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Abstract

Based on a theoretical model featuring heterogeneous retailers that may source globally and operate as chains, we derive a number of hypotheses that link trade integration to retail firm performance and to the structure of retail markets. We empirically test these predictions using Danish microdata for the period 1999 to 2008. We find that importing retailers are larger, more profitable, and have a higher propensity to have multiple shops than domestically sourcing firms. While this is partly due to self-selection, we also present evidence for improved performance caused by firms' importing activities. Moreover, we find that retail imports are associated with a higher exit probability of small retailers and greater local retail market concentration. Overall, we obtain support for the model's predictions and argue that the observed adjustments may imply additional gains from trade absent from models lacking a distribution sector.

JEL-Codes: F120, L110.

Keywords: international trade, consumer goods, retailing, retail chains, market concentration.

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1 Introduction

In recent decades advanced economies have experienced a sharp increase in consumer goods imports, leading to an unprecedented degree of import penetration across many consumer goods industries.[1] In the current paper, we aim to determine whether this growth of consumer goods imports has contributed to observed changes in the performance of retailers and the structure of retail markets. Specifically, we want to know how greater imports – more precisely the fall in trade costs behind the import growth – affect the sales, markups, and profits of retailers, and what greater imports imply for the retail industry as a whole, including market concentration, firm exit rates, and the consolidation of retailers into retail chains. The existence of such a link is suggested not only by the fact that most of these imports pass through the retail sector, but also that retailers themselves have played an active part in the rapid expansion of trade in consumer goods.[2]

Finding answers to our questions matters from both a positive and a normative perspective. From a positive perspective, understanding what drives changes in retailing, including the growth of big retailers and retail chains and the exit of small retailers, matters not only because retailing is a big sector, accounting for around 10% of employment in many countries, but also because these changes have been a major source of retail productivity growth and, more importantly, aggregate productivity growth in industrialized countries since the mid-1990s (see, for instance, Triplett and Bosworth, 2004). Our paper provides empirical evidence that the increase in consumer goods imports contributed significantly to the observed changes in retailing.

From a normative perspective, understanding what impact trade has on retailing matters, because, with retail costs and markups often accounting for 30 to 50% of retail prices (Campa and Goldberg, 2006), any increase in retail productivity or reduction in markups potentially has big welfare effects. What is more, these welfare gains would come on top of the gains typically associated with international trade, such as gains from greater product variety or production efficiency. We examine the source of these welfare gains and explain why the trade-induced changes in retail performance and structure that we detect in the data are consistent with an improvement in social welfare.

We base our analysis on Danish microdata for the period 1999 to 2008. These data are well suited for two reasons. First, developments in consumer goods trade and

[1] For instance, import penetration in the apparel market is around 94% in the United States, 95% in Germany and the UK, 85% in France, 65% in Italy, and 55% in Spain. Import penetration in the US footwear market is at 85% (Gereffi and Frederick, 2010). Average import penetration in textiles, clothing and footwear in the OECD stands at 59.4% (Nordås, 2008).

[2] In the United States, retailers (including firms that engage in both retailing and wholesaling) represent 14% of all US importing firms and account for 9% of the total value of imports (not just consumer goods) (Bernard et al., 2010a). Direct imports by retailers account for 31% of total US imports in textiles and clothing (HS 50-63), and for 34% of total US imports of footwear (HS 64-67) (Gereffi and Frederick, 2010; Bernard et al., 2010b). In Canada the top 5% of importing retailers account for 76.3% of total Canadian imports of clothing, shoes, jewellery, luggage and leather goods, and for 68.2% of all Canadian imports of electronics and appliances (Raff and Schmitt, 2016a).

retailing in Denmark mirror those in other industrialized countries; the Danish data may thus offer a glimpse into economic mechanisms that may operate in a broader set of countries. According to the quantity index published by *Statistics Denmark*, imports of goods for household consumption increased by 75% in real terms between 1999 and 2008, compared to an increase in total real imports of 50%. In nominal terms, consumer goods imports rose by around 85%, with certain types of goods experiencing growth rates well above 100% over this period.[3] Import shares rose across many consumer goods industries, most strongly in footwear (HS 64-67) from 65% in 1999 to 96% in 2008. Consumer goods thus spearheaded the overall increase in imports from 33% of GDP in 1999 to 51% in 2008.[4] Retailers in Denmark, as elsewhere, have become major direct importers of consumer goods. In 2008, retailers in Denmark, more precisely firms that report retailing as their main activity, accounted for around 12% of all firms importing consumer goods and 14% of total consumer goods import values, with retailers' shares of imports being much higher in some of the big consumer goods industries, such as furniture, toys and miscellaneous manufactured articles (33%).

Second, the Danish data contain enough information at the firm level to allow us to deal with several conceptual and empirical challenges that are specific to the study of retail markets. One such challenge consists of identifying the geographic scope of retail markets. Competition among retailers tends to be localized simply because consumers typically do not travel long distances to go shopping (Maican and Orth, 2017). This suggests, among other things, that retail market concentration should be measured at the local level. In our empirical analysis we use information on municipalities to identify local retail markets, and we compute local market concentration based on the shops in each local market. Another closely related problem stems from the fact that some retailers, typically the bigger ones, are organized as chains operating shops in several local retail markets.[5] In the data, we are able to identify the shops belonging to each retail firm, and we define retailers with more than one shop as retail chains. This allows us to study the consolidation of retailers into chains and, more precisely, to determine whether greater consumer goods imports have contributed to this consolidation.

The main economic mechanism we want to explore in our analysis builds on economies of scale in direct importing, which imply that only big retailers can afford direct im-

[3] These goods include, for instance, imports of consumer goods related to animal or vegetable fats (HS15), electrical equipment (HS84-85), transport equipment (HS86-89), and furniture and toys (HS94-98). Consumer goods are defined based on the BEC classification, which can be merged to HS six-digit product codes. Specifically, BEC product codes 112 (food and beverages, primary, mainly for household consumption), 122 (food and beverages, processed, mainly for household consumption), 522 (transport equipment, non-industrial), 61 (consumer goods not elsewhere specified, durable), 62 (consumer goods not elsewhere specified, semi-durable), and 63 (consumer goods not elsewhere specified, non-durable) are considered to be consumer goods.

[4] As a comparison, in euro area countries this ratio rose from 30% to 39% during that period.

[5] As already mentioned above, the consolidation of retailers into chains is an important phenomenon that we observe in Denmark and elsewhere. In Denmark, the number of chains increased from around 700 in 1999 to more than 1,200 in 2008. This is in line with observations in the United States, where large retail chains (with at least 100 establishments) doubled their share of US retail sales from 18.6% in 1967 to 36.9% in 1997 (Jarmin et al., 2009).

ports. Smaller retailers, if they have access to imports at all, have to rely on more expensive indirect imports via intermediaries.[6] As a consequence, big retailers benefit more from a fall in trade costs than small retailers, which has consequences for the performance of individual retailers and ultimately for retail market structure and productivity. We explore these consequences in a theoretical model of the retail industry, and then take the theoretical hypotheses to the data. In our empirical analysis, we tend to find support for the theoretical predictions. Firm-level regressions indicate that, after controlling for firm characteristics, sales, profits, and markups of directly importing retailers exceed those of domestically sourcing firms on average by 20%, 27%, and 3%, respectively. While these results could be solely due to larger and more profitable firms self-selecting into importing, further estimations based on propensity score matching techniques suggest that these performance differences are at least partly due to importing. Indeed, we estimate that import starters that were similar in observable characteristics to domestically sourcing firms before beginning to import exhibit 8% greater sales, 6% greater profits, and 2% greater markups in the year of import initiation. The estimated effects turn out to be quite persistent. For instance, we estimate that, after three years, cumulative sales of import starters are on average over 30% higher than for comparable non-importers. We also find evidence that direct importing may increase the probability of an import starter becoming a chain. This effect occurs two years after import initiation, with the probability rising by up to 16%.

Turning to the effects on retail market structure, we observe that an increase in industry-level direct imports is associated with higher exit probabilities of small retailers and, through a decrease in the overall number of retailers, with greater market concentration at the local level. Including a proxy for indirect imports of consumer goods by wholesalers and other non-retail firms in our regressions provides additional evidence that these market structure effects are indeed driven by direct retail imports. Taken together, our results offer support for the direct importing mechanism outlined by our model, and indicate a non-negligible role of direct imports of consumer goods for the performance and structure of the retail industry.

The current paper builds on the literature on the effects of trade on retail markets (recently surveyed by Raff and Schmitt, 2016a). Our theoretical model extends Raff

[6] Significant economies of scale in direct importing activities of retailers have recently been documented by Holmes and Singer (2017) for the United States. They show that big retailers like Walmart, Target and Costco, by nature of their large import volumes, face much lower "indivisibility" costs when importing goods via containers than small retailers that typically rely on intermediaries, including freight forwarders to deal with shipping companies, and on logistics firms to manage consolidation of shipments into containers. These "indivisibility" costs consist of the cost of unused container space, the cost associated with consolidation of different shipments into a single container, and the cost associated with distorting the shipment size to fit in a standard container.

Economies of scale in direct importing also stem from fixed costs of importing, including the cost of identifying and dealing with suppliers, maintaining overseas buying offices, as well as large investments in logistics, inventory management and information technology. A survey of German, Swiss and Austrian retailers by Zentes et al. (2007) suggests that these costs are very high in practice and only borne by big retailers, whereas small retailers import at most indirectly via wholesalers.

and Schmitt (2012) by endogenizing the number of shops operated by a retailer and thus introducing the decision of whether to become a chain. The shop margin arises from fixed costs per shop as in the model of Basker and Van (2010a). In Basker and Van's model, cheaper imports allow a single chain retailer to expand the number of shops, forcing smaller, single-shop competitors to exit. Our main modelling contribution can indeed be interpreted as putting their mechanism of adjustment along the shop margin into an industry equilibrium model of retailing with heterogeneous firms and endogenous market structure, as is in Raff and Schmitt (2012).[7]

Our empirical analysis is most closely related to Basker and Van (2010b), who test whether retail industries experiencing an increase in market concentration, measured by sales growth of the four largest firms, are more likely to sell goods exhibiting an increase in imports. Using US import data at the product level, they find that, indeed, product-level imports grow especially fast when these products are disproportionately sold by industries exhibiting high sales growth of the top four firms; this effect is particularly strong for imports from China and other less-developed countries (LDCs). In a counterfactual exercise, they attribute half of the growth of imports from China and other LDCs to increased retail industry concentration.

Like Basker and Van, we find a significant correlation between imports and retail market concentration. By our estimates, a 1% increase in industry-level direct imports raises the Herfindahl index of local retail market concentration, ceteris paribus, by up to 0.042%. This is not a small effect, considering that average direct imports in the estimation sample more than doubled during the sample period and that the Herfindahl index is at a relatively high level initially.[8]

Since we have access to both firm-level and shop-level data, we can examine the differential performance of direct importers and non-importers with respect to sales, markups, profits, the probability to becoming a chain, and the exit probability, and thus go deeper than Basker and Van into trying to uncover possible economic mechanisms driving the correlation between imports and retail market concentration. For instance, we can show that the sales growth of large, importing firms, which is taken as the exogenous variable by Basker and Van, can be partly attributed to import activity.

By showing how trade can help explain observed changes in retail market performance and structure, our paper complements studies that have focused on technology adoption as a driver of retail market changes.[9] Our paper can further be seen as comple-

[7] An alternative theoretical approach is suggested by Eckel (2009). In his paper, retail market concentration is also driven by imports. But it does not come from an increase in the volume of consumer goods trade, but from a rise in the number of varieties available on the world market. As retailers expand their assortment to include more imported varieties, their fixed costs rise and they have to have greater sales, markups and operating profits to cover these fixed costs.

[8] We should point out that a potentially attractive feature of Basker and Van's data is that they capture both direct and indirect imports. However, as already mentioned, we can also create a proxy for indirect imports and find that it generally does not have a statistically significant effect on retail market concentration.

[9] See, for instance, Holmes (2001), Basker et al. (2012), and Lagakos (2016). Foster et al. (2016) provide a recent survey of the literature, looking mostly at technology-driven changes in retailing.

menting the study by Holmes and Singer (2017), which examines how retailers respond to greater direct imports of consumer goods by altering the geographic structure of their import distribution.[10]

Finally, given the focus of international trade research on the manufacturing sector and the dearth of studies on the service sector in general and on retailing in particular, we want to point out how our paper compares to the more familiar research on the effects of trade exposure on manufacturing. An obvious difference regarding the effect on firm performance is that retail services are traditionally non-tradable, so that retailers typically do not face import competition and do not export. In fact, we argue that retailers typically even face very little interregional competition. At least in our sample period, retail sales not in stores (i.e. over the internet, by mail order, etc.), where import competition and exports are most likely to arise, are very low, and we exclude them from the analysis. The trade exposure of retailers in our study therefore mostly comes from the goods they import. The performance effects we measure for retailers are therefore best compared to the effects on manufacturers stemming from the import of intermediate goods (see, for instance, the recent studies of De Loecker et al. (2016) and Brandt et al. (2017) on the markup and productivity effects from reductions in input tariffs).

Regarding market structure, the non-tradability of retail services has the distinct advantage that we can, at least with a greater degree of confidence than in the case of manufacturing, measure market concentration, simply because market demarcation is easier. Retailing may therefore even offer a better opportunity than manufacturing for studying the market structure effects of importing.

The rest of the paper is organized as follows. In the next section, we present our theoretical framework and derive testable hypotheses about the effect of trade on retail markets. In section 3, we describe the data, discuss sample selection, and provide descriptive evidence. In section 4, we outline the empirical approaches for testing each hypothesis and present the corresponding results. Section 5 concludes by discussing what our results imply for social welfare and, more specifically, for the gains from trade. Proofs, summary statistics, and additional estimation results are presented in the Appendix.

Another potential driver of these changes is entry by multinational retailers (see Atkin et al., 2018).

[10] Our paper is also indirectly related to the empirical literature on exchange rate pass-through into retail prices (see, for instance, Antoniades and Zaniboni, 2016). This literature has recognized that the retail margin (i.e. costs of retailing and retailer markups) is a major factor in explaining why changes in import prices are only incompletely passed through to retail prices. Antoniades and Zaniboni, in particular, find that pass-through varies systematically by retailer size. We differ from this (short-run-oriented) literature in that we study the effects of imports in the long term, where markups and retail market structure are endogenously determined.

2 Theoretical framework

In this section, we present a simple partial equilibrium model of a retail industry, in which retail firms differ in terms of their productivity and in which the number of retail firms and the number of shops each firm operates across different local retail markets are endogenously determined. We use this model to formulate testable hypotheses about how a reduction in trade costs affects retailer performance and the structure of retail markets.

2.1 The model

Consider a country divided into R local retail markets. Each active retail firm has at least one and at most R shops, i.e. no more than one per local retail market. A firm with more than one shop, and hence operating in more than one local retail market, is called a retail chain.

Consumer preferences in each local market follow the 'random preference Hotelling' framework of Innes (2006).[11] We therefore assume that, in local market $r = 1, ..., R$, there is a measure L_r of consumers uniformly distributed around a circle of unit circumference. Each consumer visits a shop to purchase one unit of an aggregate consumption good and faces a linear transport cost τ per unit of distance to visit the shop. There are n_r shops located symmetrically on the circle. Preferences are random in the sense that each ordering of the n_r shops among the n_r locations is possible and occurs with the same relative frequency. A simple interpretation of these preferences is that, when choosing where to shop, a consumer chooses only between the two nearest shops, as in a standard address model, but the identity of the two shops depends on an unobserved, random event.[12]

We assume, for simplicity, that local markets are symmetric, and therefore drop the subscript identifying the local market. The aggregate demand q_i faced by shop i can then be shown to be linear in prices, where $q_i(p_i) = \frac{L}{n} - \frac{L}{\tau}p_i + \frac{1}{n-1}\frac{L}{\tau}\sum_{h=1,h\neq i}^{n} p_h$. We make the additional assumption that n is large enough so that demand can be approximated by:

$$q_i(p_i) = \frac{L}{n} - \frac{L}{\tau}p_i + \frac{L}{\tau}\bar{p}, \tag{1}$$

where $\bar{p}$ is the average local retail price.

