-0.063***			
	(0.003)			
lead time (0–3 days)		-0.086***		
		(0.004)		
lead time (4–7 days)		-0.071***		
		(0.003)		
lead time (8–10 days)		-0.059***		
		(0.002)		
lead time (11–14 days)		-0.045***		
		(0.002)		
ln *NER*			0.151***	0.151***
			(0.018)	(0.018)
ln *NER* × *lead time* (0–14 days)			0.009***	
			(0.002)	
ln *NER* × *lead time* (0–3 days)				0.025***
				(0.004)
ln *NER* × *lead time* (4–7 days)				0.012***
				(0.003)
ln *NER* × *lead time* (8–10 days)				0.006***
				(0.002)
ln *NER* × *lead time* (11–14 days)				0.002*
				(0.001)
Observations	8,499,445	8,499,445	8,499,445	8,499,445
Hotels	9,823	9,823	9,823	9,823
Tour operators	58	58	58	58
Countries	86	86	86	86
R^2	0.78	0.78	0.78	0.78
Tour operator × year FE	Yes	Yes	Yes	Yes
Tour operator × hotel × duration FE	Yes	Yes	Yes	Yes
Month × country FE	Yes	Yes	Yes	Yes
Lead time FE	No	No	Yes	Yes
CPI, $demand_{DEU}$	No	No	Yes	Yes

Notes: The *lead time* dummies in column (4) were included in the regression, but omitted from the table since the presence of weekly lead time fixed effects complicates their interpretability. Standard errors in parentheses are clustered at the hotel level. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Based on the assumption that consumers who book close to the departure date have higher demand elasticities, our model predicts that last-minute bookings should be associated with a higher degree of exchange rate pass-through. In general, the time profile of the customer distribution (and therefore of pricing) depends on, inter alia, the particular product and industry (e.g. Möller and Watanabe, 2010; Sweeting, 2012).[46] To substantiate the validity of our assumption, in Table 7 we explore how consumer and trip characteristics vary with booking lead time. Since older consumers tend to be wealthier and are therefore expected to have lower demand elasticities (e.g. Alessandria and Kaboski, 2011; Simonovska, 2015), we use age as a proxy for the elasticity of substitution. Column (1) shows that consumers booking last minute are younger on average. The age of the average traveler is 0.27 years lower for trips booked 11 to 14 days in advance than for the average trip and this number monotonically decreases to

[46] For example, in the airline industry, prices tend to increase for flights booked closer to the day of departure since demand of business travelers is less price elastic than that of leisure travelers (e.g. Stavins, 2001).

0.3 years (8 to 10 days), 0.69 years (4 to 7 days), and 1.4 years (0 to 3 days) as the departure date approaches.

Additional evidence comes from the characteristics of the trips that were purchased last minute. If last-minute bookers have lower incomes, one would also expect them to spend less on the holiday overall (above and beyond the hotel-duration-specific reduction in the price per person per day shown in Table 6). Column (2) reports results from a regression of the total expense per person on lead time dummies in which tour operator × hotel × duration fixed effects and country fixed effects were omitted to allow for variation along duration, hotel, and country margins. Consistent with the view that last-minute travelers have lower incomes, the overall expense on the holiday declines by 16.2% (11 to 14 days), 18.7% (8 to 10 days), 22.1% (4 to 7 days), and 27.5% (0 to 3 days) as the departure date approaches.[47] This lower overall expense can derive from a variety of different sources. Columns (3)-(5) delineate three factors that contribute to the decline in expenditure above and beyond price discounts. Last-minute travelers book trips that are 1.1 to 1.8 days shorter, to holiday destinations that are 266 to 461 kilometers closer (and hence associated with lower air fares), and to hotels that have a 0.04 to 0.06 point lower quality rating according to TripAdvisor. Therefore, last-minute bookers appear willing to comprise on duration, distance, and quality to reduce their overall expenditure on the package tour.

Table 7: Consumer and trip characteristics of last-minute bookings.

	(1) *age*	(2) ln *expense* (per person)	(3) *duration*	(4) *distance*	(5) *rating*
lead time (0–3 days)	-1.409***	-0.321***	-1.815***	-461.299***	-0.060***
	(0.066)	(0.005)	(0.031)	(24.682)	(0.006)
lead time (4–7 days)	-0.693***	-0.250***	-1.414***	-346.974***	-0.054***
	(0.048)	(0.004)	(0.022)	(20.977)	(0.006)
lead time (8–10 days)	-0.297***	-0.207***	-1.175***	-287.058***	-0.045***
	(0.051)	(0.004)	(0.019)	(18.907)	(0.005)
lead time (11–14 days)	-0.265***	-0.177***	-1.051***	-265.778***	-0.037***
	(0.044)	(0.003)	(0.018)	(18.159)	(0.004)
Number of observations	2,726,671	8,499,445	8,499,445	8,499,445	8,364,557
Number of hotels	7,683	9,823	9,823	9,823	9,114
Number of tour operators	56	58	58	58	58
Number of countries	67	86	86	86	79
R^2	0.30	0.28	0.25	0.22	0.41
Tour operator × year FE	Yes	Yes	Yes	Yes	Yes
Tour operator × hotel FE	No	No	Yes	No	No
Tour operator × location × duration FE	No	No	No	No	Yes
Tour operator × hotel × duration FE	Yes	No	No	No	No
Month × country FE	Yes	No	Yes	No	Yes
Month FE	No	Yes	No	Yes	No
Lead time FE	No	No	No	No	No

Notes: Standard errors in parentheses are clustered at the hotel level. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

In sum, traveler characteristics and consumption choices are consistent with the notion that the demand elasticity (income) of consumers increases (decreases) as the departure

[47] Note that this decline is considerably larger than the hotel-duration-specific reduction in the price per person per day shown in Table 6.

date approaches. In line with Prediction 1, firms lower their prices and absorb exchange rate fluctuations to a smaller extent in their markups for last-minute bookings, which increases pass-through into consumer prices. Therefore, there is evidence that firms successfully use price discrimination by indirectly segmenting consumers with high and low valuations in the same country by their time of purchase. Our empirical results on the effects of within-country price discrimination of consumers on pass-through mirror the findings of previous studies on pricing-to-market exploiting cross-country variation in income. In this setting, pricing-to-market is generally found to be stronger for exports to richer importing countries (e.g. Alessandria and Kaboski, 2011; Li, Ma, and Xu, 2015; Chen and Juvenal, 2016).

4.2 Seasonality of demand and capacity costs (Prediction 2)

Table 8 reports the results of how exchange rate pass-through varies with seasonality and capacity costs. Prediction 2 states that, in the high season, pass-through increases with capacity costs of hotels in holiday destination countries. While prices are unambiguously higher in the high season, the overall degree of pass-through depends on the relative importance of changes in demand and hotels' capacity costs. To quantify how seasonality affects prices, we initially estimate Equation (9) by omitting month $\times$ country fixed effects and include an indicator variable for the high season defined as the six months with the largest number of international tourist arrivals.[48] Column (1) shows that package tour prices are 22.3% higher in the high season which is consistent with Equation (6).

