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JEL Classification: F12, F14, L13

Keywords: export participation, Strategic interaction, multiple equilibria, trade policy

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Superstar Exporters: An Empirical Investigation of Strategic Interactions in Danish Export Markets*

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August 27, 2020

Abstract

In many countries, exports are highly concentrated among a few "superstar" firms. We estimate the export decisions of superstar firms as the result of a complete information, simultaneous, discrete choice, static entry game. We employ a dataset on the universe of Danish trade transactions by firm, product and destination. We also obtain detailed information on applied, preferential tariff protection from the MAcMap-HS6 database. We find evidence of strong negative competitive effects of entry: in the absence of strategic competitive effects, firms would be 53.2 percentage points more likely to export to a given market. Next, we run two counterfactual exercises. We show that failing to account for the strategic interaction among superstar exporters leads to: *(i)* overstating the probability that firms would start exporting to a market following tariff elimination by a factor of two; and, *(ii)* overstating the probability that firms would stop exporting to a market if tariffs were imposed by a factor of more than five.

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1 Introduction

In many countries, exports are highly concentrated among a few "superstar" firms (Freund & Pierola, 2015). For example, in the United States, the top 1 percent of exporters accounted for 80 percent of total exports in 2000 (Bernard et al., 2007). In Denmark, the top 1 percent of exporters accounted for 47 percent of total exports in 2007, and, on average, the top 5 firms in an industry accounted for 80 percent of exports. Motivated by these observations, we conduct an empirical analysis of export decisions where superstar firms behave strategically. Then, we use our estimated model to run two counterfactual exercises and investigate the effect of changes in tariffs on the export decisions of the superstar firms.

Our main objective is to contribute to the understanding of the role of superstars in international trade. Despite the dominance of a few large exporters in world trade, trade models have traditionally relied on a monopolistic competition setting, where firms are infinitesimal in scale, take prices as given, and compete non-strategically (see Neary, 2010). Recently, trade economists have been developing new theoretical models with oligopolistic markets; i.e., markets where only a few dominant firms compete.[1] These new models feature firms that behave strategically, so that the decision of each firm is influenced by the decisions of its competitors. However, this literature remains to date mostly theoretical, and the prediction that the export decisions of oligopolistic firms are interdependent has not been tested empirically. In this paper, we aim to fill this gap in the literature.

To develop our analysis, we apply the econometric approach in Ciliberto & Tamer (2009) to model the export decisions of firms as a complete information, simultaneous, discrete choice, static entry game. Compared to previous studies on firms' export decisions, the unit of analysis is not the individual firm but the market, defined as an

[1] See, in particular, Neary (2015), Eaton et al. (2012), Bekkers & Francois (2013), Koska & Stähler (2014) and Parenti (2018). There is an earlier literature of oligopolistic markets and trade building on Brander (1981) and Brander & Krugman (1983), but this literature has arguably remained much less influential than either the perfect competition or monopolistic competition settings; see Neary (2010) for a review.

industry-destination combination; and the outcome of interest is the market equilibrium, defined as a vector of market-specific participation decisions of all Danish superstars. The key assumption is that a firm enters an export market only if it makes non-negative profits. To solve the game we use the notion of Nash equilibrium, whereby all firms are maximizing profits and no firm would want to unilaterally change its participation decision. In a discrete choice setting, this leads to a set of moment inequalities, which we estimate using Ciliberto & Tamer (2009).

The main parameters of interest in our empirical model are the effects of the strategic interaction, or "competitive effects", which capture the effect that a firm's export decision has on its competitors' export decisions. Standard models of oligopoly predict a negative effect, as a competitor's market entry reduces other firms' profits, and thus entry. However, positive effects are possible in the presence of positive externalities including informational spillovers, which are particularly important in an international trade context.[2] While the earlier literature on entry games assumes, for identification reasons, that the competitive effect is known to be negative (see Bresnahan & Reiss (1990) and Berry (1992)), the econometric approach of Ciliberto & Tamer (2009) allows for both positive and negative effects.

We use two datasets in our analysis. First, we employ a register database provided by Denmark Statistics, which covers the universe of trade transactions by firm, product and destination. This database allows us to identify superstar exporters and to empirically model their export decisions. Second, we obtain detailed information on applied, preferential tariff protection in 2007 from the third version of the MAcMap-HS6 database (Guimbard et al., 2012). We use these data to run our policy experiments.

We find evidence of strong negative competitive effects. On average, in the absence of competitive effects superstar firms would be 53.2 percentage points more likely to export

[2]The literature on export spillovers shows that firms are more likely to start exporting to markets already served by other domestic firms; see *inter alia* Aitken et al. (1997) and Koenig et al. (2010). Choquette & Meinen (2015) present evidence on positive export spillovers based on Danish data. We differ from this literature in two respects. First, we focus on superstar exporters; i.e., the set of firms for which strategic interactions may be relevant. Second, we estimate an equilibrium model for the market outcome, which allows us to explicitly take into account the simultaneity of export decisions.

to a market. This implies that the presence of other Danish competitors in a specific export market significantly reduces profits and hence export participation. This finding has important implications for trade policy. As trade is liberalized, positive effects on profits are counter-balanced by negative effects due to competitor entry. Estimates that do not take these competitive effects into account will therefore overestimate the entry response due to trade liberalization.

We run two counterfactual exercises in order to quantify these biases. First, we simulate the effects of eliminating tariffs in markets where tariffs are imposed. Secondly, we simulate the effects of introducing tariffs in markets where trade is duty-free. In both exercises, we compute the new equilibria for the export markets, and compare results with and without competitive effects between firms. Allowing for competitive effects between firms, we find that eliminating tariffs would increase the export propensity by 6.5 percentage points while introducing tariffs would decrease the export propensity by 2.4 percentage points. In a framework without competitive effects, in contrast, these effects of trade policy on export entry and exit would be overestimated by a factor of two to five.

Finally, we find that a given superstar's effect on its competitors' export decisions depends on the number of other countries where the firm is exporting its variety. The heterogeneity in the competitive effects implies that there exist multiple equilibria, both in the identity and in the number of firms. Thus, the flexible methodology proposed by Tamer (2003) and Ciliberto and Tamer (2009) is appropriate to study the strategic behavior of superstar exporters. The finding that multiple equilibria are important empirically may be also be informative for the theoretical literature that aims at incorporating oligopolistic interactions into trade models. To date, this literature typically imposes uniqueness of the market equilibrium; e.g., by assuming sequential entry of firms as in Gaubert & Itskhoki (2018) and Eaton et al. (2012).

This paper contributes to the growing literature on the importance of large firms for aggregate fluctuations (di Giovanni & Levchenko, 2012) and on the role of superstar exporters as drivers of export patterns and comparative advantage (Freund & Pierola, 2015; Gaubert & Itskhoki, 2018). We augment this literature by modeling the strategic interaction between large exporters in their export market choices.

Our paper is also closely related to the literature on the determinants of firms' export market decisions; see, in particular, Roberts & Tybout (1997), Bernard & Jensen (2004) and Das et al. (2007). To date, this literature has treated observations on individual firms as independent. In contrast, we model the export decision as the outcome of oligopolistic strategic interactions. Our policy experiments build on previous studies that have found positive effects of tariff liberalization on export participation (Bernard et al., 2011; Buono & Lalanne, 2012). We extend this line of work by showing that the direct (positive) effect on profits as trade is liberalized is partly offset by an indirect (negative) effect resulting from the entry of competitors.[3]

Finally, we contribute to the empirical literature on models with moment inequalities, which has been steadily growing in the last few years.[4] Our paper complements Morales et al. (2019) and Dickstein & Morales (2018). Both of these two papers use moment inequality conditions, the first one to show that having similarities with a prior export destination in geographic location, language, and income per capita jointly reduces the cost of foreign market entry; the second one to show that larger firms possess better knowledge of market conditions in foreign countries.