[11] An alternative specification, more familiar to trade economists, would be to assume linear quadratic preferences as in Melitz and Ottaviano (2008). See also Raff and Schmitt (2012) for the use of these preferences. Which preference specification is used makes no difference to our hypotheses. We use the current specification to obtain a better microfoundation for consumer demand so that it becomes easier to discuss the possible welfare consequences of our results.

[12] Each shop therefore competes not just with its neighbors on the circle, but with all other local shops. This assumption is important because it allows us to derive a free-entry equilibrium in which shops have different costs, which would not be feasible in a standard address model.

Now consider the level of the firm. To enter the market, a firm incurs a sunk cost F_E, which includes the cost of setting up one shop. After entering, each firm learns its marginal retail cost c (or productivity $1/c$), which applies to all the shops it operates. The distribution of c is denoted by $G(c)$ with support on $[0, c_M]$. We let productivity follow a Pareto distribution, so that the cumulative distribution function for c is:

$$G(c) = \left(\frac{c}{c_M}\right)^k, \tag{2}$$

with $k \geq 1$.

Imports are decided at the firm level. Economies of scale in importing arise because direct importing involves a fixed cost F_I, which includes the cost of maintaining overseas buying offices and cooperating with foreign partners to source goods, the cost of information technology needed to manage complex international sourcing operations, etc. Upon entry, each firm has to decide whether to source the aggregate consumption good domestically (which may include imports sourced indirectly through wholesalers) or to rely on direct imports.[13] Purchasing the good domestically is associated with a cost of w per unit. If the firm relies on direct imports, the unit cost of the good is $t < w$, where t also includes transport and other costs associated with international trade; for simplicity, we refer to t below as the trade cost.

Another decision taken upon entry at the firm level concerns whether to become a chain and, more precisely, how many shops to operate. We assume that each additional shop beyond the one set up when the firm enters the market involves a fixed cost F_S.

The retail industry is monopolistically competitive. At the local market level, this implies that each shop, respectively firm, takes the number of active shops in the market, n, and the average local retail price, $\bar{p}$, as given when setting its price. A shop i belonging to a firm with marginal cost c obtains an operating profit of:

$$(p_i - c - x)q_i(p_i), \tag{3}$$

where $x = w$ if the firm relies on domestic sourcing, and $x = t$ if the firm is a direct importer. Using superscript D to indicate domestic sourcing, I to indicate importing, and defining $c_D \equiv \tau/n + \bar{p} - w$, a shop with marginal cost c has the following profit-maximizing prices and sales when goods are sourced domestically or imported, respectively:

$$p^D(c) = c + w + \frac{1}{2}(c_D - c); \tag{4}$$

$$p^I(c) = c + t + \frac{1}{2}(c_D - c + w - t); \tag{5}$$

$$q^D(c) = \frac{L}{2\tau}(c_D - c); \tag{6}$$

$$q^I(c) = \frac{L}{2\tau}(c_D - c + w - t). \tag{7}$$

[13] This assumption is not restrictive, since the aggregate consumption good can be interpreted as a composite good consisting of purely domestic goods and goods that may be either imported directly or sourced domestically. See Raff and Schmitt (2012) for details.

Hence c_D represents the marginal cost at which a shop belonging to a firm sourcing domestically optimally chooses zero sales and thus to be inactive, i.e. $q^D(c_D) = 0$.

A shop with marginal cost c earns an operating profit equal to:

$$\pi^D(c) = \frac{L}{4\tau}(c_D - c)^2, \text{ or} \tag{8}$$

$$\pi^I(c) = \frac{L}{4\tau}(c_D - c + w - t)^2, \tag{9}$$

depending on whether the firm relies on domestic sourcing or importing. Only shops belonging to firms with marginal costs less than or equal to c_D will remain active because only they will be able to cover their marginal cost.

The decisions of whether to import and how many shops to operate are obviously interdependent: a chain, for instance, is able to spread the fixed cost of importing across its shops and thus more likely to import than a single-shop firm. To avoid confronting the reader with a plethora of cases involving different shop-importing combinations, we make several assumptions, described below, to ensure that only firms that are productive enough to import will want to operate more than one shop. As we will show below, this captures the empirically most relevant case.

The firm that is just indifferent between domestic sourcing and direct importing is then a single-shop firm for which $\pi^D(c) = \pi^I(c) - F_I$. This condition defines a critical value of the marginal cost c_I:

$$c_I = c_D + \frac{(w-t)}{2} - \frac{2\tau F_I}{L(w-t)}, \tag{10}$$

such that firms with $c \leq c_I$ prefer importing and firms with $c > c_I$ prefer domestic sourcing. We assume that $c_I < c_D$ so that the least efficient active firms engage in domestic sourcing; sufficient conditions are given in the Appendix.

How many shops will an importing firm operate? Since, by assumption, local markets are symmetric and the fixed cost of each additional shop is constant, the answer is straightforward, namely either a single shop or R shops – one in each local market. In particular, an importing firm is indifferent as to whether to open an additional shop if $\pi^I(c) = F_S$. Denote the marginal cost at which this condition is satisfied by c_S. Since we require that $c_S < c_I$ so that, as already discussed above, only importing firms become chains, the only admissible solution is:

$$c_S = c_D + w - t - 2\sqrt{\frac{\tau F_S}{L}}. \tag{11}$$

Sufficient conditions to ensure $0 < c_S < c_I$ are given in the Appendix.

The three cut-off values of the marginal cost, c_D, c_I and c_S, define four categories of firms. The most productive firms, i.e. those with marginal cost $c \leq c_S$, import directly and operate as chains; firms whose marginal cost is in the interval $c_S < c \leq c_I$ import directly but operate only a single shop; firms in the interval $c_I < c \leq c_D$ are also single-shop firms but do not import directly; and firms with high marginal costs ($c > c_D$) are inactive.

To close the model, consider the entry decision firms face before observing their marginal costs. Firms enter the retail industry until their expected profits are zero:

$$\int_0^{c_S} \left[R\pi^I(c) - (R-1)F_S - F_I\right] dG(c) + \int_{c_S}^{c_I} \left[\pi^I(c) - F_I\right] dG(c) + \int_{c_I}^{c_D} \pi^D(c) dG(c) - F_E = 0. \tag{12}$$

2.2 Testable hypotheses

In this subsection, we examine the comparative statics of the model with regard to changes in the trade cost t and formulate corresponding hypotheses; all proofs are in the Appendix. We start by checking how the cut-off value c_D changes with t. Applying the implicit function theorem to the zero-profit condition (12) allows us to show that $dc_D/dt > 0$. This implies the following hypothesis:

Hypothesis 1 *A reduction in the trade cost forces the least efficient firms to become inactive.*

The intuition for this effect is straightforward. A reduction in the trade cost, *ceteris paribus*, raises the profits of direct importers whether they are single-shop firms or chains. To hold expected profits at zero, c_D has to decrease so as to lower the probability of being an active firm.

The sign of dc_I/dt can now be obtained from (10). We find that $dc_I/dt < 0$, which implies that a trade cost reduction induces some firms that were previously not productive enough to afford the associated fixed cost to switch to direct importing. In particular, it is the most productive non-importers that self-select into importing directly. Hence, we may state:

Hypothesis 2 *A reduction in the trade cost induces the most productive non-importers to switch to importing directly.*

What does a fall in the trade cost imply for firm performance? Holding fixed the number of shops a firm operates, we can show that the sales of direct importers rise, and so do markups because, as can be seen in (5), importers pass only half of what they save on trade costs on to consumers. In fact, this direct effect on markups dominates the indirect effect stemming from an increase in the price elasticity of demand induced by a lower c_D. Hence the profits per shop of importers rise. Firms that do not import directly experience increased pressure on their markups from the rise in the price elasticity of demand, but obviously do not enjoy any offsetting cost savings. This forces them to cut their markups and sales, which leads to lower profits.[14] These effects can be summarized as follows:

[14] These firms are single-shop firms by assumption. But obviously these results would hold at the shop level, even if the firms were chains.

Hypothesis 3 *A reduction in the trade cost (i) raises the sales, markups and profits per shop of firms that engage in direct imports; and (ii) lowers the sales, markups and profits of firms that do not import directly.*

Hypothesis 3 thus points to starkly different performance of importing and non-importing firms following a trade cost reduction. A potential strategy for testing this hypothesis is to focus on firms that switch to direct importing. While Hypothesis 2 suggests that part of the performance difference between import starters and non-importers is due to self-selection of larger, higher markup, and therefore more profitable firms, into importing, Hypothesis 3 indicates that import starters should experience an additional boost to their performance caused by their access to cheaper direct imports.

The next hypothesis is associated with the sign of dc_S/dt and thus with the effect of a trade cost reduction on the consolidation of retailers into chains. As can be seen from (11), a marginal change in t has two effects on c_S. The direct effect is negative: a reduction in the trade cost raises the profit that a direct importer can earn in each local market and thereby allows some firms to cover the fixed costs associated with operating additional shops and thus becoming a chain that were previously unable to do so; therefore c_S rises. The indirect effect comes from the zero-profit condition and is positive: a reduction in t reduces c_D and thus lowers the probability of being active, which tends to lower c_S. We can show that the direct effect dominates so that:

Hypothesis 4 *A reduction in the trade cost induces the most productive single-shop firms to add shops and become chains.*

Next, we examine how a reduction in the trade cost, by changing the marginal-cost cut-offs and the performance of individual firms, affects the aggregate performance of the retail industry and the structure of local retail markets. A simple inverse measure of average retail productivity can be computed as the mean of marginal costs of active firms:

$$\bar{c} = \frac{1}{G(c_D)} \int_0^{c_D} c dG(c) = \frac{k}{k+1} c_D. \tag{13}$$

Clearly, trade increases this measure of retail productivity by forcing the least efficient retailers to become inactive.

The average markup of active firms, μ, can be computed as:

$$\begin{aligned} \mu &= \frac{1}{G(c_D)} \left(\int_0^{c_I} \left[p^I(c) - c - t \right] dG(c) + \int_{c_I}^{c_D} \left[p^D(c) - c - w \right] dG(c) \right) && (14) \\ &= \frac{(w-t)}{2} \frac{c_I^k}{c_D^k} + \frac{c_D}{2\,(k+1)}. && (15) \end{aligned}$$

The effect of a marginal decrease in the trade cost on the average markup can be decomposed as follows:

$$\frac{d\mu}{dt} = -\frac{1}{2} \frac{c_I^k}{c_D^k} - \frac{k(w-t)}{2} \frac{c_I^k}{c_D^k} \left[\frac{1}{c_D} \frac{dc_D}{dt} - \frac{1}{c_I} \frac{dc_I}{dt} \right] + \frac{1}{2(k+1)} \frac{dc_D}{dt}. \tag{16}$$

The first term in (16) gives the direct effect: importing firms pass only half of the trade cost reduction on to consumers, the other half goes to raising their markup. This has to be weighted by the probability that the firm is an importer given that it is active, which is equal to c_I^k/c_D^k. The second term reflects the fact that a trade cost reduction tends to raise the average markup by changing the distribution of active firms in favor of higher-markup, importing firms. Specifically, a decrease in the trade cost increases the probability that the firm is an importer given that it is active (by reducing c_D and increasing c_I). The third term represents an effect that goes in the opposite direction: a decrease in t, by reducing c_D, raises the price elasticity of demand for all firms, which tends to lower the average markup.

Whether a decrease in the trade cost increases or decreases the average markup is thus ambiguous, and depends not least on the (endogenous) share of importers in the industry, here captured by c_I^k/c_D^k. We may therefore state that:

Hypothesis 5 *A reduction in the trade cost raises average retail productivity, but has an ambiguous effect on the average markup.*

From the cut-off c_D we can compute the number of active shops in a local market as:

$$n = \frac{\tau}{(c_D + w - \bar{p})}. \tag{17}$$

This number reacts to a reduction of t in two ways. First, a lower t reduces the average retail price $\bar{p}$. This price effect tends to reduce the number of active shops. Second, a decrease in t reduces c_D. This selection effect means that firms and the shops they operate become more efficient on average. This tends to increase the number of active shops. The sign of $\frac{dn}{dt}$ is therefore generally ambiguous. The price effect dominates if the fixed cost of importing is not too great. Hence we can formulate that:

Hypothesis 6 *A reduction in the trade cost lowers the number of shops in a local market if the fixed cost of importing is sufficiently small.*

Notice, however, that even if a fall in the trade cost decreases the number of shops, this does not necessarily imply an increase in market concentration at the local level. This can best be seen when writing the Herfindahl index (H) of local market concentration as follows:

$$H = \frac{1 + \sigma_q^2/\bar{q}^2}{n}, \tag{18}$$

where $\bar{q}$ denotes average sales per shop and σ_q^2 is the variance of sales (see Waterson, 1984). Thus, market concentration in a setting in which firms differ in their marginal costs, and the shops they operate therefore differ in sales, is positively related to the coefficient of variation of retail sales, $\sigma_q/\bar{q}$. That is, we have to check how lower trade costs affect the distribution of sales across shops. For the average sales per shop and the variance of sales we obtain:

Hypothesis 7 *A reduction in the trade cost raises the mean and reduces the variance of shop-level sales if the fixed cost of importing is sufficiently small.*

The effect of a lower trade cost on the Herfindahl index is therefore generally ambiguous, simply because a fall in the number of shops may be accompanied by a fall in the coefficient of variation of local retail sales. The question of how a lower trade cost affects local market concentration in retailing can therefore only be answered empirically.

3 Data

3.1 Data sources

For our empirical analysis, we use data on retail firms present in Denmark between 1999 and 2008.[15] Specifically, we make use of three data sets available from *Statistics Denmark*. The first data set, *FIRM* ("Generel Firmastatistik"), covers the population of firms active in Denmark and contains information on industry affiliation, number of employees, and other firm characteristics, such as turnover, value added, profits, and fixed and total assets.[16]

The second data set, called *UHDI* ("Udenrigshandel diskretioneret"), provides information on individual firms' export and import activities at a detailed product level and by partner country. The data fall into two categories: Intrastat (for trade among EU member states) and Extrastat (for trade with countries outside the EU). Extrastat data come from custom forms and tax authorities and cover nearly all trade, while Intrastat data are self-reported figures by Danish firms that exceed certain export and import thresholds set by the EU.[17]

The third data set, *IDAS* ("IDA arbejdsstede"), contains information at the level of the branch which, in the case of retail firms, is usually a shop. The data set includes information about the location of a branch, its industry classification as well as data about the individuals working there. We use this information to identify local retail markets and to compute Herfindahl indices for these markets. We also use it to compute the number of shops by retail firm so that we can investigate potential adjustments of retail firms to trade along the shop margin.

Thanks to a unique firm identifier, we can merge the information present in each of the data sets mentioned. Whereas *FIRM* includes the population of active firms and *UHDI* contains information on international trading activities of firms in Denmark

[15] In order to accommodate a lag structure further described below, we also make use of information for the years 1997 and 1998.

[16] We deflate firm-level domestic sales, value added and wages using the consumer price index with 2000 as the base year.

[17] For instance, in 2002, the thresholds were DKK 2.5 million for exports and DKK 1.5 million for imports. The thresholds are set each year for imports and exports separately in order to ensure coverage of 95% and 97% for imports and exports, respectively.

subject to rather small reporting thresholds, the data set *IDAS* does not include all firms present in *FIRM*. In the next subsection, we describe in more detail how we constructed the data sets used for the empirical analysis.

3.2 Sample selection

Based on the industry affiliation documented in *FIRM*, we identify all firms that report retailing as their main activity.[18] *Statistics Denmark* reports the industry affiliation at the six-digit level, where the first four digits correspond to the NACE four-digit classification. Generally, the NACE four-digit level appears most appropriate to define a retail industry.[19] However, in case of the sector "other retail sale in specialized stores" (5248), the four-digit classification is too broad, as it masks the large heterogeneity of retailer firms belonging to this industry (e.g. jewelry, sports equipment, toys, bicycles, electronics). Hence, for this industry we use a more detailed industry definition.