In our setting, producers' capacity costs are primarily due to short-run labor adjustments related, in particular, to the hiring of additional temporary staff to serve the larger number of customers during the high season. In columns (2)-(5), we therefore interact two hotel-specific measures and one country-specific proxy of capacity costs with the exchange rate and the indicator for the high season. Note that we center all continuous interaction variables, X, by subtracting their sample mean to obtain a demeaned variable $\overline{X}$. By doing so, we guarantee that the interpretation of coefficients on the main effects and lower-order interaction terms remains straightforward.

First, there is micro-level evidence suggesting that hiring costs – and hence the associated capacity costs – are convex, i.e. that marginal hiring costs (including recruitment and adaptation) increase with the number of hires (e.g. Pfann and Verspagen, 1989; Blatter, Muehlemann, and Schenker, 2012). Therefore, marginal hiring costs are, ceteris paribus, higher for larger hotels, assuming that the relative increase in staff during

[48] In Section 5, we examine the robustness of our results to a range of alternative definitions of the high season.

Table 8: Seasonality of demand and capacity costs.

	(1)	(2)	(3)	(4)	(5)
high season	0.201***				
	(0.006)				
ln *NER*		0.156***	0.162***	0.098***	0.109***
		(0.019)	(0.019)	(0.023)	(0.023)
ln *NER* × *high season*		-0.009**	-0.012***	-0.031***	-0.039***
		(0.004)	(0.004)	(0.005)	(0.006)
high season × $\overline{\ln\ rooms}$		0.025***			0.024***
		(0.006)			(0.006)
high season × $\overline{rating}$			0.034***		0.032***
			(0.006)		(0.006)
high season × $\overline{price\ level}$				0.348***	0.330***
				(0.033)	(0.033)
ln *NER* × $\overline{\ln\ rooms}$		-0.038***			-0.028***
		(0.011)			(0.010)
ln *NER* × $\overline{rating}$			-0.092***		-0.071***
			(0.014)		(0.014)
ln *NER* × $\overline{price\ level}$				0.103***	0.084***
				(0.023)	(0.024)
ln *NER* × *high season* × $\overline{\ln\ rooms}$		0.006***			0.006***
		(0.002)			(0.002)
ln *NER* × *high season* × $\overline{rating}$			0.009***		0.008***
			(0.002)		(0.002)
ln *NER* × *high season* × $\overline{price\ level}$				0.105***	0.092***
				(0.012)	(0.013)
$\overline{price\ level}$				0.208***	0.171***
				(0.057)	(0.056)
Observations	8,475,160	7,784,325	8,344,974	8,357,328	7,670,182
Hotels	9,701	8,422	9,010	9,479	8,241
Tour operators	58	58	58	58	58
Countries	76	69	71	72	66
R^2	0.73	0.78	0.78	0.78	0.78
Tour operator × year FE	Yes	Yes	Yes	Yes	Yes
Tour operator × hotel × duration FE	Yes	Yes	Yes	Yes	Yes
Month × country FE	No	Yes	Yes	Yes	Yes
Lead time FE	Yes	Yes	Yes	Yes	Yes
CPI, $demand_{DEU}$	No	Yes	Yes	Yes	Yes

Notes: The variable $\overline{X}$ denotes the demeaned counterpart of *X*. Standard errors in parentheses are clustered at the hotel level. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

the high season is the same across hotels of different size.[49] As a result, exchange rate pass-through is expected to increase with hotel size during the high season. In column (2), the (logarithm of the) number of hotel rooms is used as a measure of firm size, which is also a commonly used proxy for firm productivity.[50] In line with Section 2.3, the exchange rate elasticity decreases with hotel size as larger (and hence more productive) hotels absorb exchange rate movements in their markups to a larger extent (e.g. Berman, Martin, and Mayer, 2012; Chatterjee, Dix-Carneiro, and Vichyanond, 2013). Importantly, larger hotels charge higher prices during the high season, in line with the notion that they incur higher capacity costs and that hotels, more generally, face con-

[49] In principle, it could also be argued that larger firms benefit from economies of scale when hiring new staff. However, Manning (2006) finds evidence for diseconomies of scale in recruitment, in support of convex hiring costs.

[50] The main effect for hotel size drops out due to the presence of tour operator × hotel × duration fixed effects.

vex hiring costs. Consistent with Prediction 2, the coefficient on the interaction term between the exchange rate, the high season, and hotel size is positive and significant. During the high season, pass-through decreases by 4.9 percentage points going from the 10th to the 90th percentile of the hotel size distribution instead of 5.8 percentage points in the low season.[51] Therefore, the presence of capacity costs during the high season leads larger and more productive hotels to absorb exchange rate fluctuations to a smaller extent in their markups and to adjust their prices more, all else being equal.

Second, hiring costs tend to increase with skill requirements as the search and matching effort appears to be higher for more demanding positions (e.g. Blatter, Muehlemann, and Schenker, 2012). Therefore, capacity costs are, ceteris paribus, higher for high quality hotels, assuming that high-quality hotels have higher skill requirements. As a result, exchange rate pass-through is expected to increase with hotel quality during the high season. In column (3), we include the average rating of guests from TripAdvisor as a measure of hotel quality.[52] Consistent with Equation (7), pass-through decreases with hotel quality as the demand elasticity of the consumer price decreases with quality (Section 2.3).[53] During the high season, high-quality hotels increase their prices more than low-quality hotels, in line with the view that their capacity costs are higher. In support of Prediction 2, the coefficient of the triple interaction between the exchange rate, the high season, and hotel quality is positive and significant. Pass-through decreases by 10 percentage points going from the 10th to the 90th percentile of the hotel quality distribution instead of 11.1 percentage points in the low season. Therefore, while high-quality hotels usually charge higher markups since their guests have lower demand elasticities, the presence of higher capacity costs during high season induces them to absorb exchange rate movements less in their markups and to vary their prices more than in the low season, all else being equal.

Third, hiring costs and capacity costs more generally increase with the price level of the holiday destination country. Therefore, capacity costs are, ceteris paribus, higher in holiday destinations with a higher price level and pass-through is expected to increase with the price level of the holiday destination country during the high season. In column (4), we include interactions between the exchange rate, the season, and the price level. Note, first, that package tour prices and pass-through increase with the price level, in line with foreign wages being higher (Section 2.3). More crucially, the

[51] Note also that the interaction between the dummy variable indicating the high season and the exchange rate is negative and significant, suggesting that, in general, pass-through is lower in the high season than in the low season. This implies that the effect of changes in world demand in the high season outweighs the additional capacity costs that hotels incur.

[52] Alternatively, using ratings of guests from Booking (www.booking.com) in all analyses leads to qualitatively similar results.