This paper proceeds as follows. Section 2 presents the empirical approach. Section 3 introduces the data and discusses observed market structures. Sections 4 and 5 present results from single agent (probit) estimations and the equilibrium model, respectively. In Section 6 we do comparative statics exercises to measure the effect of changes in the exogenous variables on the export propensity of the firms. In Section 7 we perform our two counterfactual exercises where we eliminate tariffs in markets that have positive tariffs, and we introduce tariffs in markets that do not have tariffs. Section 8 concludes.

[3] An earlier theoretical literature starting with Brander & Spencer (1985) analyzes how governments may use strategic trade policy to shift profits from foreign to domestic firms. Here, instead, we only consider the effects of trade policy on the strategic interaction between domestic firms.

[4] See, e.g., Ciliberto et al. (2016), Ho & Lee (2017), Jia (2008) and Ho & Pakes (2014).

2 Empirical Model of Export Decisions

We build on previous models of export market entry (see, e.g., Roberts & Tybout, 1997), with the key innovation being that we allow for strategic interactions among superstar exporters. Our unit of observation is a market and the outcome of interest is the market equilibrium; i.e., the vector of export decisions of all potential entrants in the market. This is in contrast to the previous literature on firms' export market choices, which considers each firm's export decision in isolation.

We define a market Ic as a combination of an industry $I = 1, \dots, N_I$ and country of destination $c = 1, \dots, N_c$. For example, I might be the chocolate and confectionery industry, while c could be Germany. In each market Ic, there is a set of $i = 1, \dots K_{Ic}$ potential entrants. We further define the set of potential entrants in Section 2.2. To ease exposition, and following the terminology in the trade literature, we refer to a firm within an industry as a 'variety'. A market structure is the vector of equilibrium export decisions $\mathbf{y}_{Ic} = (y_{1Ic}, \dots y_{K_{Ic},Ic})$, where y_{iIc} is equal to 1 if variety i serves market Ic, and it is equal to 0 otherwise.

2.1 Profit Specification and Definition of the Market Equilibrium

Following Roberts & Tybout (1997), the profits of the exporters are modeled with a reduced-form expression of exogenous competitor and market characteristics that are observable to producers.[5] The profit of variety i in market Ic is given as follows:

$$\pi_{iIc} = \mathbf{X}'_{Ic}\boldsymbol{\alpha} + \mathbf{Z}'_{iIc}\boldsymbol{\beta} + \sum_{j \neq i} y_{jIc}\delta_1 + \sum_{j \neq i} y_{jIc} \cdot Z_{j\ell Ic} \cdot \delta_\ell + \sum_{j \neq i} y_{jIc} \cdot X_{hIc} \cdot \delta_h + \epsilon_{iIc}, \quad (1)$$

for $i, j \in I$. In this profit function, $\mathbf{X}_{Ic} = (X_{Ic,1}, \dots, X_{Ic,N_X})$ is a vector of N_X market-specific variables, for example the geographical distance from Denmark. $\mathbf{Z}_{iIc} = (Z_{iIc,1}, \dots Z_{iIc,N_Z})$

[5] An important difference between our work and Roberts & Tybout (1997) is that they look at a *dynamic* model of (single firm) entry, while we look at a *static* model of strategic entry with multiple firms.

is a vector of N_Z competitor- and market-specific variables, for example the number of other destinations to which variety i is exported. $\boldsymbol{\alpha} = (\alpha_1, \ldots \alpha_{N_X})$ and $\boldsymbol{\beta} = (\beta_1, \ldots \beta_{N_Z})$ are the corresponding parameter vectors to estimate.

ϵ_{iIc} is unobserved by the econometrician, but we maintain that it is observed by all players in market Ic. Thus, we model the decision of a superstar firm to export its variety $i \in I$ to destination c in the context of a complete information, simultaneous move, static discrete choice game. This is the same modeling assumption made in Bresnahan & Reiss (1990), Berry (1992), Mazzeo (2002), Tamer (2003) and Ciliberto & Tamer (2009). We maintain that in each market firms are in a long-run equilibrium.[6]

The key parameters of interest that capture the effect that a firm's export market presence has on its competitors' profits are δ_1, δ_ℓ, and δ_h. The parameter δ_1 captures the constant effect that a firm's presence has on the profits of its competitors. ℓ is one of the variables in $\mathbf{Z}_{iIc}$, and the parameter δ_ℓ measures whether the competitive effects change with changes in this firm-specific variable. Finally, h denotes one of the variables in $\mathbf{X}_{Ic}$ and the parameter δ_h captures how competitive effects vary across markets with changes in this market-specific variable.

Importantly, the model allows for both positive and negative effects of competitors on profits. This flexibility is crucial because the literature on export spillovers suggests that there may be positive interactions between firms in their export market decisions; see *inter alia* Aitken et al. (1997), Koenig et al. (2010) and Choquette & Meinen (2015). The idea is that firms may benefit from the export experience of their peers; e.g., due to informational spillovers, network effects, external scale economies in serving export markets, or other positive externalities. On the other hand, standard models of oligopolistic markets would predict negative effects of competitor entry on profits. This will be the case if competition between Danish producers is fierce, and the presence of other Danish competitors on the export market therefore reduces sales and profits. Whether the net effect of these opposing forces is positive or negative is an empirical question, and will determine the sign of the

[6]This assumption has a long tradition in both industrial organization and international trade because it allows for tractability. In the Online Appendix, we show that the identities of the export superstars, and their market-specific entry decisions, are indeed highly persistent over time.

competitive effects δ_1, δ_ℓ, and δ_h.

In each market, a firm decides to export its variety i as long as $\pi_{iIc} \geq 0$. This leads to a set of inequality conditions for all potential entrants within a market, where each firm's decision affects its competitors' decision via the competitive effects δ_1, δ_ℓ, and δ_h. In each market, we therefore have a system of K_{Ic} simultaneous inequalities (recall that K_{Ic} is the number of potential entrants in the market).

We use the pure strategy Nash Equilibrium solution concept to solve this entry game. A set of export decisions is an equilibrium outcome of the game if no individual firm can improve her pay-off by individually changing her action, taking the actions of all other potential entrants into account.

In their path-breaking contribution, Bresnahan & Reiss (1990) show that with more than two firms one must assume away any heterogeneity across firms in the effect of observable determinants of profits in order to have a model with a unique equilibrium in the number of firms. However, in three-player games, for example, where one firm is large and the other two firms are small, there can be multiple equilibria where one equilibrium includes the large firm as a monopolist while the other equilibrium has the smaller two firms as duopolists. In our analysis, one of the competitor-and-market specific variables affects the competitive effects across firms (through the parameter δ_ℓ), which, in turn, may lead to the existence of multiple equilibria. Ciliberto & Tamer (2009) provide a methodology that allows general forms of heterogeneity in the effect of the observable determinants of profits.

2.1.1 Comparison To Previous Empirical Work

Previous empirical work on firms' export decisions is to a large extent motivated by theoretical models with a continuum of monopolistically competitive, heterogeneous firms (see, e.g., Melitz, 2003). In this type of model, export decisions depend on a market-specific export threshold. The export threshold is endogenously determined by market aggregates, which in turn depend on the *mass* of firms that are present in a market.

However, any *individual* firm cannot affect the export threshold, and thus other firms' export decisions. As noted by Eaton et al. (2012), the advantage of the continuum assumption is that "(...) we can model aggregate outcomes as driven by parameters governing the distributions of individual outcomes, but not on the realization of these outcomes themselves."[7]

In a monopolistic competition set-up, we would thus predict that the δ parameters in the profit equation (1) are zero: any *individual* firm does not affect the entry decision of another firm. This parameter restriction, in turn, suggests that the export decision of each firm can be analyzed in isolation within a single equation framework (though differences in the export threshold across markets should be appropriately controlled for). For the large mass of smaller firms, the continuum assumption – and relatedly the assumption that any single firm does not affect market outcomes – might be a reasonable approximation to firm conduct. However, these assumptions become tenuous once we focus on large superstar exporters. For this subset of firms, export decisions can therefore not be analyzed within the single equation model.

2.2 Definition of Potential Entrants

Our empirical analysis exploits Danish register-data, including information on firms' export decisions. The set of potential entrants K_{Ic} in a market Ic is defined as the set of large Danish manufacturing exporters (the "superstars") which serve industry I in at least one of the export destinations c. In Section 3, we introduce the data and discuss how superstars are identified.

