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Offshoring and Patterns of Quality Growth: Evidence from Danish Apparel

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PRELIMINARY, COMMENTS WELCOME

Abstract

Recently a small empirical literature has taken off attempting to analyze the role that quality plays in our understanding of trade. In particular, the recent work of Khandelwal (2010) has brought the insights of structural IO models of demand to bear into trade data. Our work builds on this new structural literature; we use similar demand estimation techniques on a panel of Danish apparel firms from 1997 to 2010 in order to analyze how firms responded to China's entry to the WTO and the dismantling of the Multi-Fibre Agreement. We find substantial changes in the aggregate level as the distribution of quality tightens up and import competition appears to spur entry of higher quality firms and exit of lower quality producers. The reduction in trade costs leads to a massive increase in offshoring. The association of offshoring and quality depends on the quality of the sourcing country – while offshoring is generally associated with higher quality, offshoring to China is not. The reductions in trade costs also lead to changes in the distribution of prices and quality-adjusted prices. This has implications for policy as understanding the distribution of prices faced by heterogeneous consumers is key to understand how trade affects consumers along the income distribution.

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1 Introduction

Understanding product quality is instrumental to understanding the welfare gains from trade. At the aggregate level, import competition or access to new inputs can spur changes in the quality of goods that are offered to consumers. This paper seeks to understand how firms' output quality decisions are affected by changes in trade costs. Our research question is driven by two recent observations in the literature. First, there appears to be a great deal of heterogeneity in the quality of goods across countries within various aggregations of product definitions (Khandelwal, 2010; Hallak and Schott, 2011).¹ Second, there has been an explosion of growth in trades in intermediates, offshoring and supply chain disintegration (Yi, 2003). Put together, this suggests that in high-income countries, upstream producers may be sourcing from lower quality firms than they had been in the past (self-sourcing included). This naturally leads to a question of whether firms' importing of potentially lower quality inputs affects their output quality in an appreciable way.

Some current evidence from middle income countries suggest that access to *high* quality inputs from abroad can help induce quality upgrading (Eslava, Fieler and Xu., 2013). Our paper explores the opposite direction – the sourcing of inputs from low-quality producing countries by a high quality producing country. There is ambiguity in the possible response of quality: access to cheaper, potentially homogeneous inputs and a more competitive environment may lead to upgrading; however, if inputs themselves are differentiated and trade lowers the relative cost of lower quality inputs it may induce quality downgrading. Our findings both confirm and complicate previous work. At the aggregate level, we find that a large shock to trade costs was followed by a concurrent shortening of the quality ladder (i.e., the quality of goods became more similar), and a change in the distribution of quality with more weight lower on the ladder. We also see massive exit of lower end producers and entry of high end producers – suggesting that import competition may force out some low-end goods while spurring specialization in new high-end goods. At the firm level, we find that increased offshoring is associated with increasing one's ranking in the quality ladder. This is robust to a variety of controls. However, we find that when we focus on China, there is a negative association between increased offshoring to China and one's movement along the quality ladder. Cross-sectional analysis backs this up and the evidence strongly suggests that while in general sourcing from abroad seems to be associated with higher quality firms, sourcing to low-quality exporters undoes this association. When we look at how prices change we find that offshoring to low quality firms is associated

¹For example, Hallak and Schott find that the average difference between rich and poor countries by their measure to be .38 log points.

with relatively lower prices in the cross-section. This suggests that cost-savings are passed onto the consumer. However, when we adjust for relative quality, this association dissipates suggesting that cost savings from offshoring may not be as strongly reflected in prices.

When attempting to estimate the quality of goods, a host of econometric problems present themselves. Product quality itself is an unobservable and in most datasets used by trade economists there are no observable product characteristics that might act as a proxy. Moreover, there are endogeneity issues since price and quality are normally determined jointly. This has led to a literature that attempts to back out unobservable quality from information on prices and market shares, sometimes with the aid of a structural model. Following Khandelwal (2010), we employ demand models used in the IO literature to back out quality as a residual of a regression of market shares on price. We exploit a very rich dataset to construct plausibly exogenous instruments that allow us to weaken assumptions that the literature has made in the past.² The structural approach along with our instrumenting strategy allows us to model quality flexibly and separates price effects that may reflect changes to the competition faced by firms and not by changes in physical quality output.

In particular, we employ a novel dataset on Danish textile firms that contain highly disaggregated information on the import and export transactions of firms as well as information on their employees and production. With this data, we empirically document the response of quality, at the firm-product level, to changes in the opportunities for offshoring. We analyze apparel firms before and after China's entry into the WTO as well as the end of the Multi-Fibre Arrangement (MFA) – which led to the dismantling of nearly all quotas and tariffs on apparel in the EU. China entry in the WTO in late 2001 made it a part of the MFA and quotas on apparel and textile imports were slowly phased out, ending completely in 2008. As Denmark is a small country, but a member of the EU and WTO, the specific changes can be viewed as an exogenous change to Danish firms' foreign competition and their offshoring opportunities. As we will document, the industry went through a major change in the aftermath of these events, yielding substantial variation in access to and use of offshoring in the time-series as well as the cross-section. In addition, lowering the MFA induced massive import competition.

Our paper is related to several recent contributions in the literature. Both Bloom et al. (2012) and Utar (2013) provide strong evidence that increased competition from China led to massive restructuring and increased innovation, but do not explicitly focus on product quality. Kugler and

²A bevy of such datasets has led to the concurrent development of such instruments for different purposes. See e.g. Hummels et al. (2013).

Verhoogen (2012) document and model how larger and more efficient firms choose higher quality inputs and produce higher quality output that they sell at a higher price when the scope for differentiation is large enough. Closer to us, Amiti and Khandelwal (2013) extend Khandelwal’s analysis using product level data from 56 countries to the US and find that lower tariffs are associated with product upgrading for firms close to the world quality frontier, but discourage upgrading for firms distant from the frontier. Roberts et al. (2012) use firm level data about export by product and destination for Chinese footwear exporters and estimate a firm specific demand component together with a cost and an export market profitability components. They find that both the cost and demand components are related to firms’ success and they also document a reallocation of resources towards more productive and higher demand firms following the removal of EU quotas. However, none of these papers focus on how firm-level offshoring decisions in advanced economies are related to product quality. Analyzing this relationship is the aim of our paper.³

The remainder of the paper proceeds as follows. Section 2 provides a brief discussion on the Danish apparel industry as well as the Multi Fiber Arrangement and also presents some reduced form evidence about changes that occurred over time. Section 3 describes the various datasets that we use, while section 4 details our empirical methodology. Section 5 presents the results of our estimation and a discussion of the results. Section 6 concludes.

2 The Danish Apparel Industry and the End of the Multi Fibre Arrangement

The Danish apparel industry is concentrated predominantly in the medium to high end spectrum/segment of the fashion industry. Denmark has a well established reputation in producing original design. The sector represents more than 25% of the so called creative industries that were recently singled out by the Danish government as a major component for future growth. It also experienced a dramatic growth over the last decade, increasing revenue from DKK 37 billion in 2003 to DKK 56 billion in 2010.⁴

We identify our sample of firms in the apparel industry by looking at all firms that declared having produced at least one type of apparel product in the Survey of Manufacturers (see the next

³In addition to this growing empirical literature there is a theoretical literature on the interaction between offshoring and productivity that suggests offshoring affects output and wages in myriad channels that may push in opposite directions (Grossman and Rossi-Hansberg, 2008). While this literature is on productivity and quality, it suggests that the effects of offshoring on certain firm variables may be ambiguous and requires empirical analysis.

⁴See Erhvervs- og Vækstministeriet (2013), Danmark i arbejde - Vækstplan for kreative erhverv og design.

section for a detailed data description). Most firms are specialized in apparel, and we keep all firms with at least 90% of their sales in the apparel industry.⁵ An apparel product is defined as any product in the 2-digit categories 61 and 62 according to the Combined Nomenclature (CN).

Table (1) shows the most common products made by our sample of firms. As we can see, the most observed items in our dataset are relatively basic products, although they still incorporate a large Danish design component.

Starting in the 1970s, most trade in the apparel industry was governed by a series of quotas called the Multi-Fibre Arrangement (MFA), and later the Agreement on Textiles and Clothing (ATC). The MFA was phased out in several stages beginning in 1995 and ending in 2005. China entered the WTO in 2001 and by the end of 2001 had dismantled many restrictions on its textile trade and caught up to the transition path of other WTO members. Thus, China's entry into the WTO provided a large, new outsourcing opportunity for Danish firms starting around 2001. While China's entry into the WTO is the largest shock to the Danish textile industry, the phase out of the MFA/ATC in general led to large changes in the industry. In this section we outline a few of the key changes that occurred over the duration of our panel – especially in regards to the changing composition of firms engaged in the apparel trade as well as the import decisions of apparel manufacturers in particular.