[53] Empirically, for example, Bernini and Tomasi (2015), Antoniades and Zaniboni (2016), Chen and Juvenal (2016), and Auer, Chaney, and Sauré (2018) also find that pass-through is lower for higher-quality goods.

interaction between price level and high season is positive and significant, suggesting that capacity costs increase with the price level. Consistent with Prediction 2, the triple interaction between the exchange rate, the season, and the price level is positive and significant. During the high season, pass-through increases by 8.2 percentage points going from the 10th to the 90th percentile of the country price level distribution, while it increases by only 4.1 percentage points during the low season. Hence, pass-through is higher for holiday destination countries with a higher price level (and hence foreign wages), and this effect is even more pronounced during the high season due to the presence of higher capacity costs.

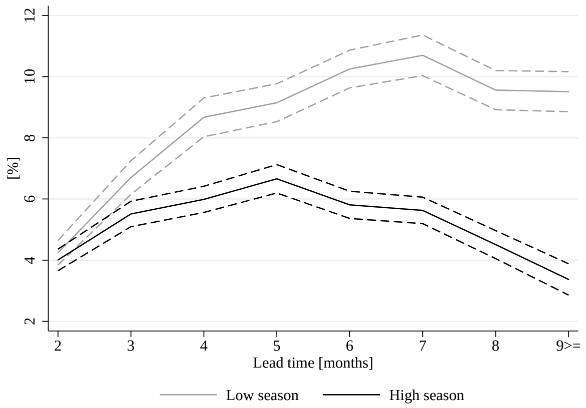
Finally, all results remain qualitatively unchanged in column (5), where we simultaneously include the country-specific and the two hotel-specific measures of capacity costs. In summary, prices and exchange rate pass-through increase in three distinct measures of capacity costs during the high season, in line with Prediction 2. While capacity costs are, in general, not directly observable, the use of three very different proxies for capacity costs provides converging evidence in support of the mechanism detailed in our theoretical model.

4.3 Advance-purchase discounts and information acquisition (Prediction 3)

A third aspect of firms' dynamic pricing policy is advance-purchase discounts granted to early bookers willing to purchase their package tours far ahead of the departure date. Figure 1 shows the evolution of the price markup relative to a tour booked one month in advance as a function of booking lead time for the high season and the low season, respectively. Prices decrease irrespective of the season in the five months leading up to the departure date and last-minute bookings always offer the lowest price. In contrast, advance-purchase discounts are predominantly granted for high-season bookings. On average, prices for the low season increase the earlier the package tour is purchased, while package tours for the high season become cheaper for trips booked five months or more in advance.

In the model, advance-purchase discounts during the high season are a result of the information acquisition of hotels used for efficient capacity planning. Offering advance-purchase discounts incentivizes customers to book early, thereby reducing hotels' uncertainty surrounding total demand during the high season and allowing them to increase capacity at an early stage at a lower cost. This yields testable Prediction 3, which states that pass-through should decrease for package tours booked well ahead of departure during the high season. To test this prediction, we estimate Equation (9) and include interactions between the exchange rate, the high season, and the 90th per-

Figure 1: Price development by season and booking lead time.



Notes: The figure shows the difference between prices of a given package tour and a tour booked one month in advance relative to prices of a tour booked one month in advance. Results are from a fixed effect regression, with the corresponding lead time dummies controlling for tour operator × hotel × duration fixed effects, tour operator × year fixed effects, and travel month × country fixed effects.

centile of booking lead time (Table 9).[54] Column (1) shows that the triple interaction between exchange rate, high season, and advance purchases is negative and significant, in direct support of Prediction 3. Pass-through decreases by 1 percentage point for advance-purchase bookings in the high season relative to those that were not booked well in advance, i.e. the exchange rate elasticity is around 6.5% lower. In line with the model, pass-through remains unchanged for advance-purchase bookings made during the low season. Overall, the results suggest that advance-purchase discounts are granted by hotels rather than tour operators since the latter would reduce distribution costs, leading to higher pass-through (e.g. Berman, Martin, and Mayer, 2012).[55]

Given that hotels use advance-purchase discounts as an information acquisition device in our model, one would expect the heterogeneous impact of advance purchases in the high season on pass-through to be more pronounced when capacity costs are higher. In other words, hotels with higher capacity costs should have a stronger incentive to offer advance-purchase discounts and, hence, pass-through for advance-purchase bookings in the high season should decrease by more for those hotels. Therefore, in columns (3)-(5) we include interactions between the exchange rate, the high season, advance-purchase bookings, and the three measures of capacity costs used before (hotel size, hotel quality, and the price level of the holiday destination country). First, the triple interaction between advance-purchases, the high season, and capacity costs is negative and significant (except for hotel quality), i.e. advance purchases in the high

[54]The 90th percentile corresponds to a booking lead time of 223 days or around seven and a half months. Using the 80th or the 95th percentile as a cut-off leaves the results qualitatively unchanged.

[55]In Section 4.4, we analyze the effects of distribution costs on pass-through in our data set in more detail.

Table 9: Seasonality, capacity costs, and advance-purchase discounts.

	(1)	(2)	(3)	(4)	(5)
Interaction variable $\overline{X}$:			ln *rooms*	*rating*	*price level*
lead time (90th percentile)	0.028***				
	(0.002)				
lead time (90th percentile) × *high season*	-0.038***	-0.054***	-0.057***	-0.055***	-0.055***
	(0.002)	(0.003)	(0.004)	(0.003)	(0.004)
ln *NER*		0.154***	0.149***	0.161***	0.095***
		(0.019)	(0.020)	(0.019)	(0.023)
ln *NER* × *high season*		-0.006	-0.007*	-0.011***	-0.031***
		(0.004)	(0.004)	(0.004)	(0.005)
ln *NER* × *lead time* (90th percentile)		0.000	0.000	0.001	0.003**
		(0.001)	(0.001)	(0.001)	(0.001)
ln *NER* × *lead time* (90th percentile) × *high season*		-0.010***	-0.011***	-0.010***	-0.011***
		(0.001)	(0.002)	(0.001)	(0.001)
high season × $\overline{X}$			0.027***	0.035***	0.379***
			(0.006)	(0.006)	(0.033)
lead time (90th percentile) × $\overline{X}$			0.008*	-0.004	-0.066***
			(0.005)	(0.006)	(0.017)
lead time (90th percentile) × *high season* × $\overline{X}$			-0.023***	0.006	-0.083***
			(0.006)	(0.006)	(0.021)
ln *NER* × $\overline{X}$			-0.038***	-0.092***	0.104***
			(0.011)	(0.014)	(0.023)
ln *NER* × *high season* × $\overline{X}$			0.006***	0.009***	0.113***
			(0.002)	(0.002)	(0.013)
ln *NER* × *lead time* (90th percentile) × $\overline{X}$			0.000	-0.002	-0.013*
			(0.001)	(0.002)	(0.007)
ln *NER* × *lead time* (90th percentile) × *high season* × $\overline{X}$			-0.005***	0.002	-0.046***
			(0.002)	(0.003)	(0.009)
$\overline{X}$					0.215***
					(0.056)
Observations	8,475,107	8,475,105	7,784,325	8,344,974	8,357,328
Hotels	9,699	9,699	8,422	9,010	9,479
Tour operators	58	58	58	58	58
Countries	76	76	69	71	72
R^2	0.78	0.78	0.78	0.78	0.78
Tour operator × year FE	Yes	Yes	Yes	Yes	Yes
Tour operator × hotel × duration FE	Yes	Yes	Yes	Yes	Yes
Month × country FE	Yes	Yes	Yes	Yes	Yes
Lead time FE	No	Yes	Yes	Yes	Yes
CPI, $demand_{DEU}$	No	Yes	Yes	Yes	Yes