Our definition of the set of potential entrants is potentially restrictive in three respects.

First, and most importantly, we limit our analysis to strategic interactions between *Danish* superstar firms (because we do not observe the export decisions of foreign or third country competitors). To the extent that products from different origins are imperfect substitutes (see, e.g., Feenstra et al., 2018), competition between two Danish firms would

[7]Thus, the export threshold can be modeled as a function of the underlying parameters of the model, including fixed and variable trade costs, the parameters governing the productivity distribution, etc.

indeed be fiercer than competition between a Danish and a foreign firm.

We may be concerned that the presence of foreign competitors could bias the estimated competitive effects. What is the likely direction of this bias? For simplicity, consider an industry with two Danish superstar firms i and j, and a set of foreign superstars. If Danish and foreign firms compete strategically, the presence of foreign superstars in a market has a negative effect on the profits (and, thus, on the export probability) of *both* firms i and j. Equivalently, in markets where fewer foreign competitors are present, we would expect the export probability of *both* Danish firms to increase. In consequence, foreign competition would result in a spuriously positive correlation between the export decisions of Danish superstar firms, implying an upward bias in the estimated competitive effects.

Second, firms which sell only on domestic markets are not included in the analysis. Excluding non-exporting firms is not very restrictive, because larger firms (for which strategic interactions are relevant) are typically active on both domestic and export markets. Nevertheless, in the Online Appendix we provide results for an extension of our model where large domestic competitors are included in the sample.

Finally, the set of potential entrants K_{Ic} only includes manufacturing firms. Wholesalers, retailers and other trade intermediaries are thus excluded from the analysis.[8] The presence of trade intermediaries may complicate our analysis of competitive effects because it implies measurement error in firms' export decisions. However, larger firms are more likely to serve foreign markets exclusively via direct exports (see, e.g., Abel-Koch, 2013). We would therefore argue that the measurement error (as well as the resulting biases) are likely to be small in our framework; cf. the Online Appendix for further discussion.

[8]In the Online Appendix, we show that our empirical results are robust to accounting for competition from non-manufacturing firms.

2.3 Identification

We now briefly discuss the identification and estimation methodology, and refer to Ciliberto & Tamer (2009) for a more detailed and comprehensive presentation.

The fundamental identification problem that we face is the one that Manski (1993) called the "reflection" problem. Firms might be exporting to the same destination because of exogenous (contextual) effects, for example, because a market is particularly attractive. Firms may export because of correlated effects, such as common supply or demand shocks (unobservable to the econometrician), so that firms' export decisions may be correlated even absent any interdependence in export decisions. Finally, the export decision is also determined by the strategic interaction between the firms (endogenous effects). One crucial concern is that if industry- or market-specific unobserved common shocks affect all potential competitors in a market and are not accounted for, we might find a spuriously positive sign for the competitive effects, δ_1, δ_ℓ, and δ_h.

Our equilibrium approach permits us to identify the competitive effects because we model the strategic interaction through a classical simultaneous equation system. To begin with, the exogenous variables in $\mathbf{X}_{Ic}$ and $\mathbf{Z}_{iIc}$ control for the exogenous observable factors that make exporting into a specific market particularly attractive. We also exploit exogenous variation across markets in the number of potential entrants, K_{Ic}. In particular, when there is only one potential firm in the market, the model reduces to the probit case, and the parameters of the exogenous variables can be point identified. As in Ciliberto & Tamer (2009), we maintain that we have a random sample of observations $(\mathbf{y}_{Ic}, \mathbf{X}_{Ic}, \mathbf{Z}_{Ic}), Ic = 1 \ldots N_{Ic}$, and $N_{Ic} \rightarrow \infty$.

Exclusion restrictions play an important role in the identification of the competitive effects. In the profit equation in (1), a subset of the competitor characteristics in $\mathbf{Z}_{iIc}$ enters only variety i's profit but not profits of its competitors $j \neq i$. These variables are assumed to fulfil the exclusion restriction. In contrast, one of the variables in $\mathbf{Z}_{iIc}$ is also allowed to affect the profits of other firms (via the parameter δ_ℓ). This variable does not fulfill the exclusion restriction.

To understand the idea behind the exclusion restrictions, it is useful to distinguish two channels through which the characteristics of competitor j may affect the export decision of firm i. First, there is an *indirect* channel: any characteristic of j that has an effect on j's export decision y_{jIc} will – through this effect on y_{jIc} – also affect the export decision of firm i. Second, there may also be a *direct* channel: for example, consider a case where an increase in competitor j's characteristic $Z_{j\ell Ic}$ implies that j competes more aggressively conditional on entry. In this case, the effect of $Z_{j\ell Ic}$ on firm i's export decision goes beyond its impact on y_{jIc}. In sum, competitor characteristics that only have an indirect effect on export decisions satisfy the exclusion restrictions, while variables that have a direct effect on export decisions do not.

We maintain that the random vector ϵ is continuously distributed on R^K independently of $X = (X_1, \ldots X_K)$ and $Z = (Z_1, \ldots Z_K)$ and has a joint distribution function F that is known to the econometrician. More specifically, we model ϵ_{iIc} as the sum of five components:

$$\epsilon_{iIc} = \eta_i + \eta_{Ic} + \eta_I + \eta_c + \eta_{iIc}. \tag{2}$$

First, we allow for random demand or supply shocks that are common across markets for a given variety, here denoted by η_i. Second, we include random shocks to profitability that are common for all competitors in a given market, here denoted by η_{Ic}. Third, we include a component that is common across markets and varieties for a given industry, η_I. Fourth, we include a component that is common across industries and varieties for a given destination, η_c. Finally, there is an idiosyncratic component η_{iIc}. All components are assumed to be drawn from standard normal distributions in four of our specifications, while a more flexible variance-covariance structure is considered in two other specifications.

2.4 Estimation

We let $\boldsymbol{\theta}$ denote the vector of parameters to be estimated.

We begin by estimating the empirical probability of observing the market structures conditional on the exogenous characteristics (including the number of potential entrants).

To estimate the conditional choice probability vector $P(\mathbf{y}|\mathbf{K},\mathbf{X},\mathbf{Z})$, we use a nonparametric conditional expectation frequency estimator that counts the fraction of times an outcome (a market structure) is observed among all the market observations with that number of potential entrants and with those exogenous characteristics.

Next, we derive the predicted choice probabilities of the market structures for the values of the exogenous variables and different parameter values. Because of the possibility of multiple equilibria, and because we do not want to introduce arbitrary equilibrium selection assumptions, we follow Ciliberto & Tamer (2009) and derive the following upper and lower bounds on conditional choice probabilities for every possible number of potential entrants:

$$\begin{aligned}\mathbf{H}_{L,K_{Ic}}(\theta,\mathbf{X},\mathbf{Z}) &\equiv \begin{bmatrix} H_L^1(\theta,X,Z) \\ \vdots \\ H_L^{2^{K_{Ic}}}(\theta,X,Z) \end{bmatrix} \leq \begin{bmatrix} \Pr(\mathbf{y}_1|X,Z) \\ \vdots \\ \Pr(\mathbf{y}_{2^{K_{Ic}}}|X,Z) \end{bmatrix} \leq \begin{bmatrix} H_U^1(\theta,X,Z) \\ \vdots \\ H_U^{2^{K_{Ic}}}(\theta,X,Z) \end{bmatrix} \\ &\equiv \mathbf{H}_{U,K_{Ic}}(\theta,\mathbf{X},\mathbf{Z}) \qquad (3)\end{aligned}$$

where $\Pr(\mathbf{y}|X,Z)$ is a $2^{K_{Ic}}$ vector of conditional choice probabilities. The inequalities are interpreted element by element.