From 1997 to 2010, imports of apparel in Denmark grew by 26.5% in real terms. However, in terms of net imports (i.e., subtracting out exports), Danish imports actually *fell* by 79.1%. This is not to say that Danish domestic production has become larger (in fact, their market share has remained relatively steady in terms of value). Rather, it implies that imported goods represent a larger component of the content of exports. This disparity paints a picture of an industry characterized by outsourcing and reexporting. That is to say, over time, firms that may have exported their own or domestically sourced production have turned to offshoring the production process. They now import finished goods and then run distribution in Europe locally.

These changes can be decomposed into firms that are pure importers and firms that manufacture and process apparel as well. For pure importers, imports increased by 43.2% over the period and decreased by 154.4% for manufacturers. Compositionally, manufacturers dropped from 18% to 2% of all apparel imports. However, within manufacturing, the *share* of apparel in imports of textile

⁵The distribution of sales is bimodal with a one peak around 90% and another around 1%. For the handful of firms between 1% and 90% of sales in apparel, we spot checked them and used industry codes to identify those firms were engaged in apparel. Leather goods, shoes and bedding do not fall under the 61 and 62 headings, so our spot checks admitted those firms to the sample.

intermediates rose by 5.8% over the length of the panel on aggregate. Moreover, this rise does not merely reflect the changing composition of firms or products. While there is much heterogeneity, the unweighted average apparel manufacturing firm increased the share of finished goods in their imports by 7.5%. This buttresses the original point – many manufacturing firms have moved from manufacturing with raw textiles to finishing and processing goods. Other firms have increased their offshore presence.

More evidence of this comes from the sourcing and exporting patterns of the firms involved. While the former underwent substantial changes, the latter changed very little. The customers of Danish apparel themselves appear to have changed little – in 1997, 85% of Danish apparel exports go to just 7 countries and these same countries constitute 75% of exports by the end of the sample. The countries themselves are all in Scandinavia and Western Europe, consistent with the idea that Denmark specializes in high quality apparel, which it exports to its rich neighbors. This pattern is similar when one breaks exports into those by pure importers and manufacturers.

While the exporting patterns change very little, there are drastic changes in the composition of imports. To discuss the changing composition of imports it helps to discuss apparel at non-manufacturing and manufacturing firms separately. For manufacturing firms, we focus predominantly on imports of raw textiles and apparel (that is to say, assembled goods that the manufacturing firms process or finish) and refer to these as intermediates. These goods constitute over the years anywhere from 40-80% of all imports done by apparel firms and on average constitute 60% of imports with a downward trend.⁶ As discussed above, there was a rise in the share of apparel in intermediate inputs for Danish firms. What is more interesting and relevant for an analysis of the global sourcing chain is the rapid increase in sourcing from Asian countries and in particular China. Figure 1 documents the rise of China in Danish apparel while Figure 2 breaks this down by domestic producers and pure offshorers and importers⁷. While movement to China was steadily growing, starting with its entry to the WTO trade with China began to rise rapidly and constitutes 45% of Danish apparel imports by the end of the sample. When we break things down by domestic producers and not, we see that offshoring to and importing from China climbs to 45% (and imports from China, Hong Kong and India climbs to 60%) for non-domestic firms and climbs from about

⁶This is actually an underestimate, especially later in the sample. Many of our firms have diversified away from consumer apparel into industrial apparel as well as other textile products such as bedding, shoes, bags, etc and also into leather goods. We don't include these in our definition of intermediates.

⁷We don't make much of this distinction, but our sample of non-domestic producers includes those Danish firms that do design at home but offshore production (pure offshorers) as well as those firms that are engaged mostly in retail, whole sale and distribution (traditional importers).

4 %to 16% for domestic producers. Moreover, in the latter group we see the collapse of work being done in Central and Eastern Europe (mostly Poland and Lithuania) and its being supplanted by trade with China and Turkey. Overall, there is robust evidence that the end of the MFA and China’s entry to the WTO resulted in massive changes in the Danish apparel industry – domestic producers moved their offshoring services from countries nearby to Asia while other firms began both offshoring to and importing directly from Asia.

3 Data

We employ several datasets provided by Statistics Denmark that paint a comprehensive picture of the apparel industry in Denmark. The key datasets are the universe of customs transactions (UHDI) as well as production data on all apparel manufacturers who employ at least 10 individuals *or* meet a revenue threshold (VARES). For each firm, we observe all of their product lines at the Combined Nomenclature (CN) 8-digit level.⁸ For each product line, we observe the product’s revenue value rounded to thousands of DKK and the number units sold. This allows us to construct unit value which we use as a proxy for price. It is well known that unit values can be a noisy measure of price – even at a highly disaggregated data the product definitions can mask heterogeneity that moves unit prices even when no price movement has occurred. Moreover, in our data set firms are prone to recording errors that are easily spotted. We clean our data in the following way:

1. Removing the top and bottom 1% in prices. In particular, we remove these *within* a product code and after removing year means. This helps remove outliers that most likely represent recording errors or unit-measure errors (e.g, unit values in the pennies or in the hundreds of thousands).
2. Removing those product lines with less than 45,000 DKK (roughly 7500 USD) deflated to the year 2000 price level. This is a similar cutoff employed by other papers in similar literature. This helps avoid rounding errors – because revenue is rounded to the thousands while units are recorded exactly, low revenue firms may end up with the same level of sales reported in our data set but radically different levels of quantity sold.
3. Removing product-years where the price differs by the median price by more than a factor of

⁸The Combined Nomenclature is the system for recording trade data used by the EU. The first 6 digits are the same as HS10 classifications and the last 2 digits are defined by the EU’s documentation. In the case of apparel, the last 2 digits distinguish weight and material used in construction of apparel.

1. This removes only a few observations that would not have been otherwise removed, but in our dataset we find that some product prices will spike in a single year by an order of magnitude from the norm. We assume these are recording errors hence their removal.

In addition to this product level data, from a third database (FIRE) we observe employment, intermediates use and capital at the firm level. As is usual in multi-product firm datasets, there is no mapping from firm-level inputs to product-level inputs so this level of disaggregation remain unobserved. In addition to data on sales and manufacturing inputs, we observe the universe of trade transactions in Denmark. The firms in both datasets can be linked together. This allows us to observe the import and export transactions of our apparel firms as well as other firms involved in the apparel industry. The import and export data includes values (without rounding) and quantities so we can construct unit values (a phrase we use interchangeably with price) for these goods as well. Combining these datasets allows us to construct our instruments, as discussed in the next section.

Our production data panel runs from 1997 to 2010, thus covering China's entry into the WTO, the beginning of the dismantling of the MFA, and the conclusion of this operation in 2005. Our data on trade begins in 1993 as does our data on employment and other firm side variables. Some of our aggregate statistics on trade exploit the full length of the panel, but mostly we focus on the time frame of 1997-2010 so that we can focus on those firms that we know are producing domestically and nothing else.

In addition to these datasets, we bring in several outside data sources. Data on quotas comes from the EC's SIGL database. This database includes product-level data on quota utilization, quota fill rates and license volume for the entire length of our panel. For data on exchange rates we used data published by the IMF's International Financial Statistics and the Federal Reserve's FRED Database.

4 Econometric Model

Before moving to the analysis of imported inputs and offshoring we first need to define more clearly our structural estimation procedure for extracting quality from price and sales data. This section outlines our econometric model, including consumer demands, timing assumptions and decision making by firms, as well as the details of mapping our model to data and instrumenting strategy.

4.1 Consumer Demand

For the estimation strategy that we'll eventually employ we need to map out two important, yet fairly general, models that will guide our results: consumer demand and firm production. We follow the recent work of Khandelwal (2010) and Amiti and Khandelwal (2013) in using the discrete choice framework common in IO and labor to model consumer demand. In particular, assume that consumer i has indirect utility for good (j, t) given by,

$$V_{ijt} = \delta_{jt} - \alpha p_{jt} + \epsilon_{ijt}$$

where δ_{jt} is a common taste for product jt , p is price and ϵ is a consumer specific taste shock for product jt . We assume that ϵ is distributed as generalized extreme value (GEV). The GEV distribution allows for more complicated substitution patterns than the more basic extreme value distribution. In particular, it allows for goods to be grouped into non-overlapping “nests.” This allows one to model the agent as first picking a nest, then conditional on their nest picking a good. Formally consumer i picks good jt iff

$$V_{ijt} \geq V_{ikt} \forall (kt)$$

Berry (1994) shows that as the number of consumers grows, the market share for product jt is given by,

$$s_{jt} = \underbrace{\frac{e^{(\delta_{jt} - \alpha p_{jt})/(1-\sigma)}}{\sum_{k \in \mathcal{J}_{g_j}} e^{(\delta_k - \alpha p_k)/(1-\sigma)}}}_{\text{Within Group Share}} \underbrace{\frac{\left(\sum_{k \in \mathcal{J}_{g_j}} e^{(\delta_k - \alpha p_k)/(1-\sigma)} \right)^{1-\sigma}}{\sum_g \left[\left(\sum_{k \in \mathcal{J}_g} e^{(\delta_k - \alpha p_k)/(1-\sigma)} \right)^{1-\sigma} \right]}}_{\text{Group Share in Total}}$$