Notes: The *lead time* (10th percentile) dummy in columns (2)-(5) was included in the regression, but omitted from the table since the presence of weekly lead time fixed effects complicates its interpretability. The variable $\overline{X}$ denotes the demeaned counterpart of X. Standard errors in parentheses are clustered at the hotel level. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

season increase with capacity costs. Prices for advance bookings in the high season fall by 3.5 percentage points going from 10th to the 90th percentiles of the hotel size distribution. Similarly, prices for advance bookings in the high season decrease by 4.0 percentage points going from the 10th to the 90th percentile of the country price level distribution. More importantly, the quadruple interaction between exchange rate, advance purchases, the high season, and capacity costs is negative and significant (with the exception of hotel quality), i.e. pass-through is lower for advance purchases in the high season if hotels have higher capacity costs. For early bookings in the high season, pass-through decreases by 0.8 percentage points going from the 10th to the

90th percentiles of the hotel size distribution. Likewise, pass-through decreases by 2.1 percentage points going from the 10th to the 90th percentile of the country price level distribution.

In summary, the empirical evidence is consistent with the view that hotels use advance-purchase discounts to plan their capacity for the high season. In line with the model, pass-through decreases for advance purchases in the high season. Moreover, this effect is more pronounced for hotels for which capacity costs are higher, i.e. those that stand to benefit the most from resolving demand uncertainty ahead of time by increasing capacity at an early stage at a lower cost.

4.4 Additional results

This section briefly summarizes additional results complementing the three main predictions of the model, which we present in detail in Section A.3 in the Appendix. It shows that pass-through is lower in time periods associated with lower demand elasticities. Furthermore, the empirical results on the relationship between distribution costs and exchange rate pass-through are consistent with the literature and the additional model predictions presented in Section 2.3.

Prediction 1 states that pass-through increases in settings where the consumer demand elasticity is higher, such as for last-minute bookings. Obviously, the converse is also true, such that pass-through is expected to decrease in periods with low demand elasticities. Generally, public holidays and school holidays are thought to be characterized by lower demand elasticities as annual leave is limited and families with school-aged children are restricted to traveling during school holidays (e.g. Candela and Figini, 2012). In an additional analysis, we examine prices and the exchange rate pass-through of package tours during public holidays and school holidays in Germany (Section A.3.1 and Table A2 in the Appendix). In line with the model prediction, prices are higher and pass-through is lower for package tours with a higher fraction of public holidays and school holidays.[56]

Apart from the predictions discussed above, the model presented in Section 2 also yields testable predictions regarding distribution costs, which are central to extensions of the model by Corsetti and Dedola (2005) to explain how exchange rate pass-through varies with, for example, firm productivity (Berman, Martin, and Mayer, 2012), across multi-product firms (Chatterjee, Dix-Carneiro, and Vichyanond, 2013), and with product quality (Chen and Juvenal, 2016). Our model contains two types of distribution costs:

[56]The results are robust to the inclusion of controls for the high season and for the proxies of capacity costs used above.

Transport costs consisting of airfares for flights to and from the holiday destination, and distribution costs of tour operators selling package tours to domestic customers. Irrespective of the kind, higher distribution costs reduce exchange rate pass-through into consumer prices in the model. The corresponding empirical results are presented in detail in Section A.3.2 and Table A3 in the Appendix.

First, the estimation results suggest that package tours sold by smaller (and hence less efficient) tour operators with higher distribution costs are associated with lower exchange rate pass-through, consistent with the model. These results are in line with Antoniades and Zaniboni (2016), who find that exchange rate pass-through increases with retailer size for fast-moving consumer goods imported into the United Arab Emirates. Similarly, results by Hong and Li (2017) indicate that cost pass-through is higher for retailers with larger market shares in the Los Angeles area. Second, we show that pass-through systematically decreases with the transport cost share in the total cost of package tours to the same hotel. Our empirical results using within-product variation in transport costs are in line with previous studies that use cross-sector (Goldberg and Campa, 2010; Berman, Martin, and Mayer, 2012; Li, Ma, and Xu, 2015) as well as cross-product variation of distribution costs and cross-country variation in transport costs (Chen and Juvenal, 2016).

5 Robustness

In the following, we assess the robustness of our empirical results by (i) addressing the issue of transaction-level heterogeneity, (ii) using a range of alternative variable definitions and additional control variables, and (iii) looking at various definitions of seasonality. The estimation results corresponding to the main coefficients of interest are reported in Tables A4-A8 in the Appendix.

One concern arises from the presence of unobserved heterogeneity at the level of the individual booking.[57] In as far as their occurrence is systematically related to changes in the exchange rate, seasonality, or booking lead time, their omission would bias our pass-through estimates. First, prices for package tours on the same date to the same hotel might vary due to the choice of different room types, board bases, and additional add-ons. For example, customers could opt for less expensive rooms and board options to compensate for higher prices resulting from a euro depreciation. To control for this transaction-level heterogeneity, we add dummy variables for room characteristics, meal type, and add-ons to the baseline specification (1.a).[58] Second, a large part of

[57]Note that similar concerns also apply to studies on exchange rate pass-through into goods prices using relatively aggregated product categories (Berman, Martin, and Mayer, 2012; Bonadio, Fischer, and Sauré, forthcoming).

[58]A subset of the data set contains information on room characteristics. These include the room type (e.g. double or

package tours in Germany are purchased at travel agencies instead of online.[59] Travel agencies might, in principle, differ in their commission agreements with tour operators. In addition, the transfer to and from the airport might be part of the overall price of the package tour and systematically vary with the domestic residence of the consumer. To control for travel agency heterogeneity and regional disparities in Germany, we include fixed effects for the postal code of travel agencies (1.b).[60] Third, airports differ in their charges for the use of airport facilities. As the departure airport (and occasionally also the destination airport) may differ for package tours to the same hotel, this introduces an additional source of heterogeneity. We address this issue by including a set of departure airport and destination airport fixed effects (1.c). Fourth, as the duration of the package tour increases, the hotel share in total costs increases since airfares can essentially be thought of as a fixed cost. While we perform within estimations throughout this paper by controlling for tour operator $\times$ hotel $\times$ duration fixed effects, we run an additional regression limiting the sample to trips with a duration of seven days, corresponding to the mode of the duration distribution (1.d). Fifth, as the number of travelers in the group increases, the number of booked hotel rooms could vary, potentially leading to shifts in the price per person per day. To increase the homogeneity of the data, we restrict the sample to bookings by single travelers (1.e) and by groups of two (1.f), respectively.