We drop a few retail industries from our sample where the economic mechanisms we want to examine are likely to be absent, e.g. because direct importing is rather infrequent, which is the case for NACE rev. 1 three-digit industry 522 (retail sale of food, beverages and tobacco in specialized stores), 525 (retail sale of second-hand goods in stores), 526 (retail sale not in stores), and 527 (repair of personal and household goods), or because the industry is heavily regulated, which is the case for industry 523 (retail sale of pharmaceutical and medical goods, cosmetic and toilet articles).[20] In total, we thus retain 24 retail industries in our analysis, which we list in Table A.3 in the Appendix.

The empirical analysis is conducted at two different levels of observation. At the first level, the firm is the unit of analysis, and we investigate firms' adjustments related to direct importing of consumer goods.[21] At the second level, we examine how aggregate indices of retail market structure derived from the theoretical model respond to consumer goods imports. For this purpose, we require a retail market demarcation that is not only based on industry affiliation, but also on the geographic scope of the

[18] We therefore do not consider firms with main activities in other industries but which potentially have branches engaging in retailing.

[19] For instance, the industry retail sale of clothing (four-digit sector 5242) is further broken down into the six-digit sub-industries retail sale of ladies' clothing, retail sale of men's clothing, retail sale of men's and ladies' clothing, and retail sale of baby articles and children's clothing. Hence, at least the former three sub-industries overlap, which makes it difficult, for example, to compute the Herfindahl index.

[20] The number of excluded firms decreases over the sample period from more that 7,000 in 1999 to less than 6,000 in 2008; their share in total retail firms' imports also decreases during that time from 9% to 7%, while their share in total retail firms' sales remains relatively stable at around 13%.

[21] Note that we clean the data by dropping observations with implausible values for key variables (e.g. negative sales) and by removing outliers in terms of the labor productivity distribution, defined as observations that deviate from median by more than five times the standard deviation. Moreover, we clean dependent variables such as sales, profits or markups by dropping observations if the year-on-year growth rate of the respective variable deviates by more than five times the standard deviation from the median.

market.

We define the geographic scope of a retail market to be a municipality. Foged and Peri (2015, p.12) find that, in Denmark, "municipalities are, even in the long run, rather self-contained labor markets." If workers on average seek employment only within their own municipality, it seems plausible to assume that this is also where they go shopping. But this raises three data-related issues. First, in 2007, a new demarcation of municipalities was introduced in Denmark that reduced the number of municipalities from more than 270 to 98. Most of the old municipalities are linked to only one new municipality. However, for a few old municipality codes, there is no one-to-one correspondence to new codes. We deal with this issue by forming some larger regional groups in order to concord the municipality codes over time. We end up with 85 regions that we use to define local retail markets.

Second, we have to deal with multi-shop firms. While we observe the location, the number of employees and the wage bill at the shop level, information on sales, for example, is only available at the firm level. In the case of multi-shop firms, we therefore need to distribute firm-level sales across shops based on a weighting scheme. Given the information available in *IDAS*, we use the share of a shop's employment in a firm's total employment as weight.

Third, we face the problem that some active firms present in *FIRM* cannot be merged to *IDAS*, implying that for these firms we do not observe information at the level of the shop. Hence, these firms are excluded from the analysis whenever shop-level information is required, as is the case in the analysis of local retail market structure. This issue concerns in particular the two NACE four-digit industries 5211 (retail sale in non-specialized stores with food, beverages or tobacco predominating) and 5212 (other retail sale in non-specialized stores) for the years 1999 to 2001. We thus exclude these industries during this period from the analysis of local retail market structure. For the remaining industries, we can merge firms that account for around 95% of retail sales in every year.

Tables A.1 and A.2 in the Appendix present summary statistics for variables used in our analysis.

3.3 Descriptive evidence

Table 1 presents a number of aggregate indicators by year for the retailers in our sample. Column (i) indicates that retailers accounted for an important share of firms importing consumer goods and that this share remained relatively constant during the sample period at around 12%.[22] Retailers also mattered with respect to the intensive margin of consumer goods imports and this involvement increased over time. As indicated by column (ii), the share of imports by retailers in total consumer goods imports increased from 9.2% in 1999 to 13.8% in 2008. Indeed, for certain product categories, retailers

[22] Over the sample period, consumer goods on average account for almost 80% of total imports of our retail firms.

accounted for a much larger share of consumer goods imports.[23]

Between 1999 and 2008, we observe an increase in average retail sales per firm from DKK 10 million to DKK 11.5 million (column iii). This increase is entirely due to direct importers whose average sales surged by almost 30%, while those of other retailers decreased by more than 15% during that period. At the same time, the share of direct imports of consumer goods in total retail sales more than doubled from 3.5% in 1999 to 7.7% in 2008 (column iv). Moreover, average imports by directly importing retailers rose by more than 60% (column v). This latter development occurred despite a significant increase in the share of directly importing retailers which rose from 7.1% to 10.8% (column vi).[24]

Finally, in order to get an idea about the degree of retail market concentration and how it has changed over time, the last column of Table 1 presents the development of the aggregate Herfindahl index computed as the sales-weighted average of the indexes in local retail markets.[25] The aggregate index remains relatively constant over time at around 0.24.

Table 2 presents additional information about the role of retail chains during the sample period, where a chain is defined as a firm that has more than one shop.[26] First of all, we see that the number of chains increased considerably during the sample period (by more than 70%). Moreover, we can observe that these firms are quite distinct since, despite constituting a relatively small group, they account for 64% of total retail turnover in 2008 (up from 55% in 1999). These firms also play a crucial role when it comes to importing; one in four chains imports directly, and, in total, chains account for around 90 % of total direct imports by retailers. Furthermore, it is worth noting that there is substantial heterogeneity across chains. While the median chain only has two shops, there also is a small number of chains with well above 100 shops. Indeed, when only focusing on chains with at least ten shops, then these chains alone account for 50% of total retail turnover in 2008.[27]

Table 3 underlines these points by distinguishing retail firms according to their import and chain status. This results in a sorting in terms of average size which is quite plausible also with respect to our theoretical model. In particular, we find that importing chain retailers are by far the largest firms in terms of average sales and number of employees, followed by non-importing chains and importing single-shop firms. Moreover, we observe that average imports by chain retailers that import directly exceed those of single-shop importers by a factor in excess of 30. Similarly, according

[23] For instance, in 2006, retailers accounted for 23% of imports of wood and articles of wood (HS 44-46), 20% of imports of raw hides and skins, leather and articles thereof (HS 41-43), 33% of imports of furniture, toys, and miscellaneous manufacturing articles (HS 94-96), and 39% of imports of art and antiques (HS 97-99).

[24] Note that the total number of retail firms remained rather constant over time.

[25] The Herfindahl index is computed according to equation (18) for local retail markets. Note that retail sectors 5211 and 5212 are excluded from these averages for the reason described in section 3.2.

[26] The information in this table is based on firms that are present both in *FIRM* and *IDAS*.

[27] Note that a firm with ten shops corresponds to the last decile of the shop distribution across all chains.

to these numbers, the unconditional probability of a chain store importing amounts to more than 25%, while that of single-shop firms lies below 10%. Overall, these results thus suggest a relationship between firm performance and import activity, which we will further analyze below.

4 Empirical analysis

The hypotheses derived from the theoretical model imply different performance of importing and non-importing firms in response to a lower trade cost that translates into structural change in the industry and, in particular, in local retail markets. In this section, we empirically test the hypotheses. We first consider the predictions related to adjustments at the firm level, and then focus on those related to structural changes at the industry and local market levels. For each hypothesis, we first lay out the empirical approach for taking it to the data, and then present the results. Further note that we use the approach by De Loecker and Warzynski (2012) in order to obtain measures of markups that vary across firms and time. We refer the reader to the Appendix for details about the estimation approach and its empirical implementation.

Notice that, since we cannot measure trade cost directly, we test the hypotheses indirectly by assuming that the observed increase in import activity during the sample period, documented in Table 1, is at least in part driven by a trade cost reduction. Throughout the empirical analysis, we focus our attention on imports from countries outside the EU15 for two main reasons. First, a significant trade cost reduction during the time period under investigation likely occurred through enhanced trade integration with respect to these markets; we therefore use "trade cost reduction" and "trade integration" interchangeably.[28] Second, by excluding EU15 economies we largely avoid data issues related to reporting thresholds (see section 3.1) and potential biases that could arise from intra-firm trade of multinational retailers headquartered in Sweden or Germany, for example.

4.1 Import activity and firm performance (H2 and H3)

According to Hypothesis 2, a decrease in the trade cost induces larger, higher markup and therefore more profitable retailers to self-select into importing. Moreover, Hypothesis 3 suggests that increased trade integration enhances these performance differences. Specifically, sales, profits, and markups of importing firms should increase, while those of non-importing firms should decrease.

[28] Examples of increased trade integration include the EU enlargement towards the East in 2004 and China's accession to the WTO in 2001.

Empirical approach (H2 and H3)

The first step of our empirical approach to test these predictions is to estimate import premia regressions while controlling for other firm-level characteristics. Specifically, we estimate the following model:

$$y_{it} = \beta_0 + \beta_1 DIMP_{it} + \beta_2 x_{i,t-1} + \alpha_{st} + \alpha_i + \epsilon_{it}, \tag{19}$$

where $DIMP_{it}$ is a dummy variable taking a value of one, if firm i imports consumer goods from at least one non-EU15 market in year t and it is zero for firms not importing from these markets;[29] y_{it} measures the logarithm of the outcome of interest, namely sales, profits, or markups, while $x_{i,t-1}$ controls for firm size (number of employees);[30] α_{st} are sector-year dummies, implying that we are comparing importing and non-importing firms within sector-year pairs. In some specifications, we also include firm fixed effects, α_i, in the regressions so that the coefficient of interest, β_1, is identified by firms experiencing a change in their import status.

Remember that both Hypothesis 2 and Hypothesis 3 suggest that importing firms perform better than non-importers, implying a positive sign for β_1. However, the explanations for a positive coefficient differ. According to Hypothesis 2, β_1 should be positive because of self-selection, whereas Hypothesis 3 indicates that performance differences may also be caused by firms' import activities due to access to cheaper products. While regressions based on equation (19) therefore provide first insights into differences between importing and non-importing firms, these regressions provide no indication of causality.

We try to address this issue by taking our cue from studies investigating the relationship between exporting/importing and the performance of manufacturing firms.[31] To this end, we focus on retail firms that start importing. Specifically, we define a dummy variable, $START_{it}$, that equals one for firms that import in period t, but did not do so in periods $t-1$ and $t-2$, while it takes on zero for firms that have not imported during all three years. We then investigate the self-selection hypothesis by testing whether import starters perform better than non-importers before the import event occurs. More precisely, we run the following regression:

$$y_{i,t-1} = \beta_0 + \beta_1 START_{it} + \beta_2 x_{i,t-1} + \alpha_{st} + \epsilon_{it}. \tag{20}$$

The differences compared to equation (19) are that we regress a lagged performance measure ($y_{i,t-1}$) on a dummy variable indicating import starters ($START_{it}$). Hence, β_1 now informs us whether import starters already differ from non-importing firms one period before the import event occurs, as suggested by Hypothesis 2.

[29] Hence, the comparison group comprises firms that source domestically only and those that also source from EU15 markets.

[30] Note that controlling for the log of the number of employees implies that we restrict the analysis to firms with at least one employee.

[31] See, for instance, De Loecker (2007) or the survey by Wagner (2007). More recently, Smeets and Warzynksi (2013) present an investigation relying on similar methods that links both exporting and importing to the performance of manufacturing firms.

Investigating Hypothesis 3, which suggests a causal relationship between importing and retail firm performance, is somewhat more involved. We try to identify this causal effect by again focusing on import starters and then applying propensity score matching (PSM) in order to create a control group of firms that do not import but exhibit a statistically similar propensity to start doing so for each import starter.[32] The variable $Start_{it}$ thus acts as a treatment dummy and we are interested in the difference between y_i^1 and y_i^0, where y_i denotes again the performance of firm i, and the superscripts 1 and 0 indicate the firm's treatment status. More formally, we wish to compute the average treatment effect on the treated defined as:

$$E[(y^1 - y^0)|Start = 1] = E[(y^1)|Start = 1] - E[(y^0)|Start = 1]. \tag{21}$$

The fundamental evaluation problem inherent in equation (21) stems from the fact that we do not observe the counterfactual outcome $E[(y^0)|Start = 1]$, i.e. the expected performance of an import starter had it not switched to importing. A strategy for addressing this problem involves the assumption that, conditional on a set of observable firm-level characteristics that are unaffected by importing, potential outcomes are independent of treatment. The latter is usually referred to as the conditional independence assumption, which implies that selection into treatment is driven by observable covariates. Intuitively, we try to construct a group of comparison firms that are as close as possible to the treated firms in terms of their propensity to start importing. To this end, we follow the insights presented by Rosenbaum and Rubin (1983, 1985) and apply PSM.[33] The first stage of the matching approach involves estimating the probability of starting to import:

$$P(Start_{it} = 1) = \Phi\{z_{i,t-1}\}, \tag{22}$$

where $\Phi(\cdot)$ is the normal cumulative distribution function, indicating that we employ a probit model; $z_{i,t-1}$ contains firm-level control variables lagged by one year, i.e. one period before import initiation. In particular, $z_{i,t-1}$ includes measures of productivity (value added per employee) and size (number of employees and total assets), since both factors are commonly associated with firms engaged in international trade.[34] Moreover, we condition on lagged sales growth and a firm's wage share in total sales. The former variable is meant to capture firms' cyclical positions, while the latter variable is a rough

[32] When separately examining the performance of direct importers and non-importers, we would have to use instruments for firm-level or industry-level imports in order to establish causal effects. Indeed, we experimented with some potential candidate variables (e.g. a country's world export supply as in Hummels et al., 2014), but the instruments generally turned out to be rather weak. Part of the problem appears to be specific to an analysis of retail firms because these firms significantly increased the number of imported varieties during the period under investigation, while the instruments proposed in the literature usually work for the intensive rather than the extensive margins of trade.

[33] Caliendo and Kopeinig (2008) present an overview of propensity score matching techniques.

[34] Note that the productivity measure is prone to the caveat that, especially in smaller retail firms, the owner (and potentially family members) may be an important part of a firm's workforce without being counted as an employee. This variable therefore tends to overestimate productivity in such instances.

measure of profitability. Note that we also include a quadratic productivity term to allow for potential non-linearities. Finally, we add four-digit NACE industry and year dummies to the probit regressions.

The second step of the matching approach involves the search for a control group that is similar to the treated firms according to the propensity score estimated by the probit model. In particular, we apply radius matching with a tight caliper and impose common support to ensure that the balancing property holds.[35] In other words, for each treated firm, we search for a control group that consists of non-importing firms that differ in terms of the propensity score by no more than a pre-specified maximum distance (i.e. a caliper of 0.001).[36] We can then compute the average treatment effect on the treated (ATT) as:

$$\text{ATT} = \frac{1}{N}\sum_{i}(y_i^1 - \sum_{j\in C_i} w_{ij} y_j^0), \tag{23}$$

where N refers to the number of treated firms, C_i to the set of control firms matched to each treated firm $i = 1, ..., N$, and w_{ij} is a weight such that $w_{ij} = \frac{1}{N_i^C}$ if $j \in C_i$ and zero otherwise, with N_i^C denoting the number of control firms. Below, we compute ATTs for levels of the performance measures indicated by Hypothesis 3. We also consider alternative variable transformations, and investigate the effects at various time horizons. To be precise, besides level effects, we also consider responses of log changes. Importantly, computing an ATT from differences in outcome variables effectively combines propensity score matching with difference-in-differences estimations. Indeed, Smith and Todd (2005) deem such a strategy especially appealing. While the approach still relies on the assumption of "selection on observables", taking differences accounts for potential biases related to time-invariant firm characteristics. We thus also consider the change in outcomes computed as the difference between post-treatment and pre-treatment log levels.

Moreover, we compute the treatment effects at various time horizons relative to the treatment year. Assuming that the import event occurs in period $p = 0$, we generate ATTs for the periods $p = -2, \ldots, 0, \ldots, 3$. Computing ATTs for pre-treatment periods functions as a placebo test. In other words, prior to treatment, we would expect that firms differ neither in terms of the control variables (as confirmed by the balancing tests) nor the outcome variables. Moreover, analyzing the ATTs at various post-treatment periods allows us to investigate the persistence of the effects. We note, though, that this type of analysis implies a more selected sample, since both treated and untreated firms have to be active for additional periods. As a result, the number of observations decreases with increasing p. Generally, independent of the time horizon considered,

[35] We present information about the balancing property in the Appendix. There, we also present results for the first-stage probit regressions.