where σ is a parameter that governs nest substitution, g indexes nests (or groups) and \mathcal{J}_g is the set of products in nest g . In the same paper he also demonstrates the following transformation of the data that allows for estimation of model parameters in a linear setting:

$$\log s_{jt} - \log s_{0t} = \delta_{jt} - \alpha p_{jt} - \delta_{0t} + \sigma \log s_{jt/g}$$

where s_{0t} is the market share of some outside good and $s_{jt/g}$ is the within group share of product jt . There are $J \times T$ observations here but a total of $(J + 1) \times T + 2$ parameters. Since we can only truly estimate $(\delta_{jt} - \delta_{0t})$ we are free to make one normalization and so we set $\delta_{0t} = 0$. This still leaves

the problem unidentified and so we adopt the practice of splitting the quality parameter into fixed effects and an error term. In particular we set, $\delta_{jt} = \delta_j^1 + \delta_t^2 + \delta_{jt}^3$ where the first term represents the average quality of good j , the second term represents a secular trend in quality growth and the third term is a product-time deviation. We will treat the last term as a regression error and so we have the new estimating equation,

$$\log s_{jt} - \log s_{0t} = \delta_j^1 + \lambda_t - \alpha p_{jt} + \sigma \log s_{j/g} + \delta_{jt}^3$$

where $\lambda_t = \delta_t^2 - \delta_{t0}$ is secular growth in quality *relative* to outside good growth – this subtlety will be very important later on. In general, δ_{jt}^3 is correlated both with price and the nest share. We will discuss our instrumenting strategy in detail in section 5. This strategy will depend on our model of firm production so we turn to that now.

4.2 Firm Decisions

We assume that the firm goes through three stages in each period – and only makes decisions in two of them. In the first stage, firms decide on their quality and production plan given expectations about costs and demand. In the second stage, a vector of costs shocks is realized and the firm produces. Finally, in the third stage, they set prices and compete. The timing here is typical in quality models and is similar to that found in Sutton (1998, 2012). The timing of the shocks is similar to that employed by Akerberg, Caves and Fraser (2006) – decisions are made after the realization of an initial TFP shock and then there is a second *ex-post* productivity shock.⁹ Notice that, as one would expect, price is mechanically correlated with quality through both its impact on the markup and the marginal cost. As usual, we solve this game using backward induction.

In the final stage of the period (after cost uncertainty has been revealed), firms set their prices and compete. Suppose as in Berry, Levinsohn and Pakes (1995) that there are F firms active on the market producing differentiated products. Each firm produces a subset Γ_f of the J products available on the market. Consider first the *short run* profit function of firm f :

⁹This timing assumption is admittedly not without loss of generality. While we do allow for predictable TFP shocks, De Loecker et al. (2013), for example, use price directly in the first stage of an OP-style production function estimation. Thus, in their model, unanticipated production shocks are by construction uncorrelated with price. In the industry we examine, apparel, the design and planning process happens, by definition, before production takes place while marketing and selling logistics occur after (Frederick and Staritz 2012). Thus, we think it reasonable to assume that “physical quality” – design and input sourcing – are determined before production cost shocks that price may respond to are realized.

$$\begin{aligned}\Pi_f &= \sum_{j \in \Gamma_f} (p_j - mc_j) q_j \\ &= \sum_{j \in \Gamma_f} (p_j - mc_j) M s_j(p, \delta; \vartheta)\end{aligned}$$

where q_j is the quantity of good j produced by the firm, p_j is the price of the product, mc_j is the marginal cost¹⁰, M is the size of the market and s is market share, that depends on the price vector, as well as the unobserved quality of the good, δ_j .¹¹ Maximizing profits with respect to price, we get the following FOC:¹²

$$s_j(p, \delta; \vartheta) + \sum_{j \in \Gamma_f} (p_j - mc_j) \frac{\partial s_j(p, \delta)}{\partial p_j} = 0$$

Given the pricing strategy, in the first stage the firm's expected profit is given by,

$$E \left(\sum_{j \in \Gamma_f} (p_j(\vec{\delta}, \epsilon) - mc(\vec{\delta}, \epsilon)) M s_j(p, \vec{\delta}; \vartheta) \right)$$

where we have momentarily used the vector notation to make explicit that the firms' decisions depend on the whole vector of choices. We assume that $mc(\delta_j, \epsilon)$ depends on quality and some vector of possible cost shifters that the firm has not yet learned. The expectation is over these shifters and of other firms' shifters (since they all jointly determine relative market shares). Firms choose quality to maximize profit, expecting a cost shock in the second stage and price competition in the final stage,

$$E \left(\sum_{j \in \Gamma_f} \left(\frac{\partial p_j}{\partial \delta_k} - \frac{\partial mc(\delta_j, \epsilon)}{\partial \delta_k} \right) s_j(p, \delta; \vartheta) + \sum_{j \in \Gamma_f} (p_j(\vec{\delta}, \epsilon) - mc(\delta_j, \epsilon)) \frac{\partial s_j}{\partial \delta_j} \right) = 0$$

After this, the shock ϵ is realized and firms produce. The crucial difference between this model and a model where quality and price are determined simultaneously is the presence of the expectation

¹⁰BLP models this as a function of the observed characteristics of each specific product w_j and an unobserved component ϖ_j . In the final stage, it is considered as given to the firm. Our assumption is that marginal cost is not known until quality decisions (now endogenous) have been made.

¹¹Since this model is for explanatory reasons rather than analytic results, we have allowed δ_j to indicate quality for both the firm and consumer; in general, all we would need is for there to exist a monotonic function $g(\xi_j) = \delta_j$ that maps from the firms' "physical quality" to the consumers' "tastes quality."

¹²While we allow for some general form of competition, as is standard in this literature we assume that the equilibrium is at the point where firms' solve their first order conditions (Caplin and Nalebuff, 1991).

operator in deciding on quality. Thus, while δ_j will depend on expectations of cost shocks, it will be uncorrelated with particular realizations. This assumption will allow us to exploit the orthogonality between certain cost shocks and unobserved quality in estimating the demand model’s parameters. This strategy parallels the proxy method of estimating production functions where one uses assumptions about timing of investment and hiring decisions relative to realization of productivity innovations to identify certain parameters.

For the eventual estimation of quality growth, we need no further assumptions on production. Our assumptions on demand structure are somewhat stronger, but follow the standard in industrial organization. We now turn to a discussion of the data as well as a more detailed look at the precise set of estimating equations and instrumenting strategy that we employ.

4.3 Nest Structure, Trade and Market Size

In the apparel industry, goods are split into knitted and crocheted wear and also woven wear. Our nests ignore this distinction and are based on combining 4 digit Combined Nomenclature codes which are the same as 4 digit HSIC codes. Thus, the nesting structure is based on the *type* of apparel product and ignores construction-method, fabric and weight (when available). The nesting structure respects gender whenever possible. In total there are 16 nests listed in Table 2 In our estimation, we remove the accessories category. This is a matter of over-aggregation *within* an 8 digit code – year to year price and quantity data is very erratic for such a broad category at the firm level. Within each nest, we observe products at the 8 digit level. These are highly disaggregated and normally include the particular type of garment, the material and sometimes characteristics or weight. For example, some products are “Men’s suits, of wool or fine animal hair, knitted or crocheted” and “Women’s knee-length stockings, measuring per single yarn less than 67 decitex, of synthetic fiber.” We will define a *variety* as a CN8 code *at* a particular firm. Thus, if 2 firms both make men’s wool suits, then they are counted as two separate varieties. This structure leaves us with around 3,000 varieties in the sample. As discussed in the section on consumer demand, we break up each variety’s quality into a fixed component, an economy-wide time varying component, and a product-time deviation.¹³

¹³At this time, our estimation ignores the distinction between domestic sales and foreign sales by firms. If exports and domestic sales are highly correlated, since we use market *share* measures instead of levels-measures, this problem is abated. In an extreme situation, if domestic sales (in quantities) were a constant fraction of total sales (i.e., $q_{ft}^{dom} = q_{ft}\theta_t$) for all firms, then there would be no problem with our estimates. If there is no systematic relationship between share of exports in output and our instruments, then our aggregation of exports and domestic quantities would lead to higher variance of our estimates but no bias. If the share of exports is systematically correlated with our instruments, then there is bias. It is difficult to sign this bias given our instrumenting strategy. In future iterations

Before discussing our instrumenting strategy, some discussion of the outside good is in order. As is typical in the demand literature, the outside good can often be very important for estimation. In our setting, because we use time-fixed effects, the choice of outside good will not matter for our estimates of any parameters or elasticities. However, the outside good will largely determine the shape of the time-fixed effects which determine aggregate changes in quality over time. This is obviously of great importance to our estimates. For the outside good we use the total quantity of imports into Denmark. This means that after quotas fall and imports into Denmark dramatically increase, the outside good grows and this influences our quality estimates. We will discuss interpreting this more in the results section. In effect, this fact leads us to focus on looking at how firms respond within time periods and over long differences instead of focusing on year-to-year differences. However, we also discuss several strategies based on movement along a unit-free quality ladder than helps to distinguish relative quality growth of firms.