While the literature on pass-through into consumer prices typically focuses on the nominal exchange rate (e.g. Gopinath and Itskhoki, 2010; Antoniades and Zaniboni, 2016), firm-level studies on pass-through into export prices often use the real exchange rate (e.g. Berman, Martin, and Mayer, 2012; Chatterjee, Dix-Carneiro, and Vichyanond, 2013). Therefore, as a robustness test, we include the monthly real exchange rate and their interactions in Equation (9) instead of only using the consumer price index as a control (2.a). Next, while we already control for monthly demand conditions in Germany at the time of travel, other domestic time-varying factors at the time of booking and the departure date, such as German school holidays that vary from year-to-year by state, might potentially have an impact on consumers' booking behavior. To address this concern, we additionally include booking month and travel month $\times$ year fixed effects (2.b). Another potential concern relates to events in the holiday destination that might have an impact on demand and therefore prices, such as changes in taste, the weather, or natural catastrophes. To control for these time-varying destination-

suite), the view (e.g. sea or mountain view), the category (e.g. standard or deluxe), and additional features (e.g. balcony or terrace), among others, all of which were coded as a set of dummy variables. Similarly, information on the board base (e.g. all-inclusive or half-board) and additional add-ons (e.g. rental car or travel insurance) are also available.

[59] In the data set, 61.9% of observations correspond to offline bookings. Recall that the model abstracts from the existence of travel agencies (see Section 2).

[60] Postal codes are the only information available on travel agencies and the only regional information available on consumers.

specific factors, we additionally include month × year × country fixed effects (2.c).[61] Another concern relates to compositional shifts in the sample arising from the potential exit and entry of products from and into the sample. For example, the results by Nakamura and Steinsson (2012) and Gagnon, Mandel, and Vigfusson (2014) suggest that product replacement can induce an attenuation bias in pass-through estimations. To address this, we focus on a sample of package tours to hotels that were sold by a given tour operator in all seven years (2.d).[62] Relatedly, while we already control for hotel fixed effects, the characteristics of hotels might potentially vary across time due to, for instance, ownership changes, facility extensions, or rebranding. Therefore, in an additional specification, we include hotel × year fixed effects to control for time-varying product-specific marginal costs (2.e) as in, for example, Chen and Juvenal (2016).

Finally, we test the robustness of our results with regard to seasonality. There is some evidence that the seasonal pattern of hotel demand may vary across regions for a single country due to, for example, regional differences in climate (e.g. Baum and Lundtorp, 2001). To address this issue, we include seasonality fixed effects at the month × province (3.a) and at the month × location level (3.b).[63] Next, alternative definitions of the high season are conceivable. First, our baseline measure for the high season is derived from the total number of visitors to a country. However, this might miss the high season of hotels in the data set insofar as seasonality varies across regions since the average visitor might choose a different hotel and location than the average German package tourist. To address this concern, under the additional assumption that the seasonal patterns of world and German tourism demand are closely aligned, we use the booking volume from the package tour data set at the country level (3.c) and province level (3.d). The latter allows the high season to vary between provinces in a given country. Alternatively, another high-season indicator that is representative of the hotels in our sample is based on price information at the country level (3.e) and province level (3.f). Second, recall that the baseline measure is calculated from data covering the same time period as our data set. However, if the seasonal pattern of visitor arrivals varies over time, the estimation assumes that hotel managers have more information available than they actually did at the time of sale. Therefore, we compute an alternative indicator for the high season that is based on the six months of highest demand for the seven years preceding the beginning of our sample (3.g). Third, as an additional robustness check, we define the high season to be those months in which the seasonality rate (the number of visitors per month relative to the average number of visitors per months) is larger than one (3.h). This captures the notion that capacity

[61] Note that this differs from the seasonality fixed effects already included in the regression which control for country-specific seasonal factors at the monthly level.

[62] Recall that we already use a balanced sample of tour operators throughout the paper.

[63] Our sample includes 449 provinces (e.g. Hawaii) and 1,701 locations (e.g. Waikiki, Honolulu).

constraints should be particularly binding for large deviations from average occupancy rates.

Tables A4-A8 show that all alternative specifications leave the estimates of exchange rate pass-through by and large unchanged in terms of sign and significance. Although the size of the coefficients varies slightly, we maintain a positive effect of last-minute bookings on pass-through, a positive effect of capacity costs in the high season on pass-through, and a negative effect of advance-purchase discounts in the high season on pass-through.

6 Concluding remarks

In this paper, we analyze both theoretically and empirically the effect of firms' dynamic pricing policies on their response to changes in the exchange rate. First, we present a theoretical model featuring price discrimination, capacity constraints, and information acquisition as motives for dynamic pricing to explain firms' heterogeneous pricing responses to exchange rate fluctuations. Second, we test the resulting model predictions using a unique German transaction-level data set of package tours at the daily frequency containing rich information on 58 tour operators and 9,823 hotels in 86 countries between 2012 and 2018. Overall, our empirical results find strong support for the predictions of the model. Pass-through is higher when firms reduce prices for consumers with high demand elasticities, such as for last-minute bookings, while pass-through is lower when firms charge higher prices to consumers with lower demand elasticities, such as during public holidays. Generally, capacity constraints of producers result in higher prices and higher pass-through. Together with demand uncertainty, capacity costs provide an impetus to offer advance-purchase discounts for information acquisition, which are associated with lower pass-through.

The heterogeneity in pass-through that we document is interesting in itself since it sheds light on how firms' prices respond to cost shocks, and it also potentially has implications for exchange rate pass-through at the aggregate level. The low aggregate pass-through into prices that is empirically observed in other studies can partly be explained by heterogeneous pricing-to-market of high-productivity firms that account for the bulk of traded goods (Berman, Martin, and Mayer, 2012). While previous work has stressed the importance of distribution costs (e.g. Nakamura and Zerom, 2010) and market structure (e.g. Auer and Schoenle, 2016), this paper highlights the role of differences in consumers' demand elasticities and producers' capacity costs resulting in time-varying marginal costs in explaining the heterogeneous response of firms to exchange rate fluctuations.

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A Appendix

A.1 Variable description and data sources

Table A1: Variable description and data sources.