[36] We implement the matching algorithm using the Stata program `psmatch2` written by Edwin Leuven and Barbara Sianesi. Note that, even though we estimate the probit model pooled across all years, we ensure exact matching by year in the second step of the matching approach.

matching is always performed at the time a firm starts importing, in line with De Loecker (2007), for example.[37]

Finally, note that we exploit the double robustness property of the regression adjusted machting estimator. To be precise, we compute ATTs by means of weighted regressions, using sampling weights obtained from the matching approach, while controlling for the covariates included in the first stage probit regression. In this way, we can ensure that the estimator is consistent if either the propensity score equation or the regression equation is correctly specified (see for instance Imbens and Wooldridge, 2009). We cluster the standard errors at the firm-level in these regressions.[38]

Results (H2 and H3)

Table 4 presents the baseline results referring to equation (19). Estimating the equation without firm fixed effects (columns i to iii), we find that importing retailers differ significantly from non-importers across all performance measures suggested by Hypothesis 3. In particular, the sales, profits, and markups of directly importing firms exceed those of their non-importing counterparts on average by 20%, 27%, and 3%, respectively (columns i to iii).[39] Significant differences are also visible when adding firm fixed effects to the regressions (columns iv to vi); i.e. a switch in import status from zero to one appears to be associated with better performance indicators. However, while these results are clearly in line with our theoretical model, we cannot distinguish between the effects related to more productive and therefore larger and more profitable firms self-selecting into importing, as implied by Hypothesis 2, and those that are caused by import activity, as suggested by Hypothesis 3.

As explained above, we investigate the self-selection hypothesis by running regressions in accordance with equation (20). The estimation results in Table 5 show that firms beginning to import in year t are indeed already larger and more profitable than non-importing firms in period $t-1$ (column i to iii). These differences amount to 9%, 5% and 2% for sales, profits, and markups, respectively. Hence, the results clearly support the self-selection mechanism proposed by Hypothesis 2. Moreover, the results presented in Table 5 may also accord with additional performance gains after the import event has occurred since performance differences are even larger in period t (columns iv to vi).

We try to shed some light on the potentially causal effect of importing on retail firm performance by applying a PSM approach, while keeping in mind that PSM, too, is based on a number of assumptions. To the extent that these assumptions are plausibly fulfilled in our context, the results presented in Table 6 indeed suggest that importing

[37] Note that we focus on the first import event of firms in our sample and do not impose any restrictions on import activity in consecutive periods.

[38] See also Goldbach et al. (2017) for a similar approach in an analysis of the effect of foreign investment on domestic investment.

[39] Computed e.g. as 19.7=(exp(0.18)-1)*100 since the dependent variables are log transformed. As a result, we consider only firms with positive profits in these estimations (around 9% of firms report zero or negative profits).

significantly impacts sales, profits and, markups of retail firms. According to these estimates, a firm that starts importing enjoys roughly 8% higher sales compared to non-importing firms in the year of import initiation (panel a). This sales premium lasts during the consecutive periods and amounts to 11% after three years. Cumulating these effects over time for firms present in all periods implies sales gains of close to 30% compared to firms sourcing domestically. We also obtain a significant ATT when considering the change in (the log of) sales as an outcome variable. In particular, on impact, the estimated effect of importing amounts to 9 percentage points higher sales growth for import starters. This effect is quite persistent when considering longer time horizons. Three years after import initiation, the growth in sales relative to pre-treatment exceeds that of non-importers by 10 percentage points.

Moreover, we find a positive impact of import activity on firms' profits which increase by more than 6% in $p = 0$ and exceed those of non-importing firms by more than 11% three years after import initiation. Regarding growth rates, significant effects are estimated which amount to 9 percentage points higher profit growth on impact and as much as 18 percentage points higher profit growth when considering long differences in period $p = 3$. Similarly, we find quite persistent effects on the markups of retailers that start to import. The results in panel c suggest that markups exceed those of non-importing firms by between 2% and 3% in periods $p = 0$ and later. Moreover, markup growth is also affected by around one to two percentage points, even though the statistical significance decreases with longer time horizons.

Finally, we note that the Appendix contains information showing that the matching approach is successful in generating samples of treated and untreated firms that are well balanced in terms of covariates. Moreover, results in Table 7 indicate that, after applying the PSM approach, sales, profits, and markups do not differ significantly between the studied treated and untreated firms prior to the import event. This table does not contain placebo results for changes in log sales in $p-1$, since such a regression is redundant given that we condition on pre-treatment sales growth in the selection model.[40] Overall, we thus find both evidence for a selection effect and indications that importing has contributed to the observed differences in the performance of importing and non-importing retailers, which is in line with Hypotheses 2 and 3.[41]

4.2 Import activity and consolidation into chains (H4)

Hypothesis 4 states that a reduction in the trade cost induces firms to add shops and thus become a retail chain.

[40] Controlling for lagged sales growth in the probit regression (and consequently also when applying the regression adjusted matching estimator) also explains why we obtain the same coefficient when considering the log of sales in $p-1$ and $p-2$ as outcome variables.

[41] In the Appendix, we present a series of robustness checks with respect to the matching approach. First, we add lagged (log-) levels of outcome variables to the first stage probit regressions. Second, we employ exact matching by year and NACE four-digit sector. Third, instead of radius matching with a tight caliper, we employ a Gaussian kernel in the matching step. Overall, our results are robust across these checks.

Empirical approach (H4)

We investigate Hypothesis 4 by applying a similar methodology as before. We begin by estimating models as depicted by equation (19) for two different outcome variables, namely a dummy variable indicating chain retailers and a dummy variable taking a value of one if a firm opens a new shop. Note that we estimate linear probability models in order to be able to include firm fixed effects. These models indicate whether importing retailers have a higher probability of being a chain and of opening a shop. Moreover, the specification with firm fixed effects relates changes in these probabilities to changes in import status.

In addition, we apply a propensity score matching approach as outlined above in order to gauge the direction of causality. Two things are worth noting here. First, in the case of the chain dummy, we restrict the sample to firms that operated as single-shop firms in $t-1$, i.e. to firms for which the chain dummy equals zero before beginning to import. Hence we investigate whether import initiation changes the probability of becoming a chain (in contrast to the probability of continuing as a chain). Second, when analyzing the probability of opening a new shop, we add the (log of the) number of shops operated in $t-1$ to the first-stage probit regression. We are thus assessing whether import initiation affects the probability of opening a new shop, comparing firms with a similar number of shops prior to importing.

Results (H4)

The OLS results are presented in Table 8. As expected, we find that importing retailers have a higher probability of being a chain and of opening a new shop. The estimated coefficients imply probability differentials amounting to roughly 6 and 2 percentage points, respectively. The coefficients of interest shrink markedly when adding firm fixed effects, while they remain statistically and economically significant also in these regressions.

In Table 9, we present results from the matching approach in order to analyze the causal relationship. On impact, we do not find a significant increase in the probability of becoming a chain. However, when considering the results in consecutive periods, there is some evidence of an effect two years after import initiation.[42] The coefficient estimate implies an effect of 1.6 percentage points, which is non-negligible when considering that the unconditional probability of being a chain amounts to only 10% in the overall sample.

Such a conclusion can also be drawn when focusing on the probability of opening a new shop. Indeed, import starters have a significantly higher probability of increasing the number of shops in period $p = 0$, amounting to one percentage point. Moreover, we also observe that import starters have a significantly higher probability of opening a

[42] Note that the chain (new shop) dummy is equal to one in periods $p = 1$ when a firm becomes a chain (opens a new shop) in period $p = 0$ or $p = 1$. The dummies are coded equivalently for period $p = 2$ and $p = 3$.

new shop two years after the import event has occurred. A coefficient estimate close to 2 percentage points again implies a quantitatively meaningful effect, considering that, in the data, the unconditional probability of adding a shop is only 3%. At the same time, we do not find significant differences in the probability of opening a new shop one year before the import event has occurred.[43] These results therefore suggest that importing has indeed contributed to the consolidation of retailers into chains, which is in line with the theoretical model's prediction.

4.3 Import activity and firm exit (H1)

Hypothesis 1 derived from our theoretical model suggests that a trade cost reduction leads to the exit of the least efficient firms.

Empirical approach (H1)

We use a different empirical approach than before to investigate this hypothesis. This is because, in this subsection, we do not only wish to analyze whether less productive or non-importing retailers have a higher exit probability. Instead, we are interested in whether these types of firms have a higher exit probability depending on trade integration. To be precise, we test Hypothesis 1 by relating an indicator of firm-level exit ($exit_{it}$) to industry-level imports. We are thus exploiting industry-level variation in import activity to assess firms' exposure to trade integration. As noted before, this implies the assumption that increased trade integration is partly captured by observed changes in imports. We emphasize that the results presented in this subsection may not reflect a causal relationship, for instance, due to simultaneity issues.

We identify exits in the data by using a variable indicating the resignation date of a firm. The indicator variable $exit_{it}$ equals one if a firm has been active in year $t-1$ and resigns from the market in year t. The comparison group of continuously active retailers comprises firms that remain in the market during both years. We then estimate the following model:

$$\begin{aligned} exit_{it} = \beta_0 + \beta_1 DIMP_{it} + \beta_2 DSIZE_{it} + \beta_3 LN(VIMP_{st}) + \beta_4 DIMP_{it} \times \\ LN(VIMP_{st}) + \beta_5 DSIZE_{it} \times LN(VIMP_{st}) + \beta_6 LN(SALES_{st}) + \alpha_s + \alpha_t + \epsilon_{it}, \end{aligned} \tag{24}$$

where $DIMP_{it}$ is a dummy variable indicating a firm's import status; $DSIZE_{it}$ is a categorical variable indicating whether firm i is among the smallest, i.e. least efficient, firms in a given year; $LN(VIMP_{st})$ denotes the value of non-EU15 consumer goods imports of retail firms belonging to sector s in year t; $DIMP_{it} \times LN(VIMP_{st})$ and $DSIZE_{it} \times LN(VIMP_{st})$ are interaction terms; and $LN(SALES_{st})$ measures total industry-level sales to control for other aggregate developments. Hence equation (24) allows us to investigate whether industry-level imports have a differential effect on the exit probability of importing and non-importing firms or of small and large retailers.

[43] A placebo regression for the chain dummy is redundant since we restrict the analysis to comparing single-shop firms in the pre-treatment period.

We compute $DSIZE_{it}$ based on the size distribution (total assets) of firms in the estimation sample. Specifically, we define firms that belong to 25th percentile of the size distribution as small. Note that we proxy for efficiency using a firm's size rather than productivity because several firms do not report any employees, thus preventing the computation of labor productivity. Since these non-reporting firms tend to be small and exit the market rather frequently, we would lose relevant information if we relied on labor productivity.[44]

Finally, note that the industry level s here refers to the 24 industries described in section 3 and in Table A.3 in the Appendix. Since our variable of interest ($ln(VIMP_{st})$) varies over this dimension, we cluster the standard errors at the sector level (Moulton, 1990). Moreover, we also present p-values derived from a wild bootstrap procedure (in brackets), given that the number of clusters is relatively small (Cameron et al., 2008).[45]

Results (H1)

The estimation results in Table 10 first of all show that importing firms have a lower and small firms have a higher probability of exiting the market.[46] The coefficient of the import dummy suggests a 2.6 percentage point lower exit probability and that of the size dummy a 16.7 percentage point higher exit probability for the respective types of firms. These results thus fit our theoretical model, in which exit occurs at the lower end of the retailer size distribution and thus among retailers that do not import.

The results in column (i) suggest that an increase in industry-level imports is, in general, associated with an increase in the exit probability of non-importing firms (coefficient β_3). However, while the interaction term with a firm's import status has the expected negative coefficient, it is not statistically significant. On the other hand, the results in column (ii) are more in line with Hypothesis 1. In this case, the coefficient for industry-level imports does not suggest a significant relationship with the exit probability of larger retailers. At the same time, the interaction between the size dummy and industry-level imports is positive and significant, which suggests that an increase in aggregate imports is associated with a higher exit probability of small retailers. This finding is confirmed by the results shown in column (iii), where both interaction terms are included simultaneously. Note that the implied effect is relatively small. Adding together the coefficients of $LN(VIMP_{st})$ and the interaction term, i.e. computing $\beta_3 + \beta_5$, the estimated effects amounts to less than 0.02 percentage points in response to an increase in sector-level imports of 1%. Overall, we thus conclude that our results are broadly in line with Hypothesis 1.

[44] Numerous empirical studies document that firm size is highly correlated with productivity. Moreover, our theoretical model suggests a direct link between size and productivity. Furthermore, as mentioned in footnote 34, a measure of labor productivity may be problematic, especially for smaller retailers, since the variable ignores the work done by firm owners.

[45] We implement this procedure in Stata using the `cgmwildboot` routine written by Judson Caskey. The null hypothesis is always imposed.

[46] Note that the import variable $LN(VIMP_{st})$ is mean-centered.

4.4 Import activity and aggregate productivity and markups (H5)

Our model indicates that the adjustments in firm performance induced by direct import activity have consequences at the aggregate retail market level. According to Hypothesis 5, we would expect to find an increase in aggregate productivity, while the effect on the aggregate markup is not clear-cut and depends, *inter alia*, on the productivity distribution of the firms.[47]

Empirical approach (H5)

We take these predictions to the data by conducting a set of regressions at the local retail market level, where a local market is defined by region r and sector s. As explained above, we observe certain variables such as sales, total assets, productivity or markups only at the firm level. Hence, for a chain retailer we have to distribute these variables across its locations in different regions. For sales and assets, we do this on the basis of the employment share of each shop in a chain's total employment. For productivity and markups, we assume that they are similar across shops belonging to the same firm. In a second step, we aggregate across shops present in a local retail market to obtain variables varying by local retail market and time. For productivity and markups, we compute a weighted average using a shop's sales as weight.[48]

We then relate market level characteristics, namely productivity and markups, to industry-level consumer goods imports:

$$y_{rst} = \beta_0 + \beta_1 LN(VIMP_{st}) + \beta_2(x_{rs,t-1}) + \alpha_{rs} + \alpha_t + \epsilon_{it}, \tag{25}$$

where y_{rst} is a market-level outcome (log-transformed); $LN(VIMP_{st})$ refers to the value of industry-level imports (as before); and $x_{rs,t-1}$ are lagged covariates to control for local retail market characteristics, namely size (measured as the sum of assets of all shops in a market) and the average wage (measured as total wage bill over total employment in a market). By including local market fixed effects (α_{rs}) in these regressions, we exploit within market variation to estimate the relationship between imports and the outcome of interest. As before, we rely on OLS estimation so that the following results should be interpreted as representing suggestive evidence for the presence of certain relationships in the data without drawing any causal conclusions. Note that we present results from both unweighted and weighted regressions, where weights are based on regional sales

[47] To put this hypothesis and the results presented below for retailers into perspective, it is useful to compare them to studies on the effects of trade liberalization on average markups and productivity in manufacturing. De Loecker et al. (2016) show, using Indian data, how a decrease in input tariffs induces manufacturers to raise their markups and thus pass only part of the tariff reduction on to consumers. This corresponds to the direct effect on markups explained in our Eq. (16). A similar effect is shown by Brandt et al. (2017) using Chinese data.

[48] Notice a slight discrepancy here between our empirical approach and the theoretical model. In a monopolistically competitive model, a firm, or, in our case, a shop, is implicitly assumed to have negligible weight in the industry.

shares of each industry. Further note that, as before, we cluster the standard errors at the industry level and also report p-values derived from a wild bootstrap procedure in brackets to account for the relatively small number of clusters.

Results (H5)

Table 11 contains the estimation results, where the first two columns refer to unweighted regressions. The results suggest that industry-level imports are indeed positively related to market-level productivity (column i). Moreover, the coefficient for aggregate markups displays a negative relationship (column ii). While the analytical standard errors imply that these coefficients are (weakly) statistically significant, p-values derived from the wild bootstrap procedure are considerably larger, indicating that there is great uncertainty around these estimates.