The $\mathbf{H}$'s are functions of $\boldsymbol{\theta}$, the set of all the parameters to be estimated, and of the distribution functions F of the random vector ϵ. Specifically, the errors η_i, η_{Ic}, η_I, η_c are each drawn from normal distributions with mean zero and variance 1/4, so that the sum of these error components has a variance that is normalized to 1. The idiosyncratic error η_{iIc} is drawn from a standard normal distribution. In columns (5) and (6) of Table 6 below, we introduce a more flexible specification, where we allow the unobservables η_{iIc} to be correlated within a market, and we estimate the variance of η_i as well as the variance of the sum of η_{Ic}, η_I, η_c.

The lower bound function $\mathbf{H}_L$ is the probability that a particular market structure is predicted to be the unique equilibrium in a market. The upper bound function $\mathbf{H_U}$

is the probability that a market structure is a unique equilibrium or one of the multiple equilibria, and so it is equal to $\mathbf{H}_L$ plus the probability that a market structure can be one of the multiple equilibria in the market. To compute these lower and upper bounds we proceed as follows.

First, we take the simulated errors, together with the exogenous variables, and an initial parameter guess, and we compute the profits of each potential entrant in a market under every possible market structure. From these profits, we determine the equilibria for each market-simulation combination. For example, in a market where there are two potential entrants, there are four possible market structures: (0,0), (0,1), (1,0), (1,1), where the first number in each pair corresponds to the entry decision of the first potential entrant, and the second number corresponds to the entry decision of the second potential entrant. A market structure is an equilibrium if none of the two potential entrants has an incentive to change its entry decision, and that can be determined by comparing the profits of each firm across market structures. Thus, (1,0), the market structure where the first firm enters and the second does not, is an equilibrium if: i) the first firm is not better off by not entering, that is, if the profit of the first firm is not negative; and, ii) if the second firm is not better off by entering, that is, the profit of the second firm would be negative in the market structure (1,1). Notice, that there might be multiple equilibria in this game. For example, (0,1) and (1,0) might both be equilibria of the entry game for this particular market-simulation draw.

Second, we use the predicted equilibria to update $\mathbf{H}_{L,K_{Ic}}$ and $\mathbf{H}_{U,K_{Ic}}$. Specifically, if there is a unique equilibrium for the simulated draw in a specific market, then this specific market-simulation increases the corresponding entry in $\mathbf{H}_{L,K_{Ic}}$ and $\mathbf{H}_{U,K_{Ic}}$ by one. If there are multiple equilibria, only the corresponding entry in the lower bound, $\mathbf{H}_{L,K_{Ic}}$, increases by one. In the example above, if there are two equilibria, (1,0) and (0,1), only $H_L^{(1,0)}$ and $H_L^{(0,1)}$ would be increased by one. $H_U^{(1,0)}$ an $H_U^{(0,1)}$ would remain unchanged. We repeat this exercise for all the markets and simulations.

Third, we take the computed values of $\mathbf{H}_{L,K_{Ic}}$ and $\mathbf{H}_{U,K_{Ic}}$ and divide them by the number of simulations (here, 100). These are now probabilities that can be used to *sandwich* the empirical probability.

Finally, the last step consists of minimizing an appropriately defined distance function constructed from the differences between the probabilities of market structures observed in the data, and the lower and upper probabilities predicted by the equilibrium model. Our inferential procedures uses the following objective function:

$$Q(\theta) = \int \left[\| \left(P(\mathbf{X}) - H_L(\mathbf{X}, \theta)\right)_- \| + \left\| \left(P(\mathbf{X}) - H_U(\mathbf{X}, \theta)\right)_+ \right\| \right] dF_x, \tag{4}$$

where $(A)_- = [a_1 1[a_1 \leq 0], \ldots, a_{2^k} 1[a_{2^K} \leq 0]]$ and similarly for $(A)_+$ for a 2^k vector A and where $\|.\|$ is the Euclidian norm. Ciliberto & Tamer (2009) show that $Q(\theta) \geq \mathbf{0}$ for all $\theta \in \Theta$ and that $Q(\theta) = \mathbf{0}$ if and only if $\theta \in \Theta$. In practice, the distance function is constructed by taking the squared difference between the empirical probabilities and the lower bounds predicted by the model whenever the first are lower than the latter; and the squared difference between the empirical probabilities and the upper bounds predicted by the model whenever the first are larger than the latter. We sum over the squared differences across markets and market structures. The parameter are estimated by minimizing this distance function.

As Tamer (2003) and Ciliberto & Tamer (2009) discuss in detail, this is a conditional moment *inequality* model, whose identified feature is the *set* Θ of parameter values that obey these restrictions for all $\mathbf{X}, \mathbf{Z}$, almost everywhere. In general, the set Θ is not a singleton. More details about the estimation and inference is provided in the Online Appendix.

3 Data and Stylized Facts

3.1 Description of Data Set

Our starting point is a data set from Denmark on the universe of export transactions. We focus on a cross-section for the year 2007, for which we have information on tariffs.

We observe the eight-digit products each firm is exporting, and to which destinations it is serving these products.

Our empirical analysis focuses on industries rather than products, because we want to account for competition across different product codes that are close substitutes. For each firm and destination, we aggregate product-level export information up to the industry-level using a correspondence table between eight-digit CN codes and four-digit NACE industry codes. The product-level data might not capture the relevant competitive effects. For example, within the "Chocolate and confectionery industry", there are different eight-digit product codes for "chocolate, not filled", "chocolate, filled", or "white chocolate". Arguably, producers within this industry are competing with each other even if they are completely specialized in different eight-digit products.

Our estimation sample includes superstar exporters, defined as firms with a share in industry-level exports of *at least five percent*.[9] For each industry, the remaining firms are bundled into a "competitive fringe". For most of the analysis, we assume that these fringe firms do not affect the market outcome, defined as the behavior of the superstar firms. This assumption is motivated by previous research arguing that small producers do not compete directly with large producers; e.g., because they produce niche products (Audretsch et al., 1999; Holmes & Stevens, 2014).

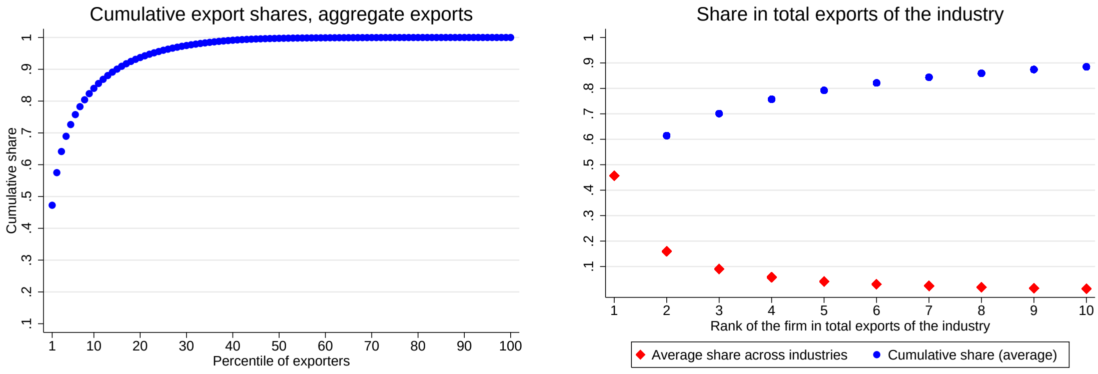
We restrict the sample in several dimensions in order to focus on the issue at hand. First, we only consider manufacturing firms; cf. the discussion in Section 2.2. Second, we want to focus on destinations where exporting is in principle attractive for Danish firms. We therefore only keep the top 100 destinations (as measured by the number of entrants across all industries) and only markets where we see positive exports of firms in our sample for at least two years over the period 2003–2007. Our final sample accounts for 72 percent of overall Danish manufacturing exports.[10]

After keeping only destinations for which key variables (GDP and distance) are avail-

[9] Note that industry membership is not based on the balance sheet information (which typically assigns firms to their "core" activity) but on the export data; firms may therefore be active in more than one industry. We record at least one superstar in each four-digit manufacturing industry.

[10] We perform a number of robustness checks regarding the construction of the sample; see the Online Appendix for details and results.