Level	Variable	Definition	Frequency	Source
Transactions				
	expense	Total price of package tour in euro	Daily	Amadeus Leisure IT GmbH
	travelers	Number of travelers in the travel group	Daily	Amadeus Leisure IT GmbH
	duration	Duration of package tour in days	Daily	Amadeus Leisure IT GmbH
	price	Price of package tour per traveler and day in euro	Daily	Amadeus Leisure IT GmbH
	lead time	Time between booking date and departure date in days	Daily	Amadeus Leisure IT GmbH
	traveler age	Average age of travelers in years	Daily	Amadeus Leisure IT GmbH
	children	Dummy variable equal to one if travel group includes children and zero otherwise	Daily	Amadeus Leisure IT GmbH
	children (aged 2-14)	Dummy variable equal to one if travel group includes children aged 2-14 years and zero otherwise	Daily	Amadeus Leisure IT GmbH
	holidays	Population-weighted and tour-specific public holiday/school holiday indicator ranging from zero to one	Daily	Destatis, schulferien.org
Tour operators				
	sales	Sales across all holiday destination countries in euro	Annual	Amadeus Leisure IT GmbH
	lag of *sales*	One year lag of sales across all holiday destination countries in euro	Annual	Amadeus Leisure IT GmbH
	bookings	Number of bookings across all holiday destination countries	Annual	Amadeus Leisure IT GmbH
Hotels				
	rooms	Total number of hotel rooms	Constant	TripAdvisor
	rating	Average customer rating from 1 (worst) to 5 (best)	Constant	TripAdvisor
Holiday destination countries				
	NER	Nominal exchange rate in euro per unit of foreign currency	Daily	Thomson Reuters, Investing
	CPI	Logarithm of index of consumer prices	Monthly	IMF, Eurostat, various national sources
	high season	Dummy variable equal to one if travel month among six highest in terms of tourist arrivals between 2012 and 2018 and zero otherwise	Monthly	Haver Analytics, IMF, Eurostat, various national sources
	price level	Price level of real GDP in purchasing power parity relative to the United States in 2011	Annual	Penn World Tables
	distance	Geodesic distance to Germany in kilometers	Constant	CEPII, GeoDist Database
Germany				
	$demand_{DEU}$	Logarithm of personal travel expenditures in euro	Monthly	Deutsche Bundesbank

A.2 Theoretical framework

A.2.1 Advance purchase discounts and information acquisition

For a given discount ι^H in the high season, and taking into account both types of consumers in the population, producer profits are given by:

$$\Pi_p(\varphi) = \frac{\theta}{2}\left[\tilde{\alpha}(\varphi) - \tilde{\beta}(\varphi)\left(\frac{\tilde{p}_r(\varphi)}{\varepsilon} + \tau + w\eta_r\right)\right]\left[\tilde{p}_r(\varphi) - \frac{w_F}{m(\varphi)} - \xi^{H,\iota}\right] \tag{A1}$$
$$+\frac{1-\theta}{2}\left[\tilde{\alpha}(\varphi) - \tilde{\beta}(\varphi)\left(\frac{\tilde{p}_r(\varphi)(1-\iota^H)}{\varepsilon} + \tau + w\eta_r\right)\right]\left[\tilde{p}_r(\varphi)(1-\iota^H) - \frac{w_F}{m(\varphi)} - \xi^{H,\iota}\right] - \Omega,$$

where $\tilde{p}_r(\varphi)$ and $\tilde{p}_r(\varphi)(1-\iota^H)$ denote the prices associated with varieties that are purchased late and early, respectively. The producer sets the price for each variety and retailer in order to maximize Equation (A1) subject to $\tilde{p}_r(\varphi)$. The resulting profit-maximizing producer price (for the variety purchased early) can then be derived as:

$$p_r(\varphi) = \tilde{p}_r(\varphi)(1-\iota^H) = \frac{\tilde{\theta}}{2}\left[\frac{w_F}{m(\varphi)} + \xi^{H,\iota} + \varepsilon\left(\frac{\tilde{\alpha}(\varphi)}{\tilde{\beta}(\varphi)} - \tau - w\eta_r\right)\right], \tag{A2}$$

where $\tilde{\theta} \equiv \frac{\theta(1-\iota^H)+(1-\theta)(1-\iota^H)^2}{\theta+(1-\theta)(1-\iota^H)^2}$. Substituting Equation (A2) into Equation (4) yields:

$$p_r^c(\varphi) = \frac{\tilde{\theta}}{4\varepsilon}\left[\frac{w_F}{m(\varphi)} + \xi^{H,\iota}\right] + \frac{2+\tilde{\theta}}{4}\frac{\tilde{\alpha}(\varphi)}{\tilde{\beta}(\varphi)} + \frac{2-\tilde{\theta}}{4}\left[\tau + w\eta_r\right]. \tag{A3}$$

Finally, Equation (8) in the main text follows from calculating the elasticity of the consumer price with respect to ε.

A.3 Additional results

A.3.1 Public holidays and school holidays

This section provides a complementary test of Prediction 1 by analyzing whether pass-through decreases (and prices increase) in periods associated with lower demand elasticities. In particular, we exploit variation in the incidence of public holidays and school holidays in Germany across time, which are thought to be characterized by less price elastic demand since families with school-aged children, for instance, are restricted to traveling during those periods. For the empirical analysis, we construct a continuous holiday variable, *holidays*, which varies between zero and one, indicating the share of days for each package tour falling on public holidays and school holidays.[64] The empirical results are presented in Table A2.

According to column (1), package tours falling exclusively on German public holidays and school holidays are on average 26% more expensive than those that do not. More importantly, the exchange rate elasticity is equal to 0.148 for the average package tour and decreases to 0.118 for trips during German public holidays and school holidays, which represents a 20.3% decrease in pass-through. In columns (2)-(6), we additionally control for variables related to the high season in holiday destination countries which might be potentially correlated with the holiday indicator. More specifically, we consecutively control for the high season, hotel size, hotel quality, the price level of the holiday destination country, and their interactions with the exchange rate as well as including all variables simultaneously in column (6). In all these alternative specification, we maintain a negative and significant coefficient on the interaction between *holidays* and the exchange rate, in direct support of Prediction 1.

[64] Since public holidays and school holidays in Germany vary between states, we first compute a population-weighted variable for every day, which is subsequently used to calculate the holiday variable for each package tour in the data set. The results are similar when using state-level GDP or household disposable income for weighting.

Table A2: Public holidays and school holidays.

	(1)	(2)	(3)	(4)	(5)	(6)
ln *NER*	0.148***	0.151***	0.154***	0.159***	0.087***	0.101***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.025)	(0.025)
$\overline{holidays}$	0.231***	0.224***	0.227***	0.224***	0.225***	0.227***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
ln *NER* × $\overline{holidays}$	-0.030***	-0.034***	-0.033***	-0.035***	-0.035***	-0.034***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
ln *NER* × $\overline{high\ season}$		-0.006	-0.009*	-0.011***	-0.027***	-0.036***
		(0.004)	(0.005)	(0.004)	(0.005)	(0.005)
high season × $\overline{rooms}$			0.027***			0.026***
			(0.006)			(0.006)
high season × $\overline{rating}$				0.031***		0.030***
				(0.006)		(0.006)
high season × $\overline{price\ level}$					0.506***	0.487***
					(0.033)	(0.033)
ln *NER* × $\overline{\text{ln rooms}}$			-0.042***			-0.031***
			(0.011)			(0.010)
ln *NER* × $\overline{rating}$				-0.098***		-0.072***
				(0.014)		(0.014)
ln *NER* × $\overline{price\ level}$					0.076***	0.058**
					(0.022)	(0.023)
ln *NER* × *high season* × $\overline{\text{ln rooms}}$			0.006***			0.006***
			(0.002)			(0.002)
ln *NER* × *high season* × $\overline{rating}$				0.007***		0.007***
				(0.002)		(0.002)
ln *NER* × *high season* × $\overline{price\ level}$					0.176***	0.161***
					(0.012)	(0.013)
$\overline{price\ level}$					0.147***	0.108**
					(0.055)	(0.054)
Observations	8,240,402	8,217,380	7,550,005	8,092,591	8,103,435	7,439,586
Hotels	9,689	9,569	8,367	8,953	9,352	8,186
Tour operators	58	58	58	58	58	58
Countries	85	75	69	71	71	66
R^2	0.80	0.80	0.80	0.80	0.80	0.80
Tour operator × year FE	Yes	Yes	Yes	Yes	Yes	Yes
Tour operator × hotel × duration FE	Yes	Yes	Yes	Yes	Yes	Yes
Month × country FE	Yes	Yes	Yes	Yes	Yes	Yes
Lead time FE	Yes	Yes	Yes	Yes	Yes	Yes
CPI, $demand_{DEU}$	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The variable $\overline{X}$ denotes the demeaned counterpart of X. Standard errors in parentheses are clustered at the hotel level. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