4.4 Instrumenting Strategy

The standard endogeneity issue in demand estimation is that price will be correlated with the unobservable demand shock. This is also true of the nest share – and in fact, the unobservable is theoretically a direct input into a product’s within nest share. Hence, estimating this model relies on locating suitable instruments. The problem of finding plausibly exogenous instruments in the structural framework is that quality and price are chosen concurrently. In fact, many “cost shifters” that an econometrician might identify – e.g., wages – are almost certainly a reflection, at least partially, of the quality of an input. Given the discussion in section 3, we believe that *unanticipated* shocks to costs may actually be plausibly correlated with price but not with quality. This idea was exploited in the work of Foster, Haltiwanger and Syverson (2008) who used structural estimates of innovations to firm’s productivity as instruments. This particular strategy relies on the idea that output and input are homogeneous and so any differences in productivity truly reflect supply-side shocks. Our environment is one of vertically differentiated goods, and so we attempt to construct cost shocks directly.

Denmark’s size and location within the EU leads to an economy where the vast majority of firms engage in some trade. Our instrumenting strategy relies on the idea that trade, via exchange rate risk, leads to unanticipated cost shocks to the firm. In particular, we will use forecast errors

of this work we hope to fully incorporate the trade activities of the firm to get a more precise estimate of domestic output.

on exchanges as instruments. Implicitly we are assuming that a firm's quality is fixed conditional on the choice of a sourcing strategy and that at least some exchange rate risk is passed through in price. The source of variation arises from cross-sectional heterogeneity in import mixes across firms. To make things more explicit, we model exchange rates as a simple exponential AR(1) process:

$$e_{ct} = e_{ct-1}^{\rho_c} \exp(\mu_c + \sigma_c z_{ct-1})$$

Taking logs this can be expressed as an AR(1):

$$\epsilon_{ct} = \mu_c + \rho_c \epsilon_{ct-1} + \sigma_c z_{ct}$$

where c indexes countries, $z_{ct} \sim \mathcal{N}(0, 1)$, σ_c is the error variance and (μ_c, ρ_c) govern the AR process. The AR(1) was chosen because of the forecasting powers of simple random walks. After estimation one can construct forecast errors as,

$$\hat{\eta}_{ct} = \epsilon_{ct} - \widehat{E}(\epsilon_{ct})$$

The instrument is given by,

$$\zeta_{ft}^1 = \sum_c \hat{\eta}_{ct} s_{ft,c}^{imps}$$

where f indexes firms and $s_{ft,c}^{imps}$ is the share of firm f 's imports that are from country c .¹⁴ Notice that this instrument is measured at the firm level, while the demand equation is at the product level. Hence, we cluster all errors at the firm level.

To instrument for the nest share parameters, we use sales weighted averages of the cost shocks across a firm's *competitors* within a nest. This is similar in spirit to the approach used by Berry, Levinsohn and Pakes (1995), who use own product characteristics as instruments for price and average characteristics of firms' competing products as instruments for their nest share. The instrument is constructed as follows:

$$\zeta_{ft}^2 = \sum_{f' \neq f} s_{f't}^{sales} \zeta_{f't}$$

Aside from the issue discussed above, there are several possible threats to internal validity, and we attempt to address them now. First of all, since sourcing strategies are endogenously determined alongside quality our first instrument may be invalid. However, since all firms engage in some trade,

¹⁴We ignore those countries that are part of the European Exchange Rate Mechanism (ERM 2) as the Danish Kroner is pegged to the Euro (and varies less than 1% around the peg).

this problem only occurs if there is a systematic relationship between quality and the exchange rate risk posed by different countries. For example, if low-quality input countries also have higher exchange rate risk than high-quality input countries, the $E(\delta_{it}|\zeta_{ft}^1) \neq 0$. However, even if this were true this does not mean that exchange rate errors and unobservable quality are not uncorrelated. I.e., $E(\delta_{it}\zeta_{ft}^1) = 0$. This will still be true by our timing assumption and given that forecast errors are mean 0.

To conclude this section we briefly discuss the clustering strategy and particular choice of estimation method. Our instruments are firm level while the unit of observation is a product. It is also plausible that unobservable quality decisions may be autocorrelated for a particular product – in fact, we assume as much as we are studying quality upgrading. To address both of these concerns, we employ the two-way clustering strategy suggested by Cameron et al. (2000). Thus we allow for arbitrary correlation of demand across products within a firm each period, and across time for each period.

5 Results

5.1 Parameter and Quality Estimates Overview

For the sake of comparison, we run an OLS estimate, simple logit model and the full-blown nested logit. The results of the estimation are shown in table 3 along with a logit model and OLS estimate for comparison. First notice the expected biases in the OLS estimate. Both price and nest share are positively correlated with unobserved quality, which drives both coefficients up. In the simple logit model, the estimate of price is pushed up a great deal – this stems from omitting the nest share and imposing overly restrictive substitution patterns. The final nested logit model successfully removes the upward bias and all coefficients are significant – this is even with our fairly conservative clustering strategy which allows for arbitrary auto-correlation in the error term within products over time and also across a firm’s products in a given year.¹⁵ Our estimated price coefficient of $-.0077$ falls comfortably in the range of parameters estimated by Khandelwal (2011) for all industries, where the median estimated coefficient was $-.001$ and the IQR for all coefficients across industries was $.070$.¹⁶

¹⁵In fact, the most conservative possible clustering strategy would be by firm and allow for arbitrary cross-product-time correlations. We found that in this case our results are *more* precisely estimated. We have chosen to report the results that work the most against us since we still find them plausible and significant.

¹⁶Khandelwal ran his regression using 2 digit SITC industries to define a goods-market, defined 6-digit products as goods and defined country-product pairs as varieties. Thus, he is estimating a more aggregated system than we

Before turning to questions about trade and offshoring, we explore the plausibility of our results by looking at several statistics implied by our structural estimates. First, we can back out implied price elasticities that are derived from the nested logit model as follows:

$$\left| \frac{d \log s_j}{d \log p_j} \right| = \varepsilon = \alpha p_j \left[\frac{1}{1 - \sigma} - s_j - \frac{\sigma}{1 - \sigma} s_{j/g} \right]$$

where α is the price coefficient and σ the substitution parameter. In the event that $\sigma = 0$ this collapses to the familiar formula for logit demand. Figure 3 contains the density of elasticities implied by our estimates. They are fairly reasonable – the mean elasticity is 1.90 and the median is 1.66. There is substantial heterogeneity within nests and table 4 contains summary statistics by nest for the 5 largest nests. In this table we see that cross-nest heterogeneity in elasticities can be very high – with women’s coats and men’s coats (not pictured) containing many of the outliers. This might reflect either model rigidity – the same substitution parameter may not be right for all nests. However the assumption keeps things simple without an enormous cost to plausibility. It may also just reflect the idea that men’s coats and women’s coats have a disproportionately large number of high quality, highly inelastically demanded goods. The range of elasticities is a bit larger in absolute magnitude than those found by Khandelwal, but we believe that makes sense here as our more disaggregated goods might be more substitutable. Importantly the magnitude of elasticities is highly correlated with quality, which again suggests that the parameters that are estimated and implied by the model display internally valid properties. It’s important to note that nothing in our estimation forces these patterns to hold.

In addition to looking at the implied elasticities, we can see how our estimates of quality correlate unit values, adjusting for various confounders – a common approach in the literature. Table 5 below summarizes the correlation between price, quality, elasticity and size. As expected, quality and price are highly correlated – but imperfectly so. Price and size, measured by employment, are more correlated than quality and size – but all signs are positive. We cannot necessarily establish causality but it speaks to the idea that larger firms can exploit market power in addition to physical quality in order to raise prices. The work of Kugler and Verhoogen (2011) suggests that quality explains the correlation between size and price. One way to see if our results are consistent with this hypothesis is to run their reduced form regression of employment on price controlling for quality.

are but we take his estimates as a useful benchmark for comparison. See Roberts et al. (2012) for a similar study of the Chinese footwear industry using firm-level export data at the product level.

To that end we run the following regression:

$$\log P_{jft} = \alpha_j + \alpha_t + \beta \log Emp_{ft} + \gamma \delta_{jft} + \epsilon_{jft}$$

where δ_{jft} is our estimate of quality. Here, we purge the regression of product (at the CN8 level, not firm-CN8 pair) level and time fixed effects. For the sake of comparison, we also run a regression with full firm-CN8 pair fixed effects model – i.e., we also look at the coefficient employing only *within* firm-product variation. The results of this set of regressions are in table 6. We can see here that when we look at the price-size correlation controlling for observed quality, the coefficient decreases. If we look only at within product-firm variation, we find that the employment effect becomes insignificant while the importance of quality goes up considerably. In either specification, we find quality to be an important piece of the size-price correlation. Our quality estimates are positively correlated with price and size in statistically significant ways and help explain away part of a phenomena that they could not do if they were just noise. We take the collective results above as important proof that the quality estimates derived by the model do capture something non-trivial about firm’s products.