When focusing on the weighted regressions, we no longer find a negative coefficient for markups (column iv). Instead, the coefficient is positive, though close to zero and estimated very imprecisely. Overall, these results therefore fit our model, which also predicts that aggregate markup effects are ambiguous. In contrast, the coefficient for productivity remains positive also when using weighted OLS (column iii). While this is also expected from the model, we note that the coefficient's p-value increases to 0.13 in the case of the wild bootstrap approach.

4.5 Import activity and local-market-level concentration (H6 and H7)

Finally, our model provides conditional predictions about the components of a local market's Herfindahl index, i.e. the number of shops, as well as the mean and the standard deviation of local retail market sales. For small enough fixed costs of importing, a reduction in trade costs would lower the number of shops (H6) and decrease the coefficient of variation of retail sales (H7). Fewer shops, ceteris paribus, imply a greater Herfindahl index of market concentration, but a lower coefficient of variation of retail sales leads to a smaller index. Hence, in theory, changes in trade costs have an ambiguous effect on the Herfindahl index.

Empirical approach (H6 and H7)

We investigate these prediction by resorting to equation (25), where y_{rst} now refers to the Herfindahl index or one of its components.[49]

[49] Note that some retail firms may operate several shops in a given local market. But shops belonging to the same firm probably do not compete with each other in prices. A similar assumption is made by Holmes (2011) and supported by evidence from Holmes on considerable self-cannibalization among Walmart stores. Treating shops by the same firm as independent shops would thus lead to an underestimation of local market concentration. To obtain a more accurate measure of market concentration, we therefore treat the shops of a given firm in region r and industry s as a single shop. The number of shops in a local market is therefore equal to the number of firms operating a shop or shops

Results (H6 and H7)

Table 12 contains the estimation results. In line with Hypothesis 6, we find that an increase in market-level imports is negatively related to the number of retailers present in a market (column i). On the other hand, the relationship between industry-level imports and average market-level sales (column ii) as well as the relationship between industry-level imports and the standard deviation of market-level sales (column iii) are estimated very imprecisely.[50] Finally, we find that a rise in imports is associated with an increase in the Herfindahl index at the local retail market level and thus a rise in local market concentration (column iv). The results are broadly similar when using a weighted regression approach (columns v to viii). By our estimates, a 1% increase in industry-level direct imports raises the Herfindahl index of local retail market concentration, ceteris paribus, by up to 0.042%. This is not a small effect, especially when considering that average market-level direct imports in the estimation sample more than doubled during the sample period and that, as shown in Table 1, the Herfindahl index is at a high level initially.

4.6 The role of indirect imports

The bottom line of our empirical analysis so far is that we tend to find support for our theoretical model. This is especially true when estimations are conducted at the firm level. But, even in the case of market-level regressions, we find relationships that are in line with model predictions, especially in cases where the theoretical model yields unambiguous comparative statics. The empirical results hence provide considerable evidence that observed changes in the performance of retailers and in structural changes in retail industries are driven at least partly by the increase in retailers' direct importing activities.

But how sure can we be that our findings are only related to retailers' direct imports, as suggested by our theoretical model? Could we not find similar effects at least for retail market structure from indirect imports of consumer goods, i.e. imports by wholesalers and other firms outside the retail sector? As far as our theoretical model is concerned, it would be straightforward, if somewhat tedious, to introduce indirect imports as an additional option for firms; this could be done without fundamentally changing the economic mechanism driving the results, at least as long as the wholesale sector is not as efficient in distributing imported goods as direct importers (see, for instance, Raff and Schmitt (2012) for further details). The bigger problem is that, as noted before, we do not observe firms' domestic sourcing activities and thus do not know whether they import goods indirectly, for instance, through wholesalers.

However, our data allow us to compute a proxy for indirect imports at the indus-

in this market.

[50] Notice, however, that the theoretical model itself does not deliver clear-cut predictions regarding the effect of imports on the number of shops and the first two moments of local retail sales. Specifically, Hypotheses 6 and 7 only hold for sufficiently small fixed costs of importing.

try level. Our strategy for generating such a proxy for indirect imports is based on exploiting two types of information available in the trade data. First, we observe a retail industry's mix of directly imported consumer good varieties. We define a retail industry's direct import share of a particular variety as:

$$sh_{scjt} = \frac{VIMP_{scjt}}{VIMP_{st}},$$

where $VIMP_{scjt}$ denotes direct imports by retail industry s of variety cj (defined by a country c and product j combination) in year t.[51] Second, we know total imports of each consumer goods variety conducted by non-retail firms, which we denote as $VIMP^{O}_{cjt}$, where superscript O indicates that these imports are generated by firms outside of the retail industry. Our proxy for a retail industry's indirect imports is then computed as:

$$VIMP^{O}_{st} = \sum_{cj} sh_{scjt} VIMP^{O}_{cjt}.$$

An important assumption underlying this measure is that an industry's direct imports are informative for its indirect imports. In particular, this variable does not capture indirect imports of varieties that are not imported by any directly importing retailer. Hence, this variable indeed is a rather rough proxy and the following results can only provide some suggestive evidence.

Table 13 presents the exit regressions, while Tables 14 and 15 present the results for market-level regressions. In each case, we run similar regressions as before, while we now also add the proxy for indirect imports to the models (and the corresponding interactions in case of the exit regressions). Interestingly, with one exception (column vi in Table 15), the variable $VIMP^{O}_{st}$ (or an interaction based on this variable) does not exhibit a statistically significant effect on an outcome of interest. Moreover, including this variable in the regressions has hardly any impact on the coefficient(s) related to direct imports. Thus, these results do indeed suggest that our findings are driven by retailers' direct import activities and are not merely related to more consumer goods imports coming to Denmark in general.

5 Conclusions

The paper used Danish microdata for the period 1999 to 2008 to examine the impact of the rapid growth of consumer goods imports on retail market performance and structure. Our results suggest that larger and more profitable retailers do not only self-select into importing, but that retailers' import activities are responsible for some of the performance differences observed between importing and non-importing firms. In particular, based on a propensity score matching approach, we find that retailers that

[51] The product dimension refers to the HS six-digit level. We concord these product codes over time following Van Beveren et al. (2012).

begin to import may have 8% greater sales, 6% greater profit, and 2% greater markups after beginning to import compared to non-importing firms. These differences are quite persistent and also hold for the growth rates of the considered performance measures. For instance, we find that cumulative sales of import starters may be up to 30% higher on average after three years than for comparable non-importers.

Regarding the other stylized facts we emphasized in the introduction, in particular the consolidation of retailers into chains, the exit of small retailers, and greater retail market concentration, we offer several pieces of evidence that link these processes to greater direct imports of consumer goods. First, in our firm-level estimations we find evidence suggesting that import initiation raises the probability of a retailer becoming a chain and adding new shops to its portfolio. We also detect indications for a positive relationship between the probability of exiting the market for small retailers and increases in sector-level direct imports. Moreover, we present evidence for a positive conditional correlation between greater direct imports and higher local retail market concentration as measured by the Herfindahl index. This increase in market concentration appears to be driven by a reduction in the number of retail firms associated with greater direct imports.

Taken together, these empirical results provide support for the economic mechanism explored in our theoretical model, namely that performance differences between importers and non-importers as well as structural changes in retailing are, *inter alia*, driven by direct importing: Due to economies of scale associated with direct importing, only big retailers and retail chains can afford direct imports, which means that they benefit more from trade cost reductions than small retailers that do not have access to these imports. We obtain additional evidence in favor of this mechanism by examining how indirect imports of consumer goods, i.e. imports by wholesalers and other firms outside the retail industry, affect retail markets in Denmark. Almost without exception, our proxy for indirect imports does not exhibit a statistically significant effect on firm exit, on aggregate retail productivity and markups, on the number of retailers, or on the Herfindahl index of retail market concentration.

We conclude that, viewed from a positive perspective, our model provides a plausible mechanism to explain some of the changes in retailing observed in Denmark and other advanced economies. Our paper thus complements the existing literature on retailing that generally attributes observed changes in retailing to technological change.

What, from a normative perspective, do our results imply for social welfare? In our theoretical model, social welfare, W, is approximately equal to:

$$W \approx 2Rn \int_0^{1/2n} (v - \tau x) L dx \tag{26}$$

$$- Rn \left(\int_0^{c_I} \left[(t + c) q^I(c)\right] dG(c) + \int_{c_I}^{c_D} \left[(w + c) q^D(c)\right] dG(c) \right) \tag{27}$$

$$- Rn_E[G(c_I)F_I + F_E] + (R - 1)n_E G(c_s)[F_I + F_E - F_S], \tag{28}$$

where the number of active shops in a given regional market, n, is related to the number of entrants, n_E, through $n = G(c_D)n_E$, and v is a consumer's reservation price for one unit of the aggregate consumption good. Thus welfare is approximately equal to consumer surplus net of the travel cost paid by consumers to reach the nearest retailer (26), minus the expected (variable) trade and production costs (27), minus the sunk cost of entry and the fixed costs of importing and operating shops in additional markets (28).[52]

Our empirical results indicate that increased consumer goods imports are negatively related to the number of retail firms, which may thus imply an increase in travel distances for consumers to reach a shop. As explained by Lagakos (2016), the social costs of greater distance are probably small in an advanced country like Denmark, where households tend to own cars and have access to efficient public transport. A greater welfare impact for an advanced economy can be expected to come from lower import prices, as retailers turn to imports instead of domestically sourced goods, and from the trade-induced shift of market share towards the bigger retailers and retail chains that import directly. The sourcing of lower-priced goods from abroad is, of course, a classic gain from trade. The increase in industry productivity stemming from a market share reallocation towards the big and therefore typically more efficient retailers is reminiscent of the effects highlighted in heterogeneous firm models of trade, such as Melitz and Ottaviano (2008). But, in the current paper, this productivity gain arises in retailing not in manufacturing, and thus represents an additional gain from trade that is not captured by traditional trade models. In the data we indeed tend to find some evidence for such a gain, namely a positive relationship between labor productivity and industry-level imports, which is, however, estimated somewhat imprecisely.

Another non-traditional gain from trade highlighted by our model consists of the potential cost savings associated with the trade-induced consolidation of shops into chains. These cost savings arise because chains can spread the fixed costs of importing (F_I) and the overhead costs that arise at the firm rather than the shop level ($F_E - F_S$) across their shops. A quantification of these welfare gains is beyond the current paper, but the strong increase in the number of retail chains and the fact that these chains are responsible for the lion's share of import activity in Danish retailing are indicative of substantial gains. That these gains are likely to be big is also suggested by Holmes (2011), who estimates the savings on distribution costs that Walmart realized when expanding the number of its stores, and by Holmes and Singer (2017), who find large savings in import costs for big retail chains like Walmart.

Any future study of the welfare gains from trade-induced changes in retailing would have to take a position on several additional aspects that we have not touched upon in our analysis. First, in many countries, retailing is highly regulated. Regulation, for instance of shop size or location, may limit the extent to to which the large, productive retailers in particular can adjust to trade (Eckel, 2009, and Raff and Schmitt, 2012).

[52] The expression is an upper bound on welfare, since the first term assumes that consumers on average travel 1/4 of the "distance" between any two shops, which would be the case if all retailers charged the same price. However, since prices vary across retailers in our setting, travel costs are strictly greater than shown here.

In the case of Denmark, retailers are subject to a zoning regulation that limits the maximum shop size.[53] The OECD indicator on the regulation of large outlets suggests that the zoning regulation in Denmark is not among the most restrictive and had been loosened somewhat at the end of our sample period.[54] But there are other countries, such as Australia, Canada and the United States, that do not systematically impose such regulations and therefore may have experienced bigger retail market adjustments to trade than Denmark. That this may indeed be the case is indicated by Basker and Van (2010b) and Holmes and Singer (2017) who document how Walmart has come to dominate both retailing and consumer goods trade in the United States.

Second, we did not examine changes in the product assortment of retailers, except to note that, over the sample period, Danish retailers substantially expanded the number of product varieties that they import directly. In the case of consumer goods, retailers, of course, play an essential role in determining the number of product varieties that consumers get to choose from, and their decisions regarding the product range are thus likely to have important welfare effects. Several recent theoretical studies explain how retailers expand their product range in response to trade liberalization, but they also show that the welfare effects may not be straightforward. Eckel (2009) explores the possibility that expanding the product range may lead to higher retail prices, thus potentially hurting consumers. He also shows that retailers may offer too little product variety compared to the social optimum. Raff and Schmitt (2016b) argue that the product range offered in equilibrium may be too broad. Their model, however, indicates that a consolidation of shops into retail chains would bring product variety closer to the socially optimal level, thus leading to additional gains that are directly related to the increase in the number of chains.

Third, we did not explore the relationship between retailers and manufacturers. As retailers are getting bigger and, as Feenstra and Hamilton (2006) suggest, gain power especially vis-à-vis overseas manufacturers, they may be tempted to use this power to extract greater rents from manufacturers. Raff and Schmitt (2009) examine this issue and show how the exercise of buyer power by retailers may lead to smaller gains from trade than indicated by models in which market power rests with manufacturers.

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[53] From 1997, the zoning law prohibited grocery stores larger than 3,000 sq.m (since 2007 larger than 3,500 sq.m) in urban areas; in rural areas, the size limit is 1,000 sq.m. For non-grocery stores, the zoning regulation implies a size limit of 2,000 sq.m, while large cities can grant three exceptions to this rule per year.

[54] The indicator is based on the following survey question: "If compliance with regulation especially designed for large outlets is required for any type of product, what is the threshold surface limit for these laws or regulations to apply (in m^2)?" See Koske et al. (2015) for a comparison of this indicator across OECD countries.

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Table 1: Retail firms over time

	i	ii	iii	iv	v	vi	vii
	Share of retail firms in total importing firms	Share of imports by retail firms in total imports	Average sales	Share of imports in sales	Average imports of importing firms	Share of importing firms	Herfindahl index
1999	12.2	9.2	10.0	3.5	5.0	7.1	0.24
2000	11.8	9.2	10.1	4.0	5.6	7.2	0.24
2001	11.9	8.9	10.3	4.0	5.8	7.0	0.25
2002	11.6	7.5	10.6	3.4	4.2	8.6	0.25
2003	12.1	8.6	10.3	4.1	4.5	9.5	0.25
2004	12.4	9.6	10.6	4.4	4.8	9.8	0.25
2005	12.6	10.9	10.7	5.4	5.7	10.1	0.24
2006	12.4	13.5	11.0	7.0	7.5	10.3	0.24
2007	12.5	13.7	11.5	7.7	8.2	10.8	0.24
2008	12.1	13.8	11.5	7.7	8.3	10.8	0.24

Notes: Sales and import values in million DKK in prices from 2000. The Herfindahl index is computed as the weighted average across local retail markets (weights are a market's yearly sales share). Imports refer to consumer goods imports.

Table 2: Retail shops over time

	i	ii	iii	iv
	No. of chains	Share in retail sales	Share of importers	Share in retail imports
1999	709	55.2	26.9	87.7
2000	755	56.9	24.8	86.9
2001	793	57.7	23.0	87.4
2002	853	63.6	26.0	86.7
2003	876	62.2	26.0	88.3
2004	960	61.7	26.7	88.4
2005	1027	64.1	27.0	89.4
2006	1094	63.5	26.6	91.0
2007	1046	63.8	28.0	91.3
2008	1264	64.1	23.4	92.3

Notes: Table is based on firms present in the data sets *FIRM* and *IDAS*. A chain is defined as a firm with at least two shops. Imports refer to consumer goods imports.

Table 3: Direct imports by chain and single-shop retailers (in 2005)

	i	ii	iii	iv
	Mean domestic sales	Mean em-ployees	Mean imports	No. of firms
Chain - importer	337.6	173.1	33.7	268
Chain - not importer	38.5	23.4	0.0	740
Not chain - importer	8.2	4.9	1.1	944
Not chain - not importer	6.6	4.0	0.0	8560

Notes: Data refer to retail firms with at least one employee that were active in 2005 and present in the data sets *FIRM* and *IDAS*. Columns i and iii in million DKK. Imports refer to consumer goods imports.