A.3.2 Distribution costs

In this section, we test whether higher distribution costs – i.e. higher local distribution costs of tour operators and higher transport costs – reduce exchange rate pass-through in line with the model predictions. The empirical results are presented in Table A3.

First, according to Equation (7), exchange rate pass-through should increase with the size of the tour operator as larger tour operators are assumed to be more efficient and thus incur lower distribution costs. Empirically, we proxy firm size by (the logarithm of) annual sales of the tour operator, ln *sales*, across all holiday destination countries in the data set.[65] The results in column (1) suggest that tour operator size is positively

[65] The identity of the tour operator in the data set is unknown such that no additional information from external

Table A3: Distribution costs.

	(1)	(2)	(3)	(4)	(5)
ln *NER*	0.147***	0.155***	0.148***	0.156***	0.168***
	(0.018)	(0.019)	(0.018)	(0.018)	(0.018)
ln *NER* × $\overline{\ln\ sales}$	0.013***				
	(0.001)				
ln *NER* × lag of $\overline{\ln\ sales}$		0.010***			
		(0.001)			
ln *NER* × $\overline{\ln\ bookings}$			0.014***		
			(0.001)		
children				-0.195***	
				(0.003)	
ln *NER* × *children*				-0.018***	
				(0.002)	
children (aged 2-14)					-0.158***
					(0.003)
ln *NER* × *children* (aged 2-14)					-0.014***
					(0.002)
Observations	8,499,445	7,445,936	8,499,445	8,499,445	2,726,670
Hotels	9,823	9,495	9,823	9,823	7,683
Tour operators	58	58	58	58	56
Countries	86	84	86	86	67
R^2	0.78	0.79	0.78	0.80	0.80
Tour operator × year FE	Yes	Yes	Yes	Yes	Yes
Tour operator × hotel × duration FE	Yes	Yes	Yes	Yes	Yes
Month × country FE	Yes	Yes	Yes	Yes	Yes
Lead time FE	Yes	Yes	Yes	Yes	Yes
CPI, $demand_{DEU}$	Yes	Yes	Yes	Yes	Yes

Notes: The variable $\overline{X}$ denotes the demeaned counterpart of X. Standard errors in parentheses are clustered at the hotel level. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

correlated with exchange rate pass-through. The exchange rate elasticity is equal to 0.127 for a tour operator at the 10th percentile of the size distribution, and increases to 0.161 for a tour operator at the 90th percentile of the size distribution, corresponding to a 26.6% increase in pass-through. As a robustness test, in columns (2) and (3), we use annual lags of ln *sales* (e.g. Berman, Martin, and Mayer, 2012), and we also employ (the logarithm of) the total number of bookings, ln *bookings*, as an alternative variable measuring size, neither of which appreciably changes the results. Altogether, we find that exchange rate pass-through is positively correlated with tour operator size irrespective of the particular measure used.

Second, according to Equation (7), the exchange rate elasticity decreases with transport costs to and from the holiday destination. Since transport costs for package tours are mainly related to expenses for international air travel, the cost share of the holiday destination country's currency is lower if transport costs are higher. In practice, we do not observe transport costs directly in our data set. Instead, we construct a proxy

sources can be added.

variable that captures variation in transport cost shares in package tour prices to the same hotel. In particular, we use information on the presence of children in the group of travelers. On international flights, children above the age of two are usually only granted a small discount (if any) relative to the adult fare as they travel in a separate seat from their parents. In contrast, large discounts for children are generally granted by hotels as children often stay in their parents' room. As a consequence, the presence of children on average increases the share of transport costs in total costs, thereby presumably reducing pass-through. Column (4) shows the results from a regression including the dummy variable *children* – equal to one if the travel groups includes children and zero otherwise – along with its interaction with the exchange rate.[66] As expected, the average price per person is on average 21.5% lower when children are present. More importantly, the exchange rate elasticity decreases significantly from 0.156 to 0.138, in line with the model prediction. As a robustness test, we only use the sample of online bookings and define a dummy variable for children aged 2 to 14 years, excluding infants for which sizeable discounts on airfares are commonly granted. Column (5) shows that while prices per day for this group are on average only 17.1% lower, the pass-through results are qualitatively unchanged. Overall, the results using within-tour-operator-hotel-duration variation in transport costs suggest that pass-through decreases with transport costs.

[66] In the data set, a dummy variable indicates the number of children for offline bookings. Online bookings include information on the age of every individual traveler which we classify to be a child if the age is below 15. According to this definition, 19.4% of bookings in the data set include at least one child.

A.4 Robustness

Table A4: Robustness – Dynamic pricing and consumer heterogeneity.

	Pass-through	S.E.	Observations
ln *NER* × *lead time* (0-3 days)			
Baseline			
(0.a) Baseline	0.023***	0.003	8,499,445
Transaction-level heterogeneity			
(1.a) Meal and room characteristics	0.022***	0.003	2,547,503
(1.b) Postal code fixed effects	0.025***	0.003	4,745,966
(1.c) Airport fixed effects	0.023***	0.003	8,365,469
(1.d) Duration of 7 days	0.045***	0.005	2,705,793
(1.e) Single traveler	0.027***	0.003	804,987
(1.f) Two travelers	0.029***	0.004	5,242,013
Variable definitions and additional controls			
(2.a) Real exchange rate	0.025***	0.004	8,499,445
(2.b) Booking and travel month fixed effects	0.024***	0.003	8,499,445
(2.c) Month × year × country fixed effects	0.021***	0.003	8,498,897
(2.d) Balanced hotel panel	0.028***	0.004	5,812,432
(2.e) Hotel × year fixed effects	0.022***	0.003	8,494,199
Seasonality			
(3.a) Month × province fixed effects	0.023***	0.003	8,499,058
(3.b) Month × location fixed effects	0.024***	0.003	8,497,630

Notes: Standard errors in parentheses are clustered at the hotel level. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table A5: Robustness – Seasonality of demand and capacity costs (hotel size).