5.2 Quality Evolution and Quality Ladders

To think about how offshoring and the entry of China more generally impacted product quality, we need to be able to measure secular growth in quality. It turns out that in this methodology this is an impossible task without making completely unrealistic assumptions. However, as we will discuss in this section this does not mean analysis is dead. Instead, we focus on comparing quality ladders overtime – that is to say, looking at the shape of the distribution of quality *within* years as well as the effect of offshoring on movement along quality ladders. In this subsection we discuss the problems of comparisons over time, introduce methods for thinking about aggregate changes and discuss aggregate changes of quality over the time series. While looking at aggregate time series makes causality difficult, we present suggestive evidence of the effect of Chinese import competition at the aggregate level. In the next subsection we focus attention on the relationship between offshoring and quality upgrading – across firm variation allows for a more careful analysis to be conducted.

Recall that time fixed effects serve as secular shifters of quality *relative* to the outside good. Hence, if there is a large shock to the supply of the foreign good (such as quotas being dismantled or tariffs decreasing), then this will be picked up as a negative *demand* shock to domestic goods.

This is the one weakness of the approach taken here and suggests that while *within* year analyses are useful, there is a certain danger in looking across time. To make this point clearer, first let us introduce the following definition of *sales* weighted quality. I.e.,

$$Qual_t = \sum_j \delta_{jt} \frac{sales_{jt}}{\sum_i sales_{it}}$$

This is the measure of aggregate quality we will focus on. Ideally it would pick up secular growth in quality and we can look at quality changes relative to this trend to determine if goods are downgrading or upgrading. Figure 8 contains the evolution of sales weighted quality. This graph appears (with some noise) to trend upward from 1997 to 2004 or so then nose-dive around 2004 and 2005 as the MFA came to a close. Then, noisily, it appears to flatten out before beginning to move up again later in the sample. A large driver in the cumulative change of quality is the time fixed effects – these are almost entirely responsible for the huge drop in 2004. This is because the time fixed effects pick up changes to the “outside good” which here represents a massive influx of foreign goods into the Danish market.

To help tease apart the economic forces at play in this quality growth we use a decomposition of aggregate quality growth that is common in the productivity growth literature. In particular, we break out quality growth into the following components:

$$Qual_t - Qual_{t-1} = \underbrace{\delta_t - \delta_{t-1}}_{\text{Time Trend}} + \underbrace{\frac{N_{entrants}}{N_t} \delta_{it}^{Entrants} - \frac{N_{exits}}{N_{t-1}} \delta_{it-1}^{Exits}}_{\text{Composition}} + \underbrace{\Delta \delta_{it}^{Stayers}}_{\text{Idiosyncratic Growth}} + \underbrace{[Cov(\delta_{jt}, s_{jt}) - Cov(\delta_{jt-1}, s_{jt-1})]}_{\text{Reallocation}}$$

where s_{jt} is the sales share of product j at time t . The first term measures the secular change in quality that partially arises from changes to the outside good. The second captures the effect of entry and exit. The third captures the changes to firms that are present in both periods. Notice that within this effect are two smaller effects: the actual idiosyncratic changes to quality of surviving firms as well as the shifts in weight that these firms receive in the aggregate calculation. The last term captures the covariance between market share and quality. A major setback of this framework is the inability to separately identify supply shocks to the outside good and any secular changes in quality – any “industry-wide” effects are captured by the δ_t terms. However, the decomposition above allows for several insights. The mean growth terms that remain (the composition and idiosyncratic growth components) measure changes in quality relative to the outside good at time t . Another

way to think about this is to rewrite each δ_{it} as $\delta_{it} - \delta_{0t}$.

Figures (5)-(7) show the time fixed effects in *levels*, the composition effects (a growth rate) and again the evolution of the covariance term in levels. One can see that the dismantling of the MFA and fall of the quotas (in as much as these drive the time fixed effects) come out as a massive negative shock in the estimates that is particularly pronounced around 2004 and 2005. The graph of fixed effects demonstrates starkly the problem in looking at estimates over time. On the other hand, the other two figures give us some useful information on aggregate movements. Figure (6) plots the contribution of entry and exit to changes in the quality. One can see that there is a sharp upward trend in this graph. Moreover, it starts negative and ends the trend positive – reversing sign around the time China enters the WTO. To interpret this figure, think of the composition effect as *where* new entrants enter on the distribution of quality. The initial negative sign suggests that before the turn of the millennium new entrants were entering at the lower end of the quality distribution and had an aggregate negative effect on mean quality. However, after some time new entrants began to be of higher quality and pushed mean quality up and were entering on the upper portion of the quality distribution. It is impossible to determine whether the radical changes in trade barriers that occurred from 2001-2005 were alone responsible for this trend. However, the figure suggests at least some response – that import competition might drive quality upgrading in the aggregate by moving it at the extensive margin. The final figure plots the evolution of the covariance term between quality and market shares. This term appears to be flat around 2003, then drops considerably and flattens out again in 2005 and onward. A lower covariance between quality and marketshare may reflect the fact that new entrants are of relatively high quality but of low market share. However, it could also reflect a trend of quality *downgrading* among larger firms. It is difficult to discern these effects from each other since much of our analysis is about movement along the quality ladder. To the extent that it is the latter, the mechanisms that drive this would be hard to understand from such an aggregated level. Depending on price elasticities, if Chinese goods are substantially cheaper than they are of lower quality, it could induce at least some firms to downgrade quality in order to lower costs and prices enough to compete. In this way, Chinese import competition may induce some downgrading. The effects are most likely heterogeneous along the quality ladder. More importantly, without more detailed firm-level analysis it is impossible to more than suggest mechanisms from the evolution of aggregate variables.

Because of the inability to separately identify secular responses to quality and competitor supply shocks we cannot directly calculate the evolution of quality overtime for individual firms. However,

we *can* focus on the shape of the quality “ladder” as well as movement along the ladder to identify the effects of foreign competition as well as offshoring at the firm level. Our notion of the quality ladder defines a good’s position on the ladder at time t as

$$l_{jt}^1 = \delta_j + \delta_{jt} - \frac{1}{n_t} \sum_{i=1}^n (\delta_i + \delta_{it})$$

that is to say, it is the good’s quality purged of the time fixed effect and demeaned. Our quality ladder is unitless but cardinal and the difference between positions is not constant but a measure of the quality difference between different products.

The changing shape of quality ladder gives insight into aggregate changes. First, in order to get a sense of how the distributions of quality change, figure (8) plots the density of the ladder measure for several years. From the figure a few interesting patterns emerge. First, the right end point is shifting left over time. This suggests that the ladder “length” is becoming smaller over time. A plot of these lengths in figure (9) confirms this fact. The plots also suggest that the higher quality firms are shifting closer to the mean while the lower quality firms don’t seem to move. A final observation about shape changes is that the weighting of the distribution changes dramatically. There is a movement to sharper peaks and a shift towards weight in the left tails. This is hard to discern in the image but a plot of the skewness (Figure (10)) reveals a sharp trend towards slightly more negative skew – from a more positive skew early in the sample. These two facts taken together suggest two facts about aggregate changes in quality – first there appears to be some convergence in quality given the shrinking ladder and second there appears to be a shift to more producers of relatively lower quality and less of higher quality. It is important *not* to conflate this with a statement about the evolution of quality. It could be the case that all firms increased their quality and low quality firms increased theirs *more* or high quality firms increased theirs *less*. It could also be the case that aggregate quality shifted downwards. What we can say is that low quality firms either experienced relatively more quality growth or less quality downgrading – establishing a clearly heterogeneous pattern of quality growth. The latter story is more consistent with intuition and suggests that it’s likely that low quality firms upgraded their quality to some degree in response to foreign competition. The evidence in this section suggests that, while it is difficult to discuss aggregate evolution, the changing shape of quality ladders can be informative on how firms respond to import competition. However, this aggregate analysis *also* conflates the import competition effect with the effect of access to new foreign inputs. In the next section we use firm-level variation in

changes in offshoring activity along to tease out the relationship between offshoring and quality.

5.3 Firms' Quality Choices and Trade Regime Switches

Now we turn to the analysis of quality decisions by firms and offshoring. We will primarily be concerned with regressions of the form:

$$l_{jt} = \alpha_g + \beta \times Offshoring_{ft} + X_{ft}\gamma' + \epsilon_{jt} \quad (1)$$

where l_{jt} is a measure of ladder position, α_g is a fixed effect at either the good or firm-good pair level, X_{ft} is a potentially empty set of controls, $Offshoring$ is a measure of offshoring activity and β is our variable of interest. We will also run regressions of the form:

$$\Delta l_{jt} = \alpha_g + \beta \times \Delta Offshoring_{ft} + X_{ft}\gamma' + \epsilon_{jt} \quad (2)$$

where the Δ operator implies changes. This is not the same as taking the first regression in differences since we allow for product specific upgrading patterns and don't necessarily difference controls. The first regression answers the question of whether in the *cross-section* of firms, those firms that offshore more are more likely to be higher on the quality ladder. The second set of regressions answers the question of whether differential changes in firms' offshoring decisions lead to a differential movement along the quality ladder. While we can't directly observe quality upgrading, if firms that begin to offshore more become relatively higher (lower) quality it is more likely than not that they are upgrading (downgrading) quality rather than offshoring induces the opposite action by their competition. Before delving into the analysis, it's important to understand that these regressions can only describe associations in the data. In fact, our model assumes that firms make offshoring and quality choice jointly. Thus, one cannot interpret a negative coefficient on offshoring as a guarantee that low quality inputs will translate to lower quality output – it implies that firms that choose to [presumably] lower the input quality have concurrently chosen to lower their output quality.