Table 4: Direct importing and firm performance - OLS (H2, H3)

	i	ii	iii	iv	v	vi
Dependent variable: Log of	Sales	Profits	Markup	Sales	Profits	Markup
$DIMP_{it}$	0.180	0.241	0.033	0.110	0.108	0.011
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.015)
$LN(EMPLOYEES_{it-1})$	0.847	0.557	-0.003	0.334	0.188	0.000
	(0.000)	(0.000)	(0.165)	(0.000)	(0.000)	(0.990)
Observations	92,021	79,251	75,370	92,021	79,251	75,370
R-squared	0.749	0.295	0.079	0.881	0.624	0.548
Firm fixed effects	no	no	no	yes	yes	yes
Mean of dependent variable	15.325	12.600	0.150	15.325	12.600	0.150

Notes: Firm-level regressions containing sector-year dummies. P-values referring to standard errors clustered at the firm level in parentheses. $DIMP_{it}$ is a dummy variable taking on unity if a firm imports consumer goods from outside EU15. $LN(EMPLOYEES_{it-1})$ refers to number of employees.

Table 5: Import starters and firm performance - OLS (H2)

	i	ii	iii	iv	v	vi
Dependent variable: Log of	Lagged (t-1)			Contemporaneous (t)		
	sales	profits	markup	sales	profits	markup
$START_{it}$	0.085	0.051	0.020	0.154	0.108	0.029
	(0.000)	(0.074)	(0.006)	(0.000)	(0.000)	(0.000)
$LN(EMPLOYEES_{it-1})$	0.838	0.515	-0.008	0.855	0.536	-0.012
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	78,220	57,556	60,752	78,220	57,556	60,752
R-squared	0.827	0.288	0.211	0.738	0.282	0.084
Mean of dependent variable	15.305	12.633	0.192	15.238	12.590	0.147

Notes: Firm-level regressions containing sector-year dummies. P-values referring to standard errors clustered at the firm level in parentheses. $START_{it}$ is a dummy variable taking on unity if a firm did not import in periods $t-2$ and $t-1$ and begins to do so in period t; it is zero for firms that have not imported during all three periods. Imports refer to consumer goods from outside EU15. $LN(EMPLOYEES_{it-1})$ refers to number of employees.

Table 6: Direct importing and firm performance - matching (H3)

	p	p+1	p+2	p+3
Panel a: Domestic sales				
$LN(SALES)$	0.084	0.084	0.104	0.110
	(0.000)	(0.000)	(0.000)	(0.000)
$\Delta LN(SALES)$	0.089	0.093	0.102	0.103
	(0.000)	(0.000)	(0.000)	(0.000)
Number of treated	1,355	1,152	943	766
Observations	69,025	54,910	41,469	31,256
Panel b: Profits				
$LN(PROFITS)$	0.064	0.097	0.090	0.115
	(0.015)	(0.002)	(0.012)	(0.004)
$\Delta LN(PROFITS)$	0.090	0.122	0.115	0.180
	(0.001)	(0.000)	(0.003)	(0.000)
Number of treated	1,041	828	645	488
Observations	50,329	36,954	26,765	18,496
Panel c: Markups				
$LN(MARKUPS)$	0.019	0.028	0.026	0.030
	(0.006)	(0.000)	(0.004)	(0.002)
$\Delta LN(MARKUPS)$	0.012	0.018	0.017	0.017
	(0.067)	(0.020)	(0.079)	(0.100)
Number of treated	1,073	872	677	523
Observations	52,598	38,976	27,854	19,863

Notes: P-values referring to standard errors clustered at the firm level in parentheses. Coefficients refer to a dummy variable indicating import initiation from non-EU15 markets ($START_{it}$) obtained from weighted firm-level regressions with weights derived by propensity score matching. Regressions control for covariates included in first-stage probit regression. Δ indicates that changes in the outcome variable are considered. Note that these differences are computed relative to pre-treatment status (i.e. relative to p-1). p refers to the year of treatment. Table A.11 in the Appendix presents means of the outcome variables considered in this table.

Table 7: Direct Importing and firm Performance - matching (H3) - placebo

	p-2	p-1
Panel a: Domestic Sales		
$LN(SALES)$	-0.005	-0.005
	(0.564)	(0.564)
Number of treated	1,355	1,355
Observations	69,025	69,025
Panel b: Profits		
$LN(PROFITS)$	0.006	-0.025
	(0.815)	(0.191)
Number of treated	911	1,041
Observations	42,536	50,329
$\Delta LN(PROFITS)$		-0.031
		(0.266)
Number of treated		911
Observations		42,536
Panel c: Markups		
$LN(MARKUPS)$	-0.001	0.007
	(0.943)	(0.231)
Number of treated	912	1,073
Observations	43,397	52,598
$\Delta LN(MARKUPS)$		0.008
		(0.260)
Number of treated		912
Observations		43,397

Notes: P-values referring to standard errors clustered at the firm level in parentheses. Coefficients refer to a dummy variable indicating import initiation from non-EU15 markets ($START_{it}$) obtained from weighted firm-level regressions with weights derived by propensity score matching. Regressions control for covariates included in first-stage probit regression. Δ indicates that changes in the outcome variable are considered. Note that these differences are computed using the $p-2$ samples, while considering the difference in the log of outcomes in $p-1$ and $p-2$. p refers to the year of treatment.

Table 8: Direct importing and consolidation into chains - OLS (H4)

	i	ii	iii	iv
Dependent variable	Chain dummy	New-shop dummy	Chain dummy	New-shop dummy
$DIMP_{it}$	0.058	0.024	0.011	0.007
	(0.000)	(0.000)	(0.023)	(0.075)
$LN(EMPLOYEES_{it-1})$	0.138	0.036	0.088	0.004
	(0.000)	(0.000)	(0.000)	(0.068)
Observations	88,319	87,437	88,319	87,437
R-squared	0.252	0.062	0.750	0.173
Firm fixed effects	no	no	yes	yes
Mean of dependent variable	0.098	0.025	0.098	0.025

Notes: Firm-level regressions containing sector-year dummies. P-values referring to standard errors clustered at the firm level in parentheses. $DIMP_{it}$ is a dummy variable taking on unity if a firm imports consumer goods from outside EU15. $LN(EMPLOYEES_{it-1})$ refers to number of employees.

Table 9: Direct importing and consolidation into chains - matching (H4)

	p-1	p	p+1	p+2	p+3
Chains					
CHAIN DUMMY		0.002	0.004	0.016	0.011
		(0.586)	(0.486)	(0.068)	(0.303)
Number of treated		1,074	887	723	582
Observations		58,318	44,968	33,323	24,461
New shops					
NEW-SHOP DUMMY	-0.002	0.010	0.010	0.022	0.019
	(0.625)	(0.054)	(0.154)	(0.017)	(0.085)
Number of treated	1,285	1,319	1,091	894	722
Observations	64,474	66,154	51,284	38,442	28,877

Notes: P-values referring to standard errors clustered at the firm level in parentheses. Coefficients refer to a dummy variable indicating import initiation from non-EU15 markets ($START_{it}$) obtained from weighted firm-level regressions with weights derived by propensity score matching. Regressions control for covariates included in first-stage probit regression. Table A.12 in the Appendix presents means of the outcome variables considered in this table.

Table 10: Direct imports and firm exit (H1)

	i	ii	iii
$DIMP_{it}$	-0.026	-0.026	-0.026
	(0.000)	(0.000)	(0.000)
$DSIZE_{it}$	0.165	0.167	0.167
	(0.000)	(0.000)	(0.000)
$LN(VIMP_{st})$	0.007	0.001	0.001
	(0.003)	(0.787)	(0.807)
	[0.018]	[0.770]	[0.786]
$DIMP_{it}\times LN(VIMP_{st})$	-0.001		0.001
	(0.617)		(0.478)
	[0.646]		[0.532]
$DSIZE_{it}\times LN(VIMP_{st})$		0.017	0.017
		(0.000)	(0.000)
		[0.016]	[0.014]
$LN(SALES_{st})$	0.020	0.019	0.019
	(0.068)	(0.075)	(0.077)
Observations	119,058	119,058	119,058
R-squared	0.067	0.071	0.071
Mean of dependent variable (exit dummy)	0.086	0.086	0.086

Notes: Firm-level regressions containing sector and year dummies. P-values referring to standard errors clustered at the sector level in parentheses. Square brackets present p-values referring to a wild bootstrap procedure with 1,000 replications. $DIMP_{it}$ is a dummy variable taking on unity if a firm imports consumer goods from outside EU15. $DSIZE_{it}$ is a dummy variable taking on unity if a firm belongs to the lower 25th percentile of the size distribution. $VIMP_{st}$ are direct sector-level consumer goods imports from outside EU15. $SALES_{st}$ are sector-level sales.

Table 11: Direct imports and market-level adjustments (H5)

	i	ii	iii	iv
	Unweighted regression		Weighted regression	
Dependent variable	$LN(PROD-UCTIVITY)$	$LN(MARK-UPS)$	$LN(PROD-UCTIVITY)$	$LN(MARK-UPS)$
$LN(VIMP_{st})$	0.022	-0.007	0.016	0.001
	(0.053)	(0.090)	(0.044)	(0.896)
	[0.204]	[0.154]	[0.128]	[0.894]
$LN(ASSETS_{rs,t-1})$	0.022	0.013	0.019	0.024
	(0.017)	(0.036)	(0.163)	(0.035)
$LN(MEANWAGE_{rs,t-1})$	0.005	-0.036	-0.019	-0.036
	(0.793)	(0.000)	(0.677)	(0.061)
Observations	13,697	13,697	13,697	13,697
R-squared	0.054	0.061	0.059	0.087
(Weighted) mean of dep. var.	12.815	0.244	12.864	0.282

Notes: Market-level regressions with market fixed effects and year dummies. Parentheses contain p-values referring to standard errors clustered at the sector level; square brackets present p-values referring to a wild bootstrap procedure with 1,000 replications. $VIMP_{st}$ are direct sector-level consumer goods imports from outside EU15. $ASSETS_{rs,t-1}$ are the sum assets of all firms present in a market. $MEANWAGE_{rs,t-1}$ refers to the average wage in the market. Weights in weighted regressions are based on industry sales shares.

Table 12: Direct imports and market-level adjustments (H6, H7)

	i	ii	iii	iv	v	vi	vii	viii
	Unweighted regression				Weighted regression			
Dependent variable	$LN(NO.\ FIRMS)$	$LN(MEAN\ SALES)$	$LN(STD.\ SALES)$	$LN(HER\text{–}FINDAHL\ INDEX)$	$LN(NO.\ FIRMS)$	$LN(MEAN\ SALES)$	$LN(STD.\ SALES)$	$LN(HER\text{–}FINDAHL\ INDEX)$
$LN(VIMP_{st})$	-0.034	0.022	0.018	0.034	-0.039	0.006	0.028	0.042
	(0.014)	(0.311)	(0.443)	(0.001)	(0.024)	(0.792)	(0.483)	(0.054)
	[0.034]	[0.508]	[0.486]	[0.014]	[0.030]	[0.884]	[0.774]	[0.134]
$LN(ASSETS_{rst-1})$	0.131	0.154	0.216	-0.080	0.103	0.163	0.212	-0.044
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.059)
$LN(MEANWAGE_{rst-1})$	-0.057	0.052	0.051	0.053	-0.035	0.059	0.061	0.063
	(0.008)	(0.001)	(0.200)	(0.003)	(0.203)	(0.420)	(0.688)	(0.163)
Observations	13,697	13,697	11,873	13,697	13,697	13,697	11,873	13,697
R-squared	0.070	0.104	0.051	0.030	0.064	0.113	0.079	0.025
(Weighted) mean of dep. var.	1.635	15.433	15.112	-1.114	2.203	15.885	15.869	-1.410

Notes: Market-level regressions with market fixed effects and year dummies. Parentheses contain p-values referring to standard errors clustered at the sector level. Square brackets present p-values referring to a wild bootstrap procedure with 1,000 replications. $VIMP_{st}$ are direct sector-level consumer goods imports from outside EU15. $ASSETS_{rs,t-1}$ are the sum of assets of all firms present in a market. $MEANWAGE_{rs,t-1}$ refers to the average wage in the market. Weights in weighted regressions are based on industry sales shares.

Table 13: Indirect imports and firm exit (H1)

	i	ii	iii
$DIMP_{it}$	-0.026	-0.026	-0.026
	(0.000)	(0.000)	(0.000)
$DSIZE_{it}$	0.165	0.167	0.167
	(0.000)	(0.000)	(0.000)
$LN(VIMP_{st})$	0.007	0.001	0.001
	(0.003)	(0.642)	(0.663)
	[0.028]	[0.696]	[0.662]
$DIMP_{it} \times LN(VIMP_{st})$	0.000		0.002
	(0.965)		(0.279)
	[0.952]		[0.378]
$DSIZE_{it} \times LN(VIMP_{st})$		0.016	0.016
		(0.000)	(0.000)
		[0.024]	[0.022]
$LN(VIMP^O_{st})$	-0.003	-0.005	-0.004
	(0.254)	(0.107)	(0.129)
	[0.494]	[0.252]	[0.292]
$DIMP_{it} \times LN(VIMP^O_{st})$	-0.004		-0.004
	(0.216)		(0.208)
	[0.216]		[0.192]
$DSIZE_{it} \times LN(VIMP^O_{st})$		0.002	0.002
		(0.808)	(0.824)
		[0.792]	[0.812]
$LN(SALES_{st})$	0.023	0.023	0.023
	(0.050)	(0.062)	(0.059)
Observations	119,058	119,058	119,058
R-squared	0.067	0.071	0.071
Mean of dependent variable (exit dummy)	0.086	0.086	0.086

Notes: Firm-level regressions containing sector and year dummies. P-values referring to standard errors clustered at the sector level in parentheses. Square brackets present p-values referring to a wild bootstrap procedure with 1,000 replications. $DIMP_{it}$ is a dummy variable taking on unity if a firm imports consumer goods from outside EU15. $DSIZE_{it}$ is a dummy variable taking on unity if a firm belongs to the lower 25th percentile of the size distribution. $VIMP_{st}$ and $VIMP^O_{st}$ are direct and indirect sector-level consumer goods imports from outside EU15, respectively. $SALES_{st}$ are sector-level sales.

Table 14: Indirect imports and market-level adjustments (H5)

	i	ii	iii	iv
	Unweighted regression		Weighted regression	
Dependent variable	$LN(PROD-UCTIVITY)$	$LN(MARK-UPS)$	$LN(PROD-UCTIVITY)$	$LN(MARK-UPS)$
$LN(VIMP_{st})$	0.022	-0.007	0.016	0.001
	(0.049)	(0.098)	(0.044)	(0.887)
	[0.200]	[0.200]	[0.130]	[0.896]
$LN(VIMP^{O}_{st})$	-0.000	-0.001	0.000	-0.003
	(0.983)	(0.875)	(0.985)	(0.801)
	[0.970]	[0.864]	[0.972]	[0.966]
$LN(ASSETS_{rs,t-1})$	0.022	0.013	0.019	0.024
	(0.017)	(0.036)	(0.153)	(0.034)
$LN(MEANWAGE_{rs,t-1})$	0.005	-0.036	-0.019	-0.037
	(0.791)	(0.000)	(0.671)	(0.054)
Observations	13,697	13,697	13,697	13,697
R-squared	0.054	0.061	0.059	0.087
(Weighted) mean of dep. var.	12.815	0.244	12.864	0.282

Notes: Market-level regressions with market fixed effects and year dummies. Parentheses contain p-values referring to standard errors clustered at the sector level. Square brackets present p-values referring to a wild bootstrap procedure with 1000 replications. $VIMP_{st}$ and $VIMP^{O}_{st}$ are direct and indirect sector-level consumer goods imports from outside EU15, respectively. $ASSETS_{rs,t-1}$ are the sum of assets of all firms present in a market. $MEANWAGE_{rs,t-1}$ refers to the average wage in the market. Weights in weighted regressions are based on industry sales shares.