Figure 1: Export Concentration in Danish Manufacturing



(a) Cumulative Shares for Aggregate Exports (b) Export Concentration by Industry

able, we are left with 98 destinations, 206 industries, and 8,938 markets.

3.2 Export Superstars and Export Concentration

Figure 1 highlights the concentration of exports among a few superstars for our sample of Danish manufacturing firms. Among all firms (including the competitive fringe), the top 1 percent of exporters account for 47 percent of overall manufacturing exports, while the top 10 percent account for 85 percent (see Figure 1(a)). While this level of concentration is somewhat lower than for example in the United States (Bernard et al., 2007), it is comparable to other European countries (see World Trade Organization, 2008).

Next, we turn to the industry level. Figure 1(b) shows that the top firms again account for the bulk of exports: on average, the largest exporter covers approximately 45 percent of industry-level exports. The top 5 exporters together have a cumulative share of 80 percent in the average industry. However, the second largest firm is typically less than half as big as the top firm in terms of exports. Together with Figure 1(a), these numbers imply that exploring the behavior of superstar exporters is crucial for understanding aggregate export patterns.

Table 1 shows that export superstars are distinctly different from the mass of fringe firms. The top panel classifies firms as superstars if the firm is a superstar in at least one of the industries in which it is active. It highlights that superstar firms are superior to

Table 1: Export Superstars vs. Fringe Firms/Varieties

	Superstar Firms		Fringe Firms	
	Mean	N	Mean	N
Number of employees	285.0	595	34.53	3,766
Log labor productivity	13.23	585	13.09	3,375
Lagged export status	0.988	595	0.861	3,766
Number of industries	16.04	595	5.145	3,766
	Superstar Varieties		Fringe Varieties	
	Mean	N	Mean	N
Share in total industry exports	0.203	798	0.002	26,295
Lagged export status	0.939	798	0.547	26,295
Number of destinations	22.45	798	3.411	26,295
Rank within firm portfolio	2.203	798	9.254	26,295
Core industry dummy	0.643	798	0.139	26,295

Notes: Superstar firms are defined as firms which have a share in industry-wide exports of 5 percent for at least one industry in which they are active. Superstar varieties are firm-industry combinations with a share in industry-wide exports of at least 5 percent.

fringe firms in many dimensions, including size, productivity, and export persistence. On average, superstar firms are active in 16 industries compared to 5 for fringe firms, though they are typically classified as superstars only in their core industry.

The lower panel of Table 1 compares key firm-industry-specific variables for superstar and fringe varieties.[11] Superstar varieties have on average a share in overall industry-wide exports of 20 percent (compared to 0.2 percent for fringe varieties). Moreover, superstar varieties are active on significantly more export markets: the average superstar variety is exported to 22 destinations, while the average fringe variety is only sold in three destinations. Again, we also find that superstar varieties have a significantly higher persistence in export status.

In the remaining analysis, our focus will be on superstar varieties.

3.3 Observed Market Structures

We are interested in the market-specific export choices of superstars, defined by a dummy variable y_{iIc} equal to one if variety i records positive exports in market Ic, where a

[11] A firm may be a superstar only in a subset of the industries in which it is active; i.e., a firm might have both superstar and fringe varieties.

Table 2: Market Structures

	Number of actual entrants								Total
Number of potential entrants K_{Ic}	0 %	1 %	2 %	3 %	4 %	5 %	6 %	7 %	No.
1	16.4	83.6							506
2	13.7	48.13	38.17						1,095
3	11.1	46.79	25.24	16.87					1,541
4	11.2	39	26.42	15.4	7.98				2,169
5	9.95	35.65	22.16	13.28	12.15	6.81			1,498
6	11.22	28.21	17.89	15.04	12.03	10.08	5.53		1,230
7	11.06	24.42	18.73	12.92	9.31	9.86	8.32	5.37	913
Total	*11.56*	*40.45*	*23.49*	*12.24*	*6.57*	*3.53*	*1.61*	*0.55*	*8,952*

Notes: The number of potential entrants is given by the number of superstar varieties with a share in total industry exports of more than 5 percent. Each cell reports the percentage of markets (industry-destination combinations) for which we observe a given number of actual entrants.

market was defined in Section 2 as a combination of an industry I and a destination c. The outcome of interest is the equilibrium market structure, given by the vector of export decisions of all potential entrants in a market.

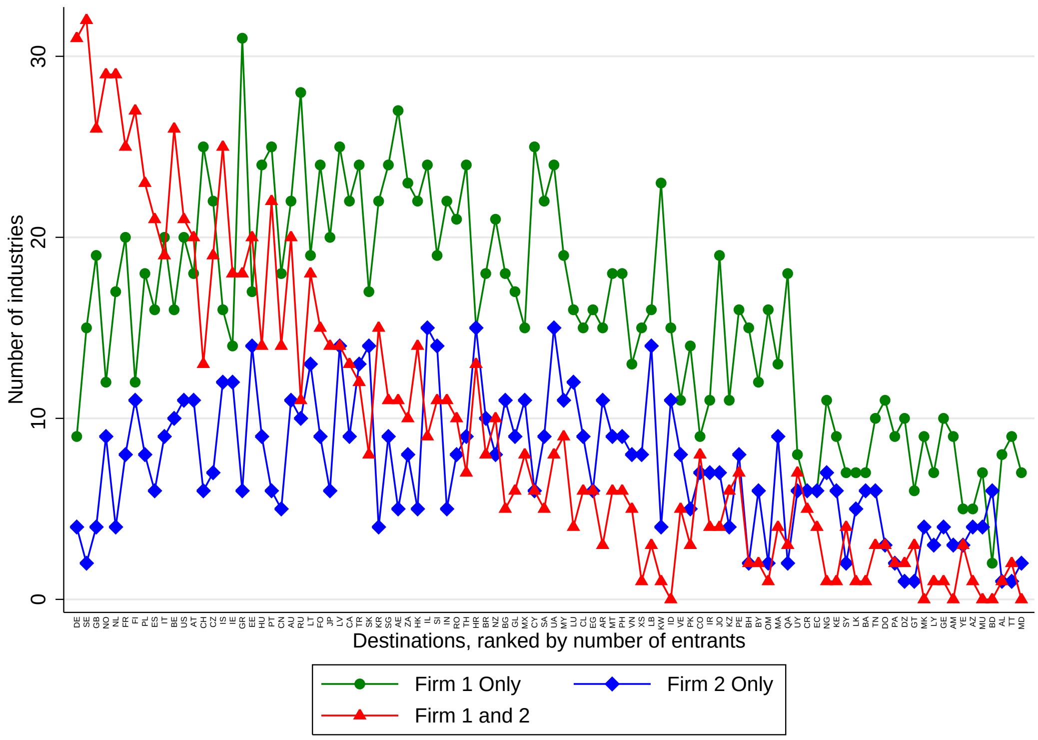
Table 2 summarizes the observed market structures in our sample, separately for markets with different numbers of potential entrants K_{Ic}. For example, there are 1,095 markets with two potential entrants. In around half of these markets (48 percent), we see only one of the two superstar firms exporting. In 38 percent of the markets, both firms export, whereas a small share of markets (14 percent) is not served by any of the two firms. Note that there are also 505 markets with only one potential entrant. As explained in Section 2, these markets do not contribute to the estimation of the competitive effects, but help identify the other parameters of the profit function.

In the last line of Table 2, we also report the market structures for all 8,938 markets (i.e., independent on the number of potential entrants). The most common market structure, accounting for 40 percent of markets, is one where we only see a single superstar firm exporting. We observe two exporters in 24 percent of the markets, and three exporters in 12 percent of the markets. Very few markets have four or more exporters.

The maximum number of potential entrants in our sample is seven, while the median is four. With up to seven potential entrants, there are up to $2^7 = 128$ different market structures that we must account for.