A final step before presenting out results is defining the measure of offshoring. We closely follow the strategy of Hummels et. al. (2013) who employed the same dataset as well as Autor et. al. (2013); we define offshoring as the log imports per head where the imports we use are the kroner *value* of all apparel and textile inputs at the firm level. In terms of the combined nomenclature this means that any imports from headings 52-55; 60-62 were used in our definition of importing. Since

we are interested in China in particular we look both at total offshoring and also at the offshoring measure applied specifically to China.

Columns (1)-(3) in table 7 show the results for specification (1). These are the results of our cross-sectional analysis. The first regression regresses offshoring on ladder position. The second regression includes a control for lagged ladder position. Finally, the third specification contains controls for firm size and log exports – these aim to control for the fact that being large or being open generally may both correlate with offshoring activity and quality. In all of our specification we include fixed effects at the firm-product level; however, using product fixed effects alone or two-way fixed effects for products and firms returns similar coefficients that are also significant. The coefficient on our offshoring measure is positive and significant in all of our specifications. To get a sense of the size, the mean ladder length across time 7.50 while the coefficient in the complete specification is .125. Thus, a 1% increase in offshoring activity is associated with a movement on the quality ladder equal to roughly .017% of its length. It is difficult to translate ladder position to quality, much less utility, as these are all abstract concepts. Nevertheless, these are not trivial numbers and demonstrate that in the cross-section of firms engaging in higher offshoring activity tend to produce higher quality products. As a reminder, our model assumes that sourcing and quality is a joint decision of the firm. This backs up the evidence put forth by authors that suggests imported inputs can induce higher quality.

In addition to looking at offshoring activity on the whole, we can focus instead on looking at particular sourcing countries. As the greatest growth in importing activity occurred with China and the biggest trade shock facing Danish apparel firms was China’s entry to the WTO and the simultaneous dismantling of apparel quotas, we focus our attention on China. We augment the regression above as follows:

$$l_{jt} = \alpha_g + \beta \times ChinaOffshoring_{ft} + X_{ft}\gamma' + \epsilon_{jt} \quad (3)$$

The regression is similar to the first except we focus on Chinese imports per head. Our controls now include total offshoring in addition to employment and exports measures. Columns (4)-(6) of table 7 report the results of this new regression, where now the $\log(Offshoring)$ refers specifically to China. The coefficients aren’t as measured precisely as before – this is partially a result of having less observations – however, the coefficients are still significant in the majority of specifications.¹⁷

¹⁷The lack of observations reflects a selection bias since many firms choose not to import from China. If we think that Chinese imports do in fact impact output quality then it could be that high quality firms never source from

The coefficients are negative, but smaller in magnitude than the overall offshoring coefficient (in fact, smaller by a full order of magnitude when both coefficients are jointly estimated). This is strong evidence that firms that source from China are producing output of lower quality than competitors. *This might be due to the fact that cost saving is the major determinant for the decision to offshore to China.* This is, to the best of our knowledge, the first evidence that sourcing inputs from a low-quality producing country can induce lower output quality. This actually mirrors previous results that focused on developing and middle income countries. Using an estimate of $-.03$ an additional percentage point of imports per head from China is associated with a position equal to about $.005\%$ lower than otherwise would be expected. To gauge the relevance of quality downgrading one also needs to know prices. To that end we also run the following regression:

$$\log Price_{jt} = \alpha_g + \alpha_t + l_{jt} + \beta \times ChinaOffshoring + X_{ft}\gamma' + \epsilon_{jt}$$

where now we regress price on quality and measures of offshoring.

The results of this regression are in Table (9) where we include the same controls as before and we add time fixed effects to demean prices. In the specification with full controls, it seems that, after controlling for quality, there is no significant impact of offshoring to China on prices.¹⁸ In the other specifications, the coefficient is significant and negative, and the coefficient remains negative in all specifications. Thus, while offshoring may lower prices, this might go away once one controls for quality. This cannot be known for certain since we *do not* observe secular trends in quality. This is also *within* year analysis, and prices *are* going down over time. The conclusion to draw with these caveats in mind is that without a way to measure quality changes over time, it's impossible to explicitly calculate the effects on consumer welfare *but* there is evidence that relative (to the mean) price decreases that result from offshoring to China are tempered by subsequent relative decrease in quality.

In addition to looking in the cross-section we can focus on *within* product movement. That is to say, we can see how the relative position of products changes over time as they change their sourcing. Table (8) presents the results from the regressions in specification (2). The first regression contains no controls while the second controls for changes in total offshoring, exports and employment in

China. This could also be part of the precision problem. We experimented with linear probability models that estimated the probability of importing from China given quality and indeed found negative coefficients. However, a careful modeling of the selection decision would require more work than is done here and we omit these regressions.

¹⁸If prices are in levels instead of logs and demeaned for each year, then the coefficients become significant but are very small in magnitude.

levels. The latter variables control for the idea that big firms might both increase their offshoring over time and also increase their quality over time. The coefficients are similar in magnitude to the coefficients from the cross-sectional regression. To interpret this regression, a firm that increases its offshoring by a percentage point will see the equivalent of a gain in ladder position equivalent to .015%. This suggests that *within* products, firms that are choosing to upgrade quality are also choosing to source more. The particular mechanisms are hard to peg down, but we hypothesize that firms that offshore or able to economize on cheaper costs abroad in order to spend more money and management time at home on product design and development.

Once again, we repeat the regressions focusing on offshoring to China. The coefficients are more precisely estimated in this specification. The coefficients are negative and similar but smaller in magnitude to the cross-sectional regression. The effects are similar and a 1% increase in imports per head from China is associated with a decline in ladder position equivalent to .003%. While this may seem small, the mean increase in offshoring post-2001 was .445 log points – or about 45%. This is much larger than offshoring growth overall – which averaged 3% growth from 2002 onward (but was much more volatile). The strong positive effect of offshoring *within* year paired with the intense growth in trade with China suggests that product quality may have grown over time. This confirms that the intuition from research on middle income countries works in rich countries trading with middle income countries. In particular, it appears that those firms that choose to increase their offshoring abroad simultaneously downgrade their quality (relative to their competitors). Without identifying aggregate quality movements it’s impossible to know if these firms are actually downgrading over time or just upgrading substantially less than their competitors. Nevertheless, the conclusion to draw, once again, is that offshoring to low quality producers reflects itself in output quality.

6 Conclusion

In this paper, we used detailed information about the products made, imported and exported by firms to estimate a demand model and recover unobserved product quality. Our demand estimates are found to be in line with to the previous literature. We also find that quality differences between firms explains the size-price relationship documented by Kugler and Verhoogen (2012). We discussed the aggregate responses to MFA. We find that firms’ product quality is strongly affected by the change in the competitive environment and offshoring opportunities. We observed a tightening of

quality ladder together with a change in the shape of the quality ladder. We also documented how offshoring was positively related to product upgrading, although offshoring to China was associated with a decline in quality. This would tend to indicate that goods imported from China are cheaper and of lower relative quality. Indeed, we find that prices are negatively related to offshoring to China, but this relationship disappears once we control for product quality. Our work therefore suggests that globalization has not only led to more competition, but has also offered new opportunities for firms to take advantage of offshoring part of their production process. This has facilitated the growth of the Danish apparel industry, at the same time that it has changed the activities that they still undertake and the type of products that they design.

Appendix – Tables

Top 5 Products (by # of Producers)	
1997-2002	2002-2010
Cotton tee shirts	Cotton tee shirts
Cotton women's jerseys	Cotton women's jerseys
Syn. fiber women's blouses	Syn. fiber women's jerseys
Syn. fiber women's trousers	Syn. fiber tee shirts
Syn. fiber women's skirts	Cotton women's blouses

Table 1: Most Popular Products

Men's	Women's	Gender Neutral
Coats and jackets	Coats and jackets	Sweaters, jerseys, cardigans
Suits, jackets, blazers, trousers	Suits, jackets, dresses, skirts, trousers	t-shirts
Shirts	Shirts, blouses	Miscellaneous
Underwear, pajamas, gowns	Underwear, lingerie, gowns	Accessories
Sweaters, jerseys, cardigans	Sweaters, Jerseys, Cardigans	
Miscellaneous	Miscellaneous	

Table 2: Description of Nests

	OLS	IV: Logit	IV: Nested Logit
Dep Var:	$\log(s_{jft}/s_{0t})$	$\log(s_{jft}/s_{0t})$	$\log(s_{jft}/s_{0t})$
p_{fjt}	-.00013 (-1.16)	-.02129* (-1.82)	-.00768* (-1.89)
$\log s_{jgft}$.901*** (95.32)		.321*** (3.43)
Fixed Effects:	Firm-Product, Year	Firm-Product, Year	Firm-Product, Year
Clusters:	Firm	Product, Firm-Year	Product, Firm-Year
n	8378	(1554,953) 7586	(1554,953) 7586
1st Stage p-value - Price	-	.0928	.0369
1st Stage p-value - Nest	-	-	.0000
2nd Stage p-value	.0000	.0000	.0000

Standard errors clustered at the firm level. Point estimates reported with t-statistics in parentheses. ***-1%, **-5%, *-10%.