Table 15: Indirect imports and market-level adjustments (H6, H7)

	i	ii	iii	iv	v	vi	vii	viii
	Unweighted regression				Weighted regression			
Dependent variable	$LN(NO.\ FIRMS)$	$LN(MEAN\ SALES)$	$LN(STD.\ SALES)$	$LN(HER\text{–}FINDAHL\ INDEX)$	$LN(NO.\ FIRMS)$	$LN(MEAN\ SALES)$	$LN(STD.\ SALES)$	$LN(HER\text{–}FINDAHL\ INDEX)$
$LN(VIMP_{st})$	-0.034	0.021	0.018	0.034	-0.039	0.004	0.026	0.042
	(0.014)	(0.331)	(0.435)	(0.001)	(0.024)	(0.850)	(0.529)	(0.055)
	[0.034]	[0.532]	[0.478]	[0.012]	[0.026]	[0.896]	[0.736]	[0.140]
$LN(VIMP^O_{st})$	0.001	0.014	-0.001	-0.005	-0.003	0.048	0.063	0.002
	(0.955)	(0.173)	(0.972)	(0.681)	(0.707)	(0.035)	(0.257)	(0.835)
	[1.000]	[0.178]	[1.000]	[0.718]	[0.712]	[0.014]	[0.350]	[0.902]
$LN(ASSETS_{rs,t-1})$	0.131	0.154	0.216	-0.080	0.104	0.159	0.206	-0.045
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.052)
$LN(WAGE_{rs,t-1})$	-0.057	0.053	0.051	0.053	-0.035	0.065	0.072	0.064
	(0.008)	(0.001)	(0.196)	(0.003)	(0.189)	(0.369)	(0.616)	(0.160)
Observations	13,697	13,697	11,873	13,697	13,697	13,697	11,873	13,697
R-squared	0.070	0.104	0.051	0.030	0.064	0.122	0.085	0.025
(Weighted) mean of dep. var.	1.635	15.433	15.112	-1.114	2.203	15.885	15.869	-1.410

Notes: Market-level regressions with market fixed effects and year dummies. Parentheses contain p-values referring to standard errors clustered at the sector level; square brackets present p-values referring to a wild bootstrap procedure with 1,000 replications. $VIMP_{st}$ and $VIMP^O_{st}$ are direct and indirect sector-level consumer goods imports from outside EU15, respectively. $ASSETS_{rs,t-1}$ are the sum of assets of all firms present in a market. $MEANWAGE_{rs,t-1}$ refers to the average wage in the market. Weights in weighted regressions are based on industry sales shares.

A Appendix

This Appendix contains supplementary material including proofs for the hypotheses derived from the theoretical model, summary statistics, details on markup estimations, and additional results in relation to propensity score matching.

A.1 Sufficient conditions for $0 < c_S < c_I < c_D$

To ensure that $c_I < c_D$, we assume that:

$$F_I > \frac{L}{4\tau} (w-t)^2 . \tag{29}$$

The condition $c_S < c_I$ requires

$$F_S > \frac{L}{\tau} \left(\frac{1}{4} (w-t) + \frac{\tau F_I}{L(w-t)} \right)^2 . \tag{30}$$

For $0 < c_S$ it is sufficient to assume that for the most efficient firm, and thus for $c = 0$, it is strictly profitable to become a chain, which requires:

$$F_S < \frac{L}{4\tau} (c_D + w - t)^2 . \tag{31}$$

A.2 Proof of Hypothesis 1

Using (2), (8) and (9), the expected zero-profit condition (12) can be rewritten as:

$$\begin{aligned}
\int_0^{c_S} \left[\frac{RL}{4\tau} (c_D + w - c - t)^2 - (R-1)F_S - F_I \right] \frac{kc^{k-1}}{c_M^k} dc \\
+ \int_{c_S}^{c_I} \left[\frac{L}{4\tau} (c_D + w - c - t)^2 - F_I \right] \frac{kc^{k-1}}{c_M^k} dc \\
+ \int_{c_I}^{c_D} \frac{L}{4\tau} (c_D - c)^2 \frac{kc^{k-1}}{c_M^k} dc - F_E = 0.
\end{aligned}$$

Applying the implicit function theorem and using the Leibniz rule, we obtain:

$$\frac{dc_D}{dt} = \frac{(R-1)c_s^k \left(w - t + c_D - \frac{k}{k+1}c_S\right) + c_I^k \left(w - t + c_D - \frac{k}{k+1}c_I\right)}{(R-1)c_s^k \left(w - t + c_D - \frac{k}{k+1}c_s\right) + (w-t)c_I^k + \frac{c_D^{k+1}}{k+1}} > 0, \tag{32}$$

since $w > t$, and $c_D > \frac{k}{k+1}c_I > \frac{k}{k+1}c_S$ due to $c_D > c_I > c_s$ and $k > 0$.

A.3 Proof of Hypothesis 2

From (10), we obtain:

$$
\begin{aligned}
\frac{dc_I}{dt} &= \frac{dc_D}{dt} - \left(\frac{1}{2} + \frac{2\tau F_I}{L(w-t)^2}\right) \\
&= \frac{dc_D}{dt} - 1 - \frac{c_D - c_I}{w-t}.
\end{aligned}
$$

Substituting for $\frac{dc_D}{dt}$, we obtain:

$$
\frac{dc_I}{dt} = \frac{Num}{Den} < 0,
$$

since:

$$
Den = (R-1)c_s^k\left(w - t + c_D - \frac{k}{k+1}c_s\right) + (w-t)c_I^k + \frac{c_D^{k+1}}{k+1} > 0,
$$

and:

$$
\begin{aligned}
Num &= (R-1)c_s^k\left(w - t + c_D - \frac{k}{k+1}c_S\right) + c_I^k\left(w - t + c_D - \frac{k}{k+1}c_I\right) \\
&\quad - \left(1 + \frac{c_D - c_I}{w-t}\right)\left[(R-1)c_s^k\left(w - t + c_D - \frac{k}{k+1}c_s\right) + (w-t)c_I^k + \frac{c_D^{k+1}}{k+1}\right] \\
&= -\frac{c_D^{k+1} - c_I^{k+1}}{k+1} - \frac{c_D - c_I}{w-t}\frac{c_D^{k+1}}{k+1} \\
&\quad - \left(1 + \frac{c_D - c_I}{w-t}\right)\left[(R-1)c_s^k\left(w - t + c_D - \frac{k}{k+1}c_s\right)\right] \\
&< 0.
\end{aligned}
$$

A.4 Proof of Hypothesis 3

Differentiating (6) and (8) with respect to t and using (32), we obtain:

$$
\frac{dq^D}{dt} = \frac{L}{2\tau}\frac{dc_D}{dt} > 0 \text{ and } \frac{d\pi^D}{dt} = \frac{L}{2\tau}(c_D - c)\frac{dc_D}{dt} > 0.
$$

Differentiating (7) and (9) with respect to t and using $\frac{dc_D}{dt} < 1$, we have:

$$
\frac{dq^I}{dt} = \frac{L}{2\tau}\left[\frac{dc_D}{dt} - 1\right] < 0 \quad \text{and} \quad \frac{d\pi^I}{dt} = \frac{L}{2\tau}(c_D + w - t - c)\left[\frac{dc_D}{dt} - 1\right] < 0.
$$

The result on markups and profits follows immediately, as markups are proportional to output.

A.5 Proof of Hypothesis 4

From (11) we have:

$$\frac{dc_s}{dt} = \frac{dc_D}{dt} - 1.$$

Note that $\frac{dc_D}{dt} < 1$, if:

$$c_D^{k+1} + kc_I^{k+1} > (k+1)\, c_I^k c_D, \tag{33}$$

where (33) is satisfied with equality for $c_D = c_I$, and the LHS increases faster with c_D than the RHS. This proves $\frac{dc_s}{dt} < 0$.

A.6 Proof of Hypothesis 6

$$\frac{dn}{dt} = \frac{\tau}{(c_D + w - \overline{p})^2}\left(\frac{d\overline{p}}{dt} - \frac{dc_D}{dt}\right). \tag{34}$$

Hence:

$$sign\left\{\frac{dn}{dt}\right\} = sign\left\{\frac{d\overline{p}}{dt} - \frac{dc_D}{dt}\right\}.$$

After substituting for$\frac{d\overline{p}}{dt}$ and $\frac{dc_D}{dt}$, we have:

$$sign\left\{\frac{dn}{dt}\right\} = sign\left\{\left(\frac{-1}{2(k+1)}\right)\frac{dc_D}{dt} + \frac{1}{2}\frac{c_I^k}{c_D^k} + \frac{k(w-t)}{2}\frac{c_I^k}{c_D^k}\left[\frac{1}{c_D}\frac{dc_D}{dt} - \frac{1}{c_I}\frac{dc_I}{dt}\right]\right\}. \tag{35}$$

For F_I equal to its lower bound ($F_I = \frac{L}{4\tau}(w-t)^2$), we have $c_D = c_I$, $\frac{dc_I}{dt} = 0$, and $\frac{dc_D}{dt} = 1$. Therefore:

$$sign\left\{\frac{dn}{dt}\right\} = sign\left\{\frac{k}{2(k+1)} + \frac{k(w-t)}{2c_D}\right\} > 0.$$

A.7 Proof of Hypothesis 7

The average sales volume of a shop is given by:

$$\bar{q} = q(\bar{p}) = \frac{L}{\tau}\left(\frac{c_D}{2(k+1)} + \frac{(w-t)}{2}\frac{c_I^k}{c_D^k}\right), \tag{36}$$

and the derivative with respect to t is:

$$\frac{d\bar{q}}{dt} = \frac{L}{2\tau}\left((w-t)\frac{c_I^{k-1}}{c_D^{k+1}}\left(c_D\frac{dc_I}{dt} - c_I\frac{dc_D}{dt}\right) - \frac{c_I^k}{c_D^k} + \frac{1}{k+1}\frac{dc_D}{dt}\right). \tag{37}$$

For F_I at its lower bound, we have $c_D = c_I$, $\frac{dc_I}{dt} = 0$, and $\frac{dc_D}{dt} = 1$. Using these values in (37), we obtain:

$$\frac{d\bar{q}}{dt} = -\frac{L}{2\tau}\left((w-t)\frac{1}{c_D} + \frac{k}{k+1}\right) < 0.$$

The variance of retail sales is given by:

$$\sigma_q^2 = \frac{L^2}{4\tau^2}\left\{\frac{kc_D^2}{(k+2)(k+1)^2} + \left((w-t)^2\left[1-\frac{c_I^k}{c_D^k}\right] + \frac{2k(c_D-c_I)(w-t)}{(k+1)}\right)\frac{c_I^k}{c_D^k}\right\}. \tag{38}$$

Evaluating the derivative at the lower bound of F_I we obtain:

$$\frac{d\sigma_q^2}{dt} = \frac{L^2}{4\tau^2}\left\{(w-t)^2\frac{k}{c_D} + \frac{2kc_D}{(k+2)(k+1)^2}\right\} > 0.$$

A.8 Summary statistics and sector definitions

Tables A.1 and A.2 contain summary statistics for the main variables used in the empirical analysis conducted at the firm level and market level, respectively. Table A.3 presents the retail sectors used in the empirical analysis.

Table A.1: Summary statistics - firm-level analyses

	obs	mean	sd	p10	p25	p50	p75	p90
$LN(SALES_{it})$	92,021	15.33	1.13	14.09	14.62	15.21	15.92	16.76
$LN(PROFITS_{it})$	79,251	12.60	1.13	11.23	12.01	12.66	13.25	13.85
$LN(MARKUP_{it})$	75,370	0.15	0.24	-0.15	-0.01	0.14	0.30	0.46
CHAIN DUMMY	88,319	0.10	0.30					
NEW-SHOP DUMMY	87,437	0.03	0.16					
$LN(EMPLOYEES_{it-1})$	92,021	1.18	1.03	0.00	0.00	1.10	1.79	2.48
$LN(PRODUCTIVITY_{it-1})$	90,900	12.75	0.48	12.23	12.51	12.74	13.03	13.33
$DIMP_{it}$	92,021	0.09	0.29					
EXIT DUMMY	119,058	0.09	0.28					
$LN(VIMP_{st})$	119,058	18.49	2.25	14.99	16.98	19.09	20.41	20.58
$LN(VIMP^{O}_{st})$	119,058	17.52	0.90	16.28	17.19	17.60	18.02	18.50

Table A.2: Summary statistics - market-level analyses

	obs	mean	sd	p10	p25	p50	p75	p90
$LN(FIRMS_{rst})$	13,697	1.63	1.08	0.00	0.69	1.61	2.30	3.09
$LN(MEAN\,SALES_{rst})$	13,697	15.43	1.03	14.42	14.79	15.24	15.84	16.71
$LN(STD.\,SALES_{rst})$	11,873	15.11	1.37	13.63	14.27	14.97	15.78	16.94
$LN(HERFINDAHL\,INDEX_{rst})$	13,697	-1.11	0.86	-2.30	-1.68	-1.06	-0.44	0.00
$LN(PRODUCTIVITY_{rst})$	13,697	12.82	0.28	12.51	12.65	12.79	12.97	13.16
$LN(MARKUP_{rst})$	13,697	0.24	0.19	0.01	0.12	0.23	0.36	0.49
$LN(ASSETS_{rst-1})$	13,697	16.34	1.59	14.40	15.24	16.22	17.38	18.51
$LN(WAGE_{rst-1})$	13,697	11.53	0.46	10.97	11.26	11.55	11.83	12.08
$LN(VIMP_{st})$	13,697	17.44	2.18	14.60	15.74	17.60	18.94	20.41
$LN(VIMP^{O}_{st})$	13,697	17.24	1.10	15.73	16.57	17.44	17.92	18.50

Table A.3: Sector classification

Nace codes	Sector description
52	Retail trade, except of motor vehicles and motorcycles; repair of personal and household goods
52.1	Retail sale in non-specialized stores
52.11	Retail sale in non-specialized stores with food, beverages or tobacco predominating
52.11.10	Grocer's shops
52.11.20	All-night shops
52.11.30	Supermarkets
52.12	Other retail sale in non-specialized stores
52.12.10	Variety stores
52.12.20	Department stores
52.4	Other retail sale of new goods in specialized stores
52.41	Retail sale of textiles
52.41.00	Retail sale of textiles
52.42	Retail sale of clothing
52.42.10	Retail sale of ladies' clothing
52.42.20	Retail sale of men's clothing
52.42.30	Retail sale of men's and ladies' clothing
52.42.40	Retail sale of baby articles and children's clothing
52.43	Retail sale of footwear and leather goods
52.43.10	Retail sale of footwear
52.43.20	Retail sale of leather goods
52.44	Retail sale of furniture, lighting equipment and household articles n.e.c.
52.44.10	Retail sale of furniture
52.44.20	Retail sale of carpets
52.44.30	Retail sale of furnishing fabrics
52.44.40	Retail sale of kitchen utensils, glass and china
52.44.50	Retail sale of articles for lighting
52.45	Retail sale of electrical household appliances and radio and television goods
52.45.10	Retail sale of electric household appliances
52.45.20	Retail sale of radio and television goods
52.45.30	Retail sale of records, CDs, cassettes, etc.
52.45.40	Retail sale of musical instruments
52.46	Retail sale of hardware, paints and glass
52.46.10	Retail sale of hardware
52.46.20	Retail sale of building materials
52.46.30	Retail sale of paints and wallpaper
52.48	Other retail sale in specialized stores
52.48.05	Retail sale of watches and clocks
52.48.10	Retail sale of watches, clocks and jewellery
52.48.15	Retail sale of jewellery
52.48.20	Retail sale of glasses
52.48.25	Retail sale of photographic equipment
52.48.30	Gift shops
52.48.35	Art shops and galleries
52.48.40	Retail sale of stamps and coins
52.48.45	Retail sale of sports goods
52.48.50	Retail sale of toys and games

52.48.55	Retail sale of pleasure boats and parts thereof
52.48.60	Retail sale of bicycles and mopeds
52.48.65	Retail sale of computers, office machinery and standard software
52.48.70	Retail sale of telecommunications equipment
52.48.75	Florist's shops
52.48.80	Retail sale of plants and seeds
52.48.85	Retail sale of pet animals
52.48.90	Retail sale of fuel oils and solid fuels for households
52.48.95	Sex shops
52.48.99	Retail sale of other goods

Notes: Sector definition used in paper: NACE four-digit except for sector 5248, where a more detailed sector definition is used. Usually, the six-digit sector codes are used; the exceptions are the aggregation of sectors 524805-524815, 524865-524870, and 524875-524880.