Table 2 reports the *number* of entrants in each market, but does not allow us to

Figure 2: Market Structures for Top 2 Firms



distinguish market structures by the *identity* of the entrants. Figure 2, instead, considers the identity of the exporting firms. We rank firms by their share in total industry-wide exports and focus on the top 2 competitors within an industry (which we refer to as Firm 1 and Firm 2). On the horizontal axis, the destinations are ranked by their popularity, which is measured by the number of actual entrants across all industries. On the vertical axis, we plot the frequency of market structures in that destination, where we distinguish between markets where (*i*) only Firm 1 enters, (*ii*) only Firm 2 enters, and (*iii*) both Firm 1 and Firm 2 enter.[12] As expected, it is more likely that the top 2 competitors both enter in the most popular destinations, such as Germany, Sweden, and Great Britain. Moreover, the number of industries in which we see both firms exporting sharply declines in the more difficult destinations.

Since Firm 1 is the top competitor, it should be more likely that Firm 1 is the sole

[12]We exclude markets with no entrants and markets where other firms beside the top 2 enter. We also exclude industries with only one potential entrant.

exporter in a given destination; and this is indeed reflected in Figure 2. However, there are also many instances where Firm 2 exports to a destination and Firm 1 does not.[13] This pattern in the data is at odds with the basic model of firm heterogeneity in Melitz (2003), where any market served by Firm 2 should also be served by Firm 1. Eaton et al. (2011) explain this type of pattern with random firm-and-market specific entry shocks. Importantly, our empirical model laid out in Section 2 explicitly allows for such random shocks to profitability as well. In addition, we will argue that the existence of markets where only Firm 2 exports can (partly) be explained by the strategic interaction between firms, where the presence of Firm 2 preempts entry of Firm 1.

3.4 Variable Definitions

Table 3 summarizes the exogenous variables governing the profit function. Many of these variables are included in logs in the empirical model (see below), but to ease interpretation we report summary statistics for variables in levels here.

Competitor-Specific Variables

First, we discuss the variables included in the vector $\mathbf{Z}_{iIc}$.

We count the number of industries where a firm is an exporter, and we call this variable *Firm Industries*$_i$. We also rank the firm's varieties (i.e., the industries in which the firm exports) by total export sales and we call this variable *Variety Rank*$_i$. These two variables vary only across competitors. They are inspired by the literature on multi-product firms, which emphasizes economies of scope in exporting multiple products; see *inter alia* Eckel & Neary (2010), Bernard et al. (2011) and Mayer et al. (2014). Thus, we would expect firms which are active in more industries, and thus have a higher value of *Firm Industries*$_i$, to be more likely to serve a given market. Moreover, the literature predicts that multi-product firms are more likely to export their core product to a given market, and that

[13] This finding is closely related to the fact that exporting firms do not adhere to a strict hierarchy of export destinations (in the sense that any firm exporting to the $m+1$-th most popular market also exports to the m-th most popular market); see Lawless (2009) and Eaton et al. (2011).

Table 3: Summary Statistics

	Mean	Std dev	N
Competitor-specific variables $\mathbf{Z}_{iIc}$			
Firm Industries$_i$	23.31	20.03	37,256
Variety Rank$_i$	1.731	1.937	37,256
Variety Destinations$_{iIc}$	30.07	24.08	37,256
Market-specific variables $\mathbf{X}_{Ic}$			
GDP$_c$	857.3	2,010	37,256
Geographical Distance$_c$	4.066	3.968	37,256
Industry Size$_I$	91,677	68,522	37,256
HHI$_{Ic}$	0.192	0.138	36,708
Tariff$_{Ic}$	0.0401	0.147	36,078
Tariff$_{Ic} > 0$	0.424	0.494	36,078

Notes: The table reports summary statistics for all control variables included in the vectors $\mathbf{Z}_{iIc}$ and $\mathbf{X}_{Ic}$ and used in our empirical model. GDP is measured in billion USD; Geographical Distance is measured in 1000km; and Industry size is measured in million DKK.

the probability of exporting decreases as we move away from the firm's core competency. This prediction is captured by the variable *Variety Rank*$_i$.

Next, for each variety and destination, we count the number of *other* destinations to which the variety is exported and call this variable *Variety Destinations*$_{iIc}$. The idea here is that varieties are more likely to be exported to a given market the more successful they are on other markets: for example, firms may learn about their export profitability from exporting to other destinations (see Albornoz et al. (2012), Morales et al. (2019)); demand may be correlated across markets (see e.g. Nguyen (2012)); and – more in general – being successful on other markets may be a sign that the variety offers characteristics highly demanded by consumers.

Market-Specific Variables

Next, we review the variables which are included in the vector $\mathbf{X}_{Ic}$. Recall that a market Ic is a combination of an industry I and a destination c.

We use information on GDP from the World Development Indicators (WDI) and geographical distance from the CEPII's GeoDist database to measure market size and transportation costs. We denote these variables *GDP*$_c$ and *Distance*$_c$.

For each industry, *Industry Size*$_I$ denotes the total revenue at manufacturing firms with positive exports in this industry. We include this variable to control for differences across industries in the role of the competitive fringe. To understand this modeling choice, consider the ideal framework where there is a dominant set of firms (the superstars) and a fringe of competitive firms. In such a model, competitive firms will enter if the superstars do not cover all of the market demand, which would happen if the competitive fringe has lower costs, or if the market size (total demand) is large. Since the former is not likely to be the case, we maintain that the industry size proxies for the role of the competitive fringe.

In some of our specifications, we also include the market-specific Herfindahl-Hirschman index, HHI_{Ic}. To construct this variable, we use information on trade by product, exporter, and importer from the BACI database of the CEPII. We aggregate these data up to the industry-country-pair level in order to match the market definition in our empirical model. HHI_{Ic} is then defined as the sum of squared import shares across all import origins. A higher value of HHI_{Ic} implies that the import market is more concentrated. We use this variable to control for competition from non-Danish competitors.[14]

Tariffs

We employ data on applied, preferential tariff protection in 2007 from the third version of the MAcMap-HS6 database (Guimbard et al., 2012) to construct the variable Tariff_{Ic}.[15] We aggregate product-level tariffs up to the industry level, weighting products by their importance for overall Danish exports. The average tariff across markets in our sample is 4 percent (see Table 3). However, Figure 3 shows that exports are duty-free in the majority of markets. Thus, we also construct an indicator variable $\mathit{Tariff}_{Ic} > 0$ equal to one for markets with positive tariffs, and zero otherwise.

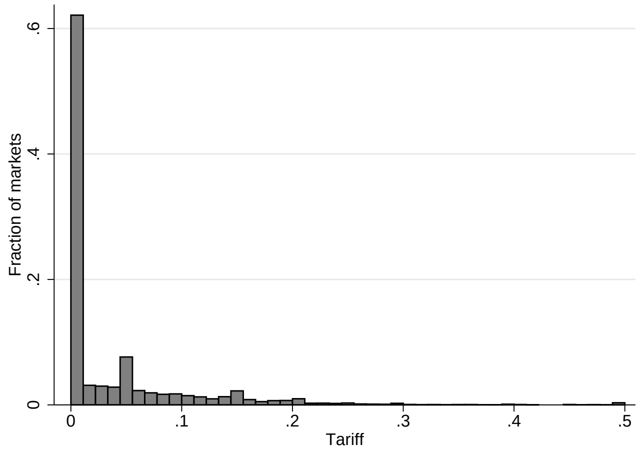
Standardization and Discretization of Variables

In the following, all variables (except for indicator variables) are standardized. When we estimate the equilibrium model in Section 5, we furthermore discretize all variables. The

[14]There are slightly fewer observations for this variable because a few products that appear in the Danish data are not included in the BACI database.

[15]We thank Houssein Guimbard for giving us access to these data.

Figure 3: Distribution of Tariffs



Note: Tariffs are capped at 50 percent.

discretization is described in detail in Section A in the Online Appendix. In the case of the variable $Tariff_{Ic}$, the very long tail of the distribution (see Figure 3) would leave us with few observations in each bin. Thus, in the equilibrium model we employ the indicator variable $Tariff_{Ic} > 0$.

Note that all control variables in Table 3 (except for indicator variables and the HHI) are included in logs in the empirical model.