All estimation done using Stata's *xtivreg2*.

Table 3: Demand Estimation for Domestic Apparel

Nest	Mean	Q25	Q50	Q75
Women's Dresses	2.17	1.15	2.06	2.88
Women's Shirts	1.65	.911	1.61	2.16
Men's Suits	2.53	1.39	2.27	3.36
Women's Sweaters	1.45	.690	1.24	1.99
Women's Coats	3.43	2.07	3.33	4.82

Table 4: Detail on Elasticity Estimates

	<i>Quality</i>	$\log(\textit{Price})$	$\log(\textit{Employment})$	<i>Elasticity</i>
<i>Quality</i>	1			
$\log(\textit{Price})$.1408	1		
$\log(\textit{Employment})$.0978	.1785	1	
<i>Elasticity</i>	.2234	.9210	.1749	1

Table 5: Correlation between Price, Size and Quality

	(KV)	(1)	(2)
Dep Var: $\log P_{jft}$			
$\log Emp_{ft}$.1130*** (2.92)	.0989*** (2.72)	.0123 (.44)
δ_{jft}		.0509*** (12.92)	.1189*** (5.83)
Fixed Effects:	Year, CN8	Year, CN8	Year, Firm-CN8
Cluster:	Firm	Firm	Firm
	177	177	177
<i>N</i>	8132	8132	8132

Standard errors clustered at the firm level. Point estimates reported with t-statistics in parentheses. ***-1%, **-5%, *-10%.

Table 6: Estimating the Size-Price Correlation

	Offshoring in General			Offshoring to China		
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(\text{Offshoring})$.088*** (3.26)	.055* (1.94)	.125*** (4.16)	-.025 (-1.55)	-.031** (-2.38)	-.020* (-1.66)
l_{jt-1}		.359*** (11.01)	.334*** (10.93)		.321*** (8.29)	.301*** (8.44)
Fixed Effects:	Firm-CN8	Firm-CN8	Firm-CN8	Firm-CN8	Firm-CN8	Firm-CN8
Cluster:	Firm	Firm	Firm	Firm	Firm	Firm
	168	137	137	93	81	81
N	8009	5371	5371	5402	3705	3699

Standard errors clustered by Stata's `xtreg` command. Point estimates reported with t-statistics in parentheses. ***-1%, **-5%, *-10%.

Table 7: Offshoring and Quality Ladder Position in the Cross-Section

Dep Var: Δl_{it}	Offshoring in General		Offshoring to China	
	(1)	(2)	(3)	(4)
$\Delta \log(\text{Offshoring})$.084*** (2.99)	.112*** (4.37)	-.014* (-1.94)	-.021** (-2.53)
Fixed Effects:	Firm-CN8	Firm-CN8	Firm-CN8	Firm-CN8
Cluster:	Firm	Firm	Firm	Firm
	133	133	67	67
N	5298	5277	3323	3317

Standard errors clustered by Stata's `xtreg` command. Point estimates reported with t-statistics in parentheses. ***-1%, **-5%, *-10%.

Table 8: Offshoring and Quality Ladder Position – Differences

Dep Var: $\log Price$	(1)	(2)	(3)
$\log(\text{ChinaOffshoring})$	-1.27*** (-2.39)	-.925* (-1.78)	-.773 (-1.46)
l_{jt}		.138*** (7.63)	.138*** (7.45)
Fixed Effects:	Firm-CN8	Firm-CN8	Firm-CN8
Cluster:	Firm	Firm	Firm
	93	93	93
N	5402	5402	5396

Standard errors clustered by Stata's `xtreg` command. Point estimates reported with t-statistics in parentheses. ***-1%, **-5%, *-10%. Coefficients are reported multiplied by 100.