A.9 Markup estimation

As noted in the main text, we obtain a measure for firm-level markups following the methodology of De Loecker and Warzynski (2012), which builds on insights from Hall (1988) and relies on fairly modest assumptions; specifically, the approach rests on the assumptions that firms minimize costs and that there is at least one variable input that is free of adjustment costs. The methodology does not depend on a particular type of competition or functional form of demand, and it accommodates a variety of (static) price setting models. Specifically, the markup of firm i in period t, μ_{it}, can be obtained from the following relationship:

$$\mu_{it} = \frac{\varepsilon_{it}^{X}}{\alpha_{it}^{X} / exp(u_{it})}, \tag{39}$$

where α_{it}^{X} is the share of input X in total output of firm i, u_{it} is a correction factor for unobserved shocks to production, and ε_{it}^{X} represents the output elasticity of input X. While α_{it} is directly observable in our data, we require estimates of ε_{it}^{X} and u_{it}. Following De Loecker and Warzynski (2012), we obtain both objects by estimating a translog value added production function, as explained further below. Note that we use the output elasticity of labor to recover firm-level markups. Given the highly flexible labor market in Denmark, considering labor as the variable input that is free of adjustment costs appears reasonable.

We estimate the production function using a control function approach to deal with simultaneity problems related to unobserved productivity shocks. Specifically, we follow the insights of Ackerberg, Caves and Frazer (2015), while relying on material inputs to proxy for unobserved productivity, as suggested by Levinsohn and Petrin (2003).[55] The approach involves estimating the output elasticities using GMM techniques with the identifying assumption that productivity follows a first order Markov process. The adjustment factor u_{it} is obtained from the first stage of the estimation algorithm, as also recently documented by Brandt et al. (2017).

The implementation of the estimation approach requires firm-level variables on value added, labor, capital, and materials, which we obtain from the *FIRM* data set. We deflate value added, material inputs, and the capital stock using the consumer price index, a material goods price deflator, and a capital goods price deflator, respectively. The wage bill used to compute markups is also reported in the *FIRM* data set.[56]

Table A.4 presents estimates of the median output elasticities and markups by aggregated retail sector. Note that we estimate the production function separately for each of the sectors presented in the table. Additional summary statistics for markups are presented in Table A.1. Median markups of retail firms amount to 15% (the mean equals 20%), while the tables display a considerable degree of heterogeneity of markups across both sectors and firms.

[55] As suggested by De Loecker and Warynski, we control for a firm's import and export status in the estimation approach.

[56] When computing the markups, we trim the first and last percentiles of u_{it}, α_{it}^{X}, and μ_{it} to account for some extreme observations in the data.

Table A.4: Median output elasticities and markups by sector

	coeff. labor	coeff. capital	markup	obser- vations
Retail sale of textiles, apparel, footwear,	0.739	0.112	1.095	22,994
and leather goods	(0.118)	(0.058)	(0.297)	22,994
Retail sale of furniture, lighting equipment,	0.798	0.106	1.127	7,978
and household articles n.e.c.	(0.122)	(0.059)	(0.318)	7,978
Retail sale of electrical household app-	0.764	0.113	1.063	5,290
liances and radio and television goods	(0.107)	(0.053)	(0.285)	5,290
Retail sale of hardware, paints and glass	0.800	0.091	1.145	5,432
	(0.132)	(0.052)	(0.314)	5,432
Retail sale in non-specialized stores	0.780	0.147	1.167	18,196
(supermarkets, department stores)	(0.091)	(0.066)	(0.275)	18,196
Other retail sale in specialized stores	0.787	0.116	1.203	31,848
	(0.139)	(0.058)	(0.321)	31,848
All sectors	median	1.150		
	mean	1.199		

Notes: Standard deviation in parentheses.

A.10 Additional PSM results

In this section, we present some additional information about the propensity score matching (PSM) approach. First, we present estimation results for the probit model estimated in the first stage of the matching approach in Table A.5. The table contains results for the outcome variables sales, profits, and markups referring to the period $p = 0$. The covariates indicate plausible relationships. Larger firms (measured by total assets) have a higher probability of starting to import. The same holds for more productive firms as indicated by the positive coefficients of the (de-meaned and squared) productivity terms. Moreover, firms with larger sales growth are more likely to become importers. In Table A.6, we present results related to the balancing properties after applying radius matching with a caliper of 0.001. The results show that the matching strategy indeed leads to very similar means of the covariates. In particular, the p-values indicate that we can never reject the null hypothesis of equal means and we obtain very low numbers for the standardized bias. The balancing properties also hold when considering matched samples with outcomes in later periods. Table A.7 shows that the mean standardized bias is always well below three also in later periods (see Caliendo and Kopening (2008) for a discussion of the size of the standardized bias). This is also true for the alternative matching approaches depicted in the table. ATTs for these alternative matching approaches are presented in consecutive tables. First, we add the lagged (log-) level of the outcome variable to the probit model. We present these results in Table A.8, while noting that Imbens and Wooldridge (2009) point out that the inclusion of lagged outcomes may imply different identifying restrictions on the data. Second, Table A.9 contains results referring to exact matching by year and NACE four-digit sector which is a more restrictive matching approach. Third, results in Table A.10 are obtained when applying matching with a Gaussian kernel (bandwidth of 0.001). Overall, results are qualitatively similar across these tables. Finally, Tables A.11 and A.12 present means of the dependent variables considered in Tables 6 and 9 in the main text.

Table A.5: Probit regressions for samples with outcomes at p=0

	SALES	*PROFITS*	*MARKUPS*
$LN(PRODUCTIVITY_{it-1})$	0.016	-0.007	0.074
	(0.594)	(0.856)	(0.076)
$LN(EMPLOYEES_{it-1})$	0.033	0.037	0.061
	(0.179)	(0.191)	(0.034)
$SALESGROWTH_{it-1}$	0.106	0.091	0.081
	(0.000)	(0.003)	(0.012)
$WAGESHARE_{it-1}$	-0.269	-0.258	-0.124
	(0.093)	(0.201)	(0.556)
$LN(ASSETS_{it-1})$	0.155	0.150	0.158
	(0.000)	(0.000)	(0.000)
$LN(PRODUCTIVITY_{it-1})^2$	0.084	0.118	0.118
	(0.000)	(0.001)	(0.010)
Observations	77401	57362	60589
Pseudo R-square	0.0694	0.0706	0.0752

Notes: Table presents results from probit regressions with a dummy variable indicating import initiation from non-EU15 markets as dependent variable. Regressions contain NACE four-digit industry and year dummies. P-values in parentheses. $PRODUCTIVITY_{it-1}$ refers to value added per employee; $EMPLOYEES_{it-1}$ to number of employees; $SALESGROWTH_{it-1}$ to growth in domestic sales; $WAGESHARE_{it-1}$ to the share of wages in total sales; $ASSETS_{it-1}$ to total assets; and $LN(PRODUCTIVITY_{it-1})^2$ to the square of (demeaned) log productivity. $LN(\cdot)$ indicates log transformation.

Table A.6: Balancing properties after radius matching for samples with outcomes at p=0

	Mean Treated	Mean Control	standardized bias	p-value
Outcome Variable: $LN(SALES_{it})$				
$LN(PRODUCTIVITY_{it-1})$	12.797	12.794	0.6	0.881
$LN(EMPLOYEES_{it-1})$	1.305	1.297	0.7	0.862
$SALESGROWTH_{it-1}$	0.132	0.136	-0.9	0.821
$WAGESHARE_{it-1}$	0.178	0.177	1.4	0.709
$LN(ASSETS_{it-1})$	14.748	14.739	0.8	0.840
$LN(PRODUCTIVITY_{it-1})^2$	0.243	0.254	-2.0	0.604
Outcome Variable: $LN(PROFITS_{it})$				
$LN(PRODUCTIVITY_{it-1})$	12.858	12.853	1.4	0.763
$LN(EMPLOYEES_{it-1})$	1.249	1.253	-0.4	0.937
$SALESGROWTH_{it-1}$	0.127	0.128	-0.2	0.957
$WAGESHARE_{it-1}$	0.171	0.170	1.1	0.801
$LN(ASSETS_{it-1})$	14.713	14.712	0.1	0.980
$LN(PRODUCTIVITY_{it-1})^2$	0.178	0.181	-0.8	0.866
Outcome Variable: $LN(MARKUPS_{it})$				
$LN(PRODUCTIVITY_{it-1})$	12.818	12.813	1.3	0.764
$LN(EMPLOYEES_{it-1})$	1.472	1.477	-0.5	0.916
$SALESGROWTH_{it-1}$	0.112	0.117	-1.1	0.811
$WAGESHARE_{it-1}$	0.186	0.186	0.6	0.884
$LN(ASSETS_{it-1})$	14.903	14.902	0.1	0.985
$LN(PRODUCTIVITY_{it-1})^2$	0.172	0.177	-1.9	0.693

Notes: Table presents information about balancing properties of covariates after radius matching with a caliper of 0.001 for outcome variables sales, profits, and markups. $PRODUCTIVITY_{it-1}$ refers to value added per employee; $EMPLOYEES_{it-1}$ to number of employees; $SALESGROWTH_{it-1}$ to growth in domestic sales; $WAGESHARE_{it-1}$ to the share of wages in total sales; $ASSETS_{it-1}$ to total assets; and $LN(PRODUCTIVITY_{it-1})^2$ to the square of (demeaned) log productivity. $LN(\cdot)$ indicates log transformation.

Table A.7: Mean standardized bias after applying various matching approaches across all considered time horizons

	p	p+1	p+2	p+3
Baseline matching approach				
Sales	1.096	0.906	0.906	0.906
Profits	0.667	0.974	0.974	0.974
Markups	0.914	1.036	1.036	1.036
Lagged level of outcome variable included				
Sales	1.151	0.570	1.549	1.099
Profits	1.005	1.529	0.803	0.994
Markups	0.748	1.015	1.035	1.265
Exact matching by year and sector				
Sales	0.827	0.845	1.722	0.994
Profits	0.850	0.816	1.457	0.870
Markups	1.177	1.086	1.733	1.580
Matching using a Gaussian kernel				
Sales	0.556	0.650	1.105	0.989
Profits	0.719	2.154	1.912	1.017
Markups	0.771	0.828	1.266	0.859

Notes: Table presents information about the mean of the standardized bias of covariates in the probit model after applying the matching approach.

Table A.8: Direct importing and firm performance - matching (H3) with lagged outcomes in first-stage probit regression

	p	p+1	p+2	p+3
Domestic Sales				
$LN(SALES)$	0.098	0.092	0.121	0.118
	(0.001)	(0.009)	(0.002)	(0.008)
$\Delta LN(SALES)$	0.087	0.084	0.101	0.105
	(0.000)	(0.000)	(0.000)	(0.000)
Number of treated	1,354	1,154	943	943
Observations	68,871	54,635	41,479	31,357
Profits				
$LN(PROFITS)$	0.082	0.103	0.099	0.138
	(0.021)	(0.010)	(0.033)	(0.009)
$\Delta LN(PROFITS)$	0.072	0.095	0.090	0.122
	(0.012)	(0.006)	(0.033)	(0.015)
Number of treated	1,040	831	647	495
Observations	50,464	37,131	26,649	18,571
Markups				
$LN(MARKUPS)$	0.016	0.025	0.023	0.024
	(0.028)	(0.003)	(0.016)	(0.017)
$\Delta LN(MARKUPS)$	0.017	0.022	0.024	0.023
	(0.014)	(0.007)	(0.017)	(0.033)
Number of treated	1,076	876	679	522
Observations	52,418	39,312	28,075	19,974

Notes: P-values referring to standard errors clustered at the firm level in parentheses. Coefficients refer to a dummy variable indicating import initiation from non-EU15 markets ($START_{it}$) obtained from weighted firm-level regressions with weights derived by propensity score matching. Regressions control for covariates included in first-stage probit regression. Δ indicates that changes in the outcome variable are considered. Note that these differences are computed relative to pre-treatment status (i.e. relative to p-1.)

Table A.9: Direct importing and firm performance - matching (H3) by year and sector

	p	p+1	p+2	p+3
Domestic Sales				
$LN(SALES)$	0.085	0.085	0.103	0.116
	(0.000)	(0.000)	(0.000)	(0.000)
$\Delta LN(SALES)$	0.089	0.092	0.109	0.108
	(0.000)	(0.000)	(0.000)	(0.000)
Number of treated	1,331	1,127	910	734
Observations	52,961	40,638	30,093	20,852
Profits				
$LN(PROFITS)$	0.067	0.076	0.087	0.094
	(0.013)	(0.015)	(0.020)	(0.024)
$\Delta LN(PROFITS)$	0.099	0.103	0.116	0.151
	(0.000)	(0.002)	(0.004)	(0.002)
Number of treated	1,018	807	624	471
Observations	38,517	27,529	18,774	11,441
Markups				
$LN(MARKUPS)$	0.023	0.027	0.025	0.025
	(0.002)	(0.001)	(0.009)	(0.016)
$\Delta LN(MARKUPS)$	0.014	0.016	0.016	0.011
	(0.045)	(0.049)	(0.102)	(0.315)
Number of treated	1,043	848	646	495
Observations	38,146	26,531	17,658	11,740

Notes: P-values referring to standard errors clustered at the firm level in parentheses. Coefficients refer to a dummy variable indicating import initiation from non-EU15 markets ($START_{it}$) obtained from weighted firm-level regressions with weights derived by propensity score matching. Regressions control for covariates included in first-stage probit regression. Δ indicates that changes in the outcome variable are considered. Note that these differences are computed relative to pre-treatment status (i.e. relative to p-1.)

Table A.10: Direct importing and firm performance - matching (H3) using a Gaussian kernel

	p	p+1	p+2	p+3
Domestic Sales				
$LN(SALES)$	0.081	0.082	0.102	0.115
	(0.000)	(0.000)	(0.000)	(0.000)
$\Delta LN(SALES)$	0.088	0.092	0.101	0.109
	(0.000)	(0.000)	(0.000)	(0.000)
Number of treated	1,368	1,165	953	775
Observations	77,384	62,505	49,951	39,470
Profits				
$LN(PROFITS)$	0.069	0.101	0.092	0.098
	(0.009)	(0.001)	(0.011)	(0.013)
$\Delta LN(PROFITS)$	0.091	0.118	0.119	0.159
	(0.001)	(0.000)	(0.002)	(0.001)
Number of treated	1,049	841	657	504
Observations	57,348	43,375	32,794	24,518
Markups				
$LN(MARKUPS)$	0.022	0.030	0.027	0.029
	(0.002)	(0.000)	(0.003)	(0.002)
$\Delta LN(MARKUPS)$	0.012	0.018	0.015	0.015
	(0.069)	(0.016)	(0.103)	(0.149)
Number of treated	1,088	888	691	541
Observations	60,567	46,524	35,930	27,504

Notes: P-values referring to standard errors clustered at the firm level in parentheses. Coefficients refer to a dummy variable indicating import initiation from non-EU15 markets ($START_{it}$) obtained from weighted firm-level regressions with weights derived by propensity score matching. Regressions control for covariates included in first-stage probit regression. Δ indicates that changes in the outcome variable are considered. Note that these differences are computed relative to pre-treatment status (i.e. relative to p-1.)

Table A.11: Mean of outcome variables in Table 6

	p	p+1	p+2	p+3
$LN(SALES)$	15.383	15.395	15.418	15.480
$LN(SALES)$	-0.038	-0.041	-0.023	0.001
Observations	69,025	54,910	41,469	31,256
Profits				
$LN(PROFITS)$	12.774	12.836	12.894	12.992
$LN(PROFITS)$	-0.001	0.036	0.095	0.170
Observations	50,329	36,954	26,765	18,496
Mark-ups				
$LN(MARKUPS)$	0.165	0.171	0.175	0.178
$LN(MARKUPS)$	-0.029	-0.028	-0.016	-0.009
Observations	52,598	38,976	27,854	19,863

Notes: Mean refers to a weighted average with weights obtained from the matching approach.

Table A.12: Mean of outcome variables in Table 9

	p-1	p	p+1	p+2	p+3
CHAIN DUMMY		0.016	0.032	0.055	0.069
Observations		58,318	44,968	33,323	24,461
NEW-SHOP DUMMY	0.018	0.019	0.032	0.044	0.052
Observations	64,474	66,154	51,284	38,442	28,877

Notes: Mean refers to a weighted average with weights obtained from the matching approach.