4 Results from a Single Equation Probit Model

In this section, we estimate a model where the simultaneity of entry decisions is not accounted for. Thus, the model in Equation (1) reduces to a (standard) single equation probit model, where the unit of analysis is the firm-industry-destination (and not the market). Our main explanatory variable of interest is the number of other superstar competitors that enter a given export market, $\sum_{j \neq i} y_{jIc}$, and we denote its corresponding parameter in the simple probit model by δ_{probit}. Importantly, $\sum_{j \neq i} y_{jIc}$ is taken as exogenous in this section, while it is modelled as an equilibrium outcome of the entry game in Section 5. δ_{probit} is therefore conceptually different from the competitive effect δ_1 in Equation 1.

4.1 Benchmark Specifications

Table 4 reports the parameter estimates and standard errors for different specifications with and without market random effects and with different sets of control variables. In addition to the variables listed in Table 3, we also control for variation across industries in the number of potential competitors, K_{Ic}. Including K_{Ic} in the estimation is important because the number of *potential* competitors gives the upper bound for the number of *actual* competitors faced in a market. Relatedly, the number of potential entrants is a crucial source of exogenous variation in previous empirical works on entry (cf. Berry (1992), for example). In fact, we will use the variation in K_{Ic} in the full equilibrium analysis, and we want to be able to compare results from both approaches.

Table 5 reports marginal effects based on columns (3) to (5) of Table 4. We calculate the marginal effect of competitor entry as the change in the predicted probability of exporting if a firm does not face any competition in the foreign market (i.e., if the count of competitors active in market Ic is set equal to zero). The marginal effect of all other variables is computed as the change in predicted probability when the variable is increased by one unit.[16] For the standardized control variables, the marginal effects thus correspond to the effects of increasing each variable by one standard deviation.

Column (1) of Table 4 includes a set of basic controls but does not account for unobserved market heterogeneity. The main parameter of interest is δ_{probit}, which is the coefficient on the count of the number of competitors active in market Ic. The estimate of δ_{probit} is positive and significant. Thus, the presence of a competitor in a market is predicted to increase the export probability, which supports the spillover hypothesis. Note, however, that positive market-specific random shocks to profitability, η_{Ic}, may increase the export probability of all firms. The positive estimate of δ_{probit} in column (1) may thus be confounded with market attractiveness.

To address this concern, column (2) adds market-level random effects η_{Ic}.[17] We now

[16] In the econometrics literature, this method of calculating marginal effects is referred to as the "finite-difference method". The approach will facilitate comparison with results from the equilibrium model.

[17] We constrain the variance of the random effects to be equal to one. This restriction facilitates comparison of the results with those from the equilibrium model in Section 5.

Table 4: Parameter Estimates from the Simple Probit Model

	Dependent Variable: Variety Export Status, by Market					
	(1)	(2)	(3)	(4)	(5)	(6)
δ_{probit}	0.118***	-0.550***	-0.560***	-0.580***	-0.589***	-0.621***
	(0.007)	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)
$Potential\ K_{Ic}$	-0.099***	0.093***	0.095***	0.098***	0.104***	0.139***
	(0.006)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)
$Firm\ Industries_i$	0.027***	0.056***	0.048***	0.039***	0.041***	0.028**
	(0.010)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
$Variety\ Rank_i$	0.033***	-0.027**	-0.023*	-0.023*	-0.023*	-0.006
	(0.009)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
$Variety\ Destinations_{iIc}$	0.827***	1.111***	1.147***	1.186***	1.191***	1.178***
	(0.011)	(0.014)	(0.015)	(0.015)	(0.015)	(0.015)
GDP_c	0.376***	0.743***	0.794***	0.837***	0.842***	0.871***
	(0.008)	(0.015)	(0.016)	(0.016)	(0.016)	(0.017)
$Geographical\ Distance_c$	-0.415***	-0.804***	-0.804***	-0.774***	-0.610***	-0.812***
	(0.009)	(0.015)	(0.016)	(0.017)	(0.021)	(0.017)
$Industry\ Size_I$	-0.116***	-0.030**	-0.019	-0.030*	-0.006	-0.051***
	(0.009)	(0.015)	(0.016)	(0.016)	(0.016)	(0.018)
HHI_{Ic}			-0.037**	-0.080***	-0.087***	-0.077***
			(0.015)	(0.015)	(0.015)	(0.015)
$Tariff_{Ic}$				-0.175***		-0.188***
				(0.014)		(0.015)
$Tariff_{Ic} > 0$					-0.672***	
					(0.040)	
$\overline{Variety\ Rank}_{-i}$						0.013
						(0.024)
$\overline{Variety\ Destinations}_{-iIc}$						0.165***
						(0.026)
$\overline{Firm\ Industries}_{-i}$						-0.039
						(0.024)
Observations	37,256	37,256	36,708	36,078	36,078	35,594
Number of markets	8,952	8,952	8,816	8,664	8,664	8,180
Market random effects	No	Yes	Yes	Yes	Yes	Yes

Notes: The table gives coefficient estimates from a probit model for the firm-industry-destination specific export status. All specifications except for column (1) include market (industry-destination) random effects. δ_{probit} is the coefficient on the count of other competitors that are active in a market. $Potential\ K_{Ic}$ denotes the number of potential entrants in a market. All other control variables (except for the indicator variable $Tariff_{Ic} > 0$) are standardized. Standard errors in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

find a negative estimate of δ_{probit}, in line with standard models of strategic interaction: the presence of competitors decreases profits, and hence the probability of exporting to market Ic. The same pattern of sign reversal after accounting for market unobserved

Table 5: Marginal Effects in the Simple Probit Model

	Dependent Variable: Variety Export Status, by Market		
	(3)	(4)	(5)
N Competitor Entrants ($\sum_{j \neq i} y_{jIc}$)[a]	0.2005	0.2029	0.204
Competitor-specific variables $\mathbf{Z}_{iIc}$[b]			
Firm Industries$_i$	0.0115	0.0092	0.0096
Variety Rank$_i$	-0.0055	-0.0053	-0.0053
Variety Destinations$_{iIc}$	0.2626	0.2658	0.2659
Market-specific variables $\mathbf{X}_{Ic}$[b]			
Potential K_{Ic}	0.0226	0.023	0.0242
GDP$_c$	0.1868	0.1927	0.1932
Geographical Distance$_c$	-0.1787	-0.1694	-0.1352
Industry Size$_I$	-0.0045	-0.0069	-0.0015
HHI$_{Ic}$	-0.0087	-0.0185	-0.0201
Tariff$_{Ic}$		-0.0405	
Tariff$_{Ic} > 0$			-0.0683

Notes: The table reports marginal effects for columns (3) to (5) of Table 4. All control variables (except for *Potential* K_{Ic} and *Tariff*$_{Ic} > 0$) are standardized. [a] The marginal effect of competitor entry is calculated as the change in the predicted probability of exporting if a firm does not face any competition in the foreign market (i.e., if the count of competitors active in market Ic is set equal to zero). [b] Marginal effects are computed as the change in predicted probability when the variable is increased by one unit.

heterogeneity is found in previous studies (e.g., Ciliberto et al., 2016).

In column (3), we additionally control for the level of concentration in the import market. Including HHI_{Ic} does, however, not have a large impact on the estimated coefficient δ_{probit}, which is very similar to the estimate in column (2). Based on column (3), we predict the probability of exporting to increase by 20.05 percentage points as the number of competitors faced in an export market is reduced to zero; see Table 5. The magnitude of the effect is thus quite large.

We expect competition to be tougher in markets with higher levels of concentration, and this should reduce the export probability of Danish firms. The estimated effect of HHI_{Ic} in column (3) confirms this intuition. However, the corresponding marginal effect is rather small: a one standard deviation increase in HHI_{Ic} reduces the market-specific export probability by 0.9 percentage points.

In columns (4) and (5) of Tables 4 and 5, we show that export participation is less likely in markets with higher tariffs. The tariffs are measured by the continuous variable

Tariff_{Ic} in column (4)[18] and the binary variable $\mathit{Tariff}_{Ic} > 0$ in column (5). We find that one standard deviation increase in tariffs is predicted to decrease export participation by 4.05 percentage points. When we employ the binary tariff variable, we find that firms are 6.83 percentage points less likely to export to destination markets with positive tariffs.