Table 9: Offshoring, Quality and Prices in the Cross-Section

Appendix – Figures

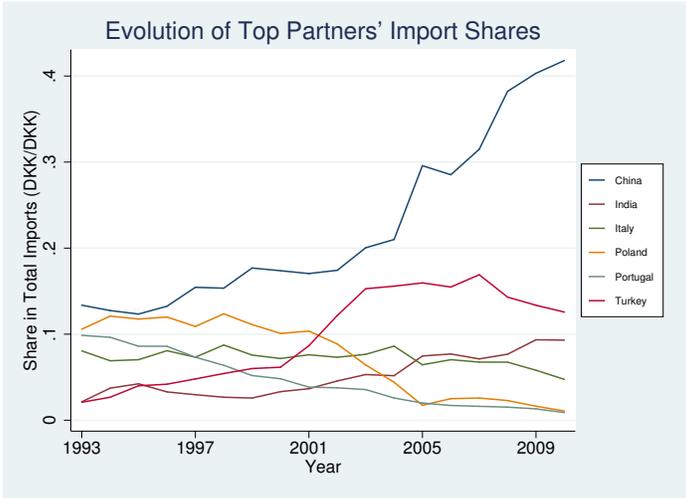


Figure 1: Changes in the Danish Apparel Industry

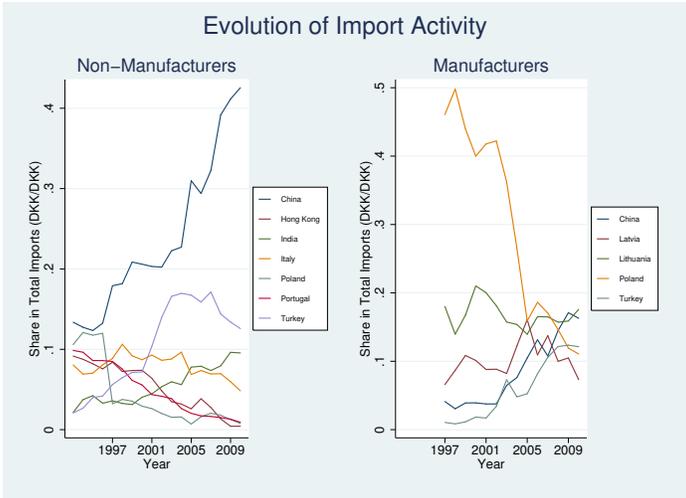


Figure 2: Growth of Chinese Share in Apparel Imports

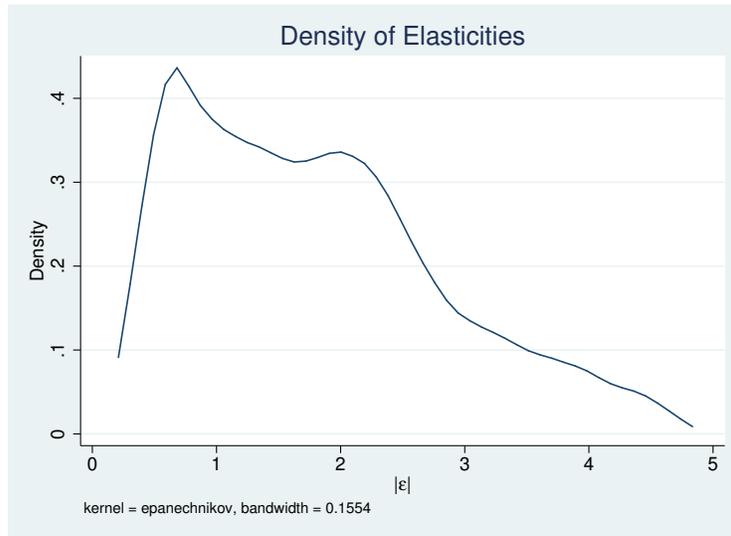


Figure 3: Density of Elasticities

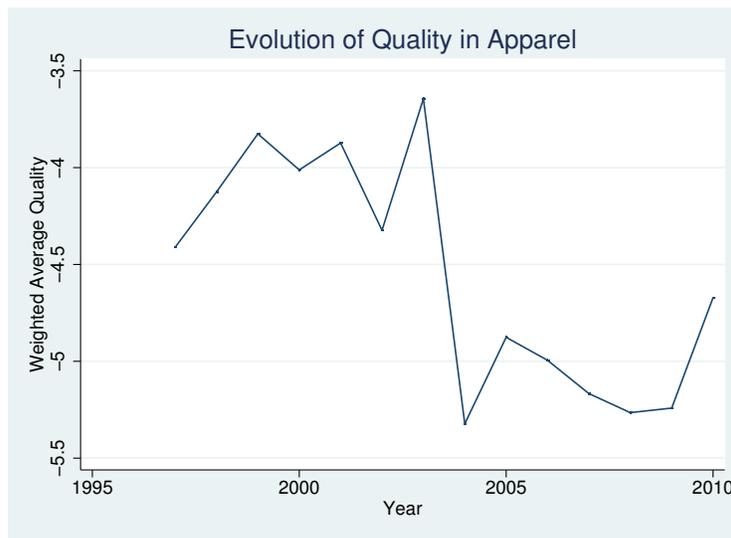


Figure 4: Evolution of Quality

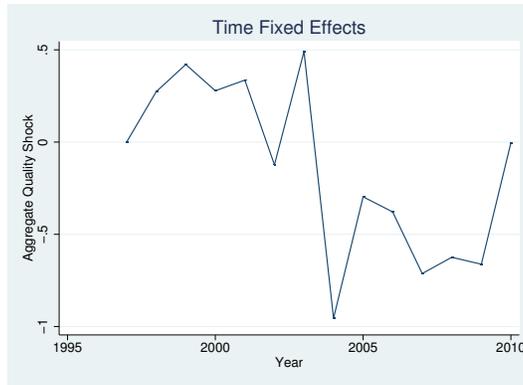


Figure 5: Series of Time Fixed Effects

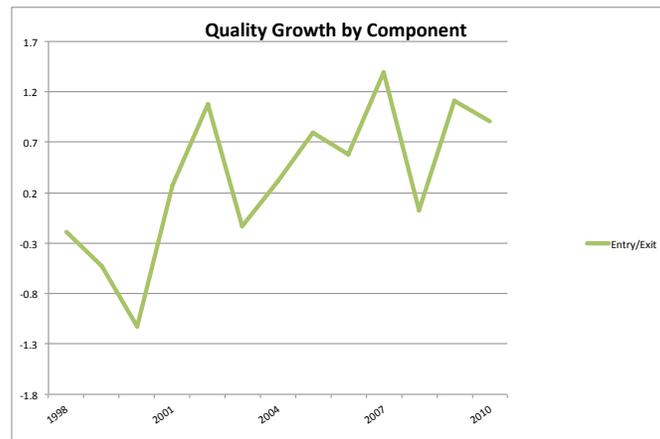


Figure 6: Entry/Exit Component of Quality Growth



Figure 7: Market Share-Quality Covariance Evolution

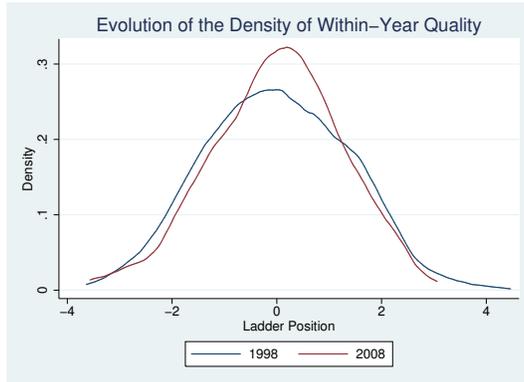


Figure 8: Evolution of Quality Ladders

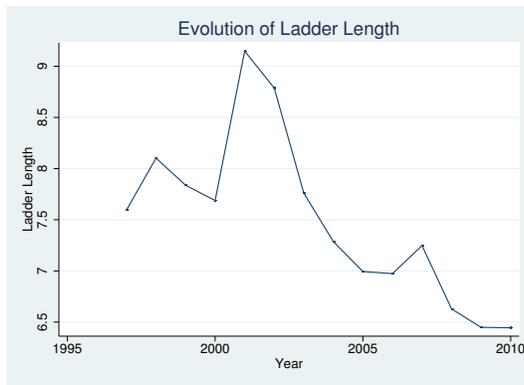


Figure 9: Evolution of Ladder Length

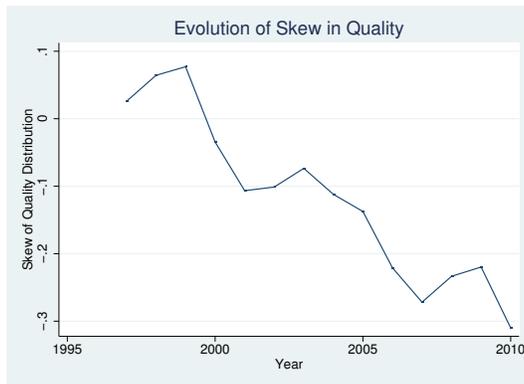


Figure 10: Evolution of Skew in Quality Ladder Distribution

References

- [1] Daniel Akerberg, Kevin Caves, and Garth Frazer. Structural identification of production functions. Technical report, University Library of Munich, Germany, 2006.
- [2] Mary Amiti and Amit K. Khandelwal. Import competition and quality upgrading. NBER Working Papers 15503, National Bureau of Economic Research, Inc, November 2009.
- [3] David H. Autor, David Dorn, and Gordon H. Hanson. The china syndrome: Local labor market effects of import competition in the united states. *American Economic Review*, 103(6):2121–68, October 2013.
- [4] Andrew B. Bernard, Stephen James Redding, and Peter K. Schott. Comparative advantage and heterogeneous firms. *Review of Economic Studies*, 74(1):31–66, 2007.
- [5] Steven Berry. Estimating discrete-choice models of product differentiation. *RAND Journal of Economics*, 25(2):242–262, 1994.
- [6] Steven Berry, James Levinsohn, and Ariel Pakes. Automobile prices in market equilibrium. *Econometrica*, 63(4):841–90, 1995.
- [7] Nicholas Bloom, Mirko Draca, and John Van Reenen. Trade induced technical change? the impact of chinese imports on innovation, it and productivity. NBER Working Papers 16717, National Bureau of Economic Research, Inc, January 2011.
- [8] Irene Brambilla, Amit K. Khandelwal, and Peter K. Schott. China’s experience under the multi-fiber arrangement (mfa) and the agreement on textiles and clothing (atc). In *China’s Growing Role in World Trade*, NBER Chapters, pages 345–387. National Bureau of Economic Research, Inc, 2010.
- [9] Paula Bustos. Trade liberalization, exports, and technology upgrading: Evidence on the impact of mercosur on argentinian firms. *American Economic Review*, 101(1):304–40, 2011.
- [10] Andrew Caplin and Barry Nalebuff. Aggregation and imperfect competition: On the existence of equilibrium. *Econometrica*, 59(1):25–59, January 1991.

- [11] Jan K. De Loecker, Pinelopi Koujianou Goldberg, Amit Kumar Khandelwal, and Nina Pavcnik. Prices, markups and trade reform. NBER Working Papers 17925, National Bureau of Economic Research, Inc, 2012.
- [12] Marcela Eslava, Ana Cecilia Fieler, and Daniel Yi Xu. Trade, competition and quality-upgrading: A theory with evidence from colombia. 2012 Meeting Papers 471, Society for Economic Dynamics, 2012.
- [13] Gene M. Grossman and Esteban Rossi-Hansberg. Trading tasks: A simple theory of offshoring. *American Economic Review*, 98(5):1978–97, 2008.
- [14] Juan Carlos Hallak and Peter K. Schott. Estimating cross-country differences in product quality. *The Quarterly Journal of Economics*, 126(1):417–474, 2011.
- [15] David L. Hummels, Rasmus Jørgensen, Jakob Roland Munch, and Chong Xiang. The wage effects of offshoring: Evidence from danish matched worker-firm data. NBER Working Papers 17496, National Bureau of Economic Research, Inc, 2011.
- [16] Amit Kumar Khandelwal. The long and short (of) quality ladders. *Review of Economic Studies*, 77(4):1450–1476, 2010.
- [17] Maurice Kugler and Eric Verhoogen. Plants and imported inputs: New facts and an interpretation. *American Economic Review*, 99(2):501–07, 2009.
- [18] Maurice Kugler and Eric Verhoogen. Prices, plant size, and product quality. *Review of Economic Studies*, 79(1):307–339, 2012.
- [19] Mark J. Roberts, Daniel Yi Xu, Xiaoyan Fan, and Shengxing Zhang. A structural model of demand, cost, and export market selection for chinese footwear producers. NBER Working Papers 17725, National Bureau of Economic Research, Inc, January 2012.
- [20] John Sutton. *Technology and Market Structure: Theory and History*, volume 1. The MIT Press, 1 edition, 2001.
- [21] John Sutton. *Competing in Capabilities: The Globalization Process*. Oxford University Press, 2012.
- [22] Håle Utar. When the floodgates open: "northern" firms' response to removal of trade quotas on chinese goods. Technical report, Bielefeld University, 2012.

- [23] Eric Verhoogen. Trade, quality upgrading, and wage inequality in the mexican manufacturing sector. *The Quarterly Journal of Economics*, 123(2):489–530, 2008.
- [24] Kei-Mu Yi. Can vertical specialization explain the growth of world trade? *Journal of Political Economy*, 111(1):52–102, February 2003.

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