	Pass-through	S.E.	Observations
ln *NER* × *high season* × ln *rooms*			
Baseline			
(0.a) Baseline	0.006***	0.002	7,784,325
Transaction-level heterogeneity			
(1.a) Meal and room characteristics	0.010***	0.002	2,331,706
(1.b) Postal code fixed effects	0.003*	0.002	4,341,734
(1.c) Airport fixed effects	0.006***	0.002	7,665,298
(1.d) Duration of 7 days	0.017***	0.004	2,494,814
(1.e) Single traveler	0.024***	0.005	738,912
(1.f) Two travelers	0.008***	0.002	4,803,635
Variable definitions and additional controls			
(2.a) Real exchange rate	0.006***	0.002	7,784,325
(2.b) Booking and travel month fixed effects	0.006***	0.002	7,784,325
(2.c) Month × year × country fixed effects	0.006***	0.002	7,783,838
(2.d) Balanced hotel panel	0.004*	0.002	5,407,546
(2.e) Hotel × year fixed effects	0.005***	0.002	7,779,717
Seasonality			
(3.a) Month × province fixed effects	0.005***	0.002	7,783,988
(3.b) Month × location fixed effects	0.002*	0.001	7,782,705
(3.c) *High season* (booking volume - country)	0.006***	0.002	7,806,760
(3.d) *High season* (booking volume - provinces)	0.003**	0.001	7,806,760
(3.e) *High season* (prices - country)	0.005***	0.002	7,806,760
(3.f) *High season* (prices - provinces)	0.005***	0.001	7,806,760
(3.g) *High season* (pre-sample)	0.006***	0.002	7,577,711
(3.h) *High season* (seasonality rate > 1)	0.006***	0.002	7,784,325

Notes: Standard errors in parentheses are clustered at the hotel level. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table A6: Robustness – Seasonality of demand and capacity costs (hotel quality).

	Pass-through	S.E.	Observations
ln *NER* × *high season* × *rating*			
Baseline			
(0.a) Baseline	0.009***	0.002	8,344,974
Transaction-level heterogeneity			
(1.a) Meal and room characteristics	0.014***	0.002	2,503,787
(1.b) Postal code fixed effects	0.007***	0.002	4,657,593
(1.c) Airport fixed effects	0.009***	0.002	8,213,431
(1.d) Duration of 7 days	0.026***	0.005	2,668,637
(1.e) Single traveler	0.017***	0.005	791,759
(1.f) Two travelers	0.012***	0.002	5,143,403
Variable definitions and additional controls			
(2.a) Real exchange rate	0.009***	0.002	8,344,974
(2.b) Booking and travel month fixed effects	0.010***	0.002	8,344,974
(2.c) Month × year × country fixed effects	0.010***	0.002	8,344,485
(2.d) Balanced hotel panel	0.008***	0.003	5,719,284
(2.e) Hotel × year fixed effects	0.010***	0.002	8,340,066
Seasonality			
(3.a) Month × province fixed effects	0.012***	0.002	8,344,643
(3.b) Month × location fixed effects	0.009***	0.002	8,343,296
(3.c) *High season* (booking volume - country)	0.010***	0.002	8,369,119
(3.d) *High season* (booking volume - provinces)	0.008***	0.002	8,369,119
(3.e) *High season* (prices - country)	0.008***	0.002	8,369,119
(3.f) *High season* (prices - provinces)	0.006***	0.002	8,369,119
(3.g) *High season* (pre-sample)	0.010***	0.002	8,127,855
(3.h) *High season* (seasonality rate > 1)	0.010***	0.002	8,344,974

Notes: Standard errors in parentheses are clustered at the hotel level. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table A7: Robustness – Seasonality of demand and capacity costs (price level).

	Pass-through	S.E.	Observations
ln *NER* × *high season* × *price level*			
Baseline			
(0.a) Baseline	0.147***	0.014	8,357,328
Transaction-level heterogeneity			
(1.a) Meal and room characteristics	0.176***	0.016	2,513,204
(1.b) Postal code fixed effects	0.190***	0.016	4,655,791
(1.c) Airport fixed effects	0.147***	0.014	8,224,041
(1.d) Duration of 7 days	0.042*	0.022	2,700,225
(1.e) Single traveler	0.146***	0.025	787,117
(1.f) Two travelers	0.191***	0.015	5,141,986
Variable definitions and additional controls			
(2.a) Real exchange rate	0.205***	0.017	8,357,328
(2.b) Booking and travel month fixed effects	0.216***	0.017	8,357,328
(2.c) Month × year × country fixed effects	0.008	0.035	8,356,831
(2.d) Balanced hotel panel	0.164***	0.016	5,712,127
(2.e) Hotel × year fixed effects	0.065***	0.012	8,352,282
Seasonality			
(3.a) Month × province fixed effects	0.163***	0.014	8,356,948
(3.b) Month × location fixed effects	0.173***	0.015	8,355,590
(3.c) *High season* (booking volume - country)	0.130***	0.014	8,381,666
(3.d) *High season* (booking volume - provinces)	0.116***	0.009	8,381,666
(3.e) *High season* (prices - country)	0.078***	0.017	8,381,666
(3.f) *High season* (prices - provinces)	0.080***	0.008	8,381,666
(3.g) *High season* (pre-sample)	0.128***	0.015	8,138,505
(3.h) *High season* (seasonality rate > 1)	0.155***	0.014	8,357,328

Notes: Standard errors in parentheses are clustered at the hotel level. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table A8: Robustness – Advance-purchase discounts and information acquisition.

	Pass-through	S.E.	Observations
ln *NER* × *lead time* (90th percentile) × *high season*			
Baseline			
(0.a) Baseline	-0.010***	0.001	8,475,105
Transaction-level heterogeneity			
(1.a) Meal and room characteristics	-0.010***	0.002	2,541,019
(1.b) Postal code fixed effects	-0.008***	0.001	4,730,651
(1.c) Airport fixed effects	-0.010***	0.001	8,341,155
(1.d) Duration of 7 days	-0.010**	0.005	2,705,115
(1.e) Single traveler	-0.010***	0.003	803,538
(1.f) Two travelers	-0.009***	0.001	5,222,557
Variable definitions and additional controls			
(2.a) Real exchange rate	-0.008***	0.001	8,475,105
(2.b) Booking and travel month fixed effects	-0.006***	0.001	8,475,105
(2.c) Month × year × country fixed effects	-0.013***	0.001	8,474,589
(2.d) Balanced hotel panel	-0.012***	0.001	5,799,351
(2.e) Hotel × year fixed effects	-0.009***	0.001	8,469,952
Seasonality			
(3.a) Month × province fixed effects	-0.009***	0.001	8,474,724
(3.b) Month × location fixed effects	-0.010***	0.001	8,473,333
(3.c) *High season* (booking volume - country)	-0.010***	0.001	8,499,445
(3.d) *High season* (booking volume - provinces)	-0.009***	0.001	8,499,445
(3.e) *High season* (prices - country)	-0.014***	0.001	8,499,445
(3.f) *High season* (prices - provinces)	-0.007***	0.001	8,499,445
(3.g) *High season* (pre-sample)	-0.009***	0.001	8,255,963
(3.h) *High season* (seasonality rate > 1)	-0.005***	0.001	8,475,105

Notes: Standard errors in parentheses are clustered at the hotel level. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.