Next, we briefly discuss results for our competitor-specific variables included in the vector $\mathbf{Z}_{iIc}$. In line with the literature on multi-product exporters, we find a positive effect of $\mathit{Firm\ Industries}_i$: firms with a larger industry portfolio are more likely to serve a given export market. Similarly, the effect of $\mathit{Variety\ Rank}_i$ is negative in most columns that include market random effects η_{Ic}. Thus, the export probability falls from the firm's core industry to its peripheral industries. A variety's presence in other destinations ($\mathit{Variety\ Destination}_{iIc}$) captures the general attractiveness of the variety to consumers across all destinations. Accordingly, it raises the destination-specific export probability. The corresponding marginal effect is sizable: we predict that a one standard deviation increase in $\mathit{Variety\ Destination}_{iIc}$ increases the export probability by 26 percentage points.

Recall from Section 2.3 that exclusion restrictions will play an important role in the identification of the competitive effects in the equilibrium model, and that these exclusion restrictions rely on elements of the vector $\mathbf{Z}_{iIc}$. A variable satisfies the exclusion restriction if it affects the decision of firm i to serve an export market without *directly* affecting the decision of its competitors j. In the last column of Table 4, we include average competitor characteristics as control variables in the simple probit model.[19] If we find a significant coefficient for one of these averages, that variable is unlikely to fulfill the exclusion restriction. Column (6) shows that $\overline{\mathit{Variety\ Destinations}}_{-iIc}$ enters with a positive coefficient and that the variable is highly statistically significant. In the equilibrium model, it will therefore be important to allow the competitive effects to vary with the set of destinations to which a firm is exporting. The other two averages of competitor characteristics, $\overline{\mathit{Variety\ Rank}}_{-i}$ and $\overline{\mathit{Firm\ Industries}}_{-i}$, in contrast, do not affect variety

[18] Following common practice in the literature (see, e.g., Debaere & Mostashari (2010)), tariffs are included as $\ln(1 + \mathrm{Tariff}_{Ic})$. In particular, $1 + \mathrm{Tariff}_{Ic}$ can be interpreted as the price increase on the import market which is due to the tariff.

[19] Here, markets with only one potential entrant are excluded from the sample, because we cannot compute average competitor characteristics.

i's export decision, suggesting that these variables fulfill the exclusion restriction.

Finally, we also briefly discuss the effects of market-specific control variables. We find that the superstar firms are more likely to export in industries with more potential entrants K_{Ic}, which suggests that the number of potential entrants is picking up some exogenous attractiveness of the market. As predicted by the gravity equation, we also find that varieties are more likely exported to larger and geographically closer markets. A one standard deviation increase in GDP increases the probability of firms' being present in a market by roughly 19 percent, while a one standard deviation increase in distance reduces the probability by 14 to 18 percent. The effect of industry size, $\textit{Industry Size}_I$, is negative but only marginally significant.

To summarize, our probit estimations suggest that negative effects due to competition between superstar exporters outweigh any positive effects from informational spillovers; i.e., the net effect is negative. Notably, this finding is quite different from previous results in the extensive literature on export spillovers. In contrast to that literature, we focus on superstar firms here. It is in fact only for such a sample of large firms that we would expect oligopolistic strategic interactions to be important.

4.2 Falsification Test

Before we turn to the equilibrium model, we briefly discuss a falsification test that we implement in the single equation probit model; details for this analysis are provided in the Online Appendix. In the falsification test, we analyze how the entry behavior of superstar firms in industry I depends on the entry decisions of superstar firms from other, unrelated industries $I' \neq I$. Superstar firms interact strategically only if they are competing with each other on output markets, and we would thus expect that negative effects of competitor entry should only be present within industries, but not across industries.

We proceed as follows. For each market Ic, we randomly draw $K_{Ic} - 1$ superstars from different industries I'. We next count the number of randomly drawn superstars from industries I' which entered destination c. We denote the parameter on this variable by $\delta_{unrelated}$.[20] Including the count of superstars from industries I' as an additional control variable in the single equation probit model, we find that $\widehat{\delta}_{unrelated}$ is greater than zero and statistically significant for all 50 simulations. The associated marginal effects are, however, small: if all 'unrelated' superstars would exit a market, we would predict the export probability to decrease by 4.6 to 6.6 percentage points.

Importantly, we thus confirm that negative effects of competitor entry are present only *within* industries, substantiating our interpretation that these negative effects are due to strategic interactions between competing firms. How could we rationalize these positive effects of other firms' export decisions that are working *across* across industries? One plausible interpretation is that there are destination-specific informational spillovers that work not only within industries but also across industries. Choquette & Meinen (2015) provide empirical evidence of such spillovers, that are due to input-output linkages across firms.

4.3 Robustness Analysis

In the Online Appendix to this paper, we also provide an extensive robustness analysis for the single equation probit model, where we consider *(i)* extensions to include additional control variables (e.g., firm productivity or competition/spillovers from the competitive fringe); *(ii)* alternative ways of constructing the sample (e.g., including more than the top-100 destinations); *(iii)* alternative definitions of the superstar firms (e.g., defining superstar firms based on their share in total industry revenue, rather than total industry exports); and *(iv)* variation in δ_{probit} across industries.

5 Results from the Equilibrium Model

We now present the estimation results for the equilibrium model. The object of interest is either the set Θ or the (possibly partially identified) true parameter $\theta \in \Theta$. We report

[20]Note how drawing $K_{Ic} - 1$ superstars from other industries eases comparability of the estimated effects within and across industries, δ_{probit} and $\delta_{unrelated}$

confidence regions for θ. The confidence regions for the latter are weakly larger than for the former, and coincide asymptotically in the case of point identification. To build the confidence regions we use the methodology of Chernozhukov et al. (2007).[21]

Column (1) of Table 6 presents estimations results for the specification with our basic control variables and only the constant competitive effect δ_1, so that $\delta_\ell = 0$ and $\delta_h = 0$. There are three exogenous variables (GDP_c, $Distance_c$ and $Industry\ Size_I$) that are common among the potential entrants. Additionally, there are three variables ($Firm\ Industries_i$, $Variety\ Rank_i$ and $Variety\ Destinations_{iIc}$) that are specific to the potential entrants, and thus are assumed to fulfill the exclusion restriction (cf. Section 2.3).

The parameter δ_1 is estimated to be in [-8.308,-4.858]. Thus, the effect is negative and statistically significant as predicted in standard oligopoly models: the presence of other Danish competitors in a market reduces profits, and therefore the export probability. Furthermore, any potential informational spillovers seem to be too small to counterbalance these negative competitive effects.

The signs of the control variables broadly reflect results from the simple probit model. In particular, $Variety\ Destinations_{iIc}$, GDP_c and $Distance_c$ are statistically significant and estimated with the expected signs. The coefficients of the other two competitor-specific variables ($Firm\ Industries_i$, $Variety\ Rank_i$) are, however, no longer statistically significant. Interestingly, we now find a positive effect of $Industry\ Size_I$. This is also different from the probit regressions, where the estimated effect was negative, though often not statistically significant. We interpret this as evidence that the superstar firms are more likely to export if the competitive fringe, here proxied by the variable $Industry\ Size_I$, is larger.

Columns (2) and (3) add the market-specific Herfindahl-Hirschmann Index HHI_{Ic} and the binary variable $Tariff_{Ic} > 0$, respectively. Including these control variables does not have a marked effect on δ_1. The negative coefficient estimate of HHI_{Ic} implies that Danish superstars are less likely to enter markets where imports are more concentrated. The effect

[21] We remark here that, as in Ciliberto & Tamer (2009), these confidence sets are constructed by reporting the minimum and maximum values for each individual parameter, and that this does not imply that any combination of individual parameters, each one of which lying within the minimum and the maximum, will belong to the identified set.

Table 6: Estimates from the Equilibrium Model

	(1)	(2)	(3)	(4)	(5)	(6)
Constant Competitive Effect (δ_1)	[-8.308,-4.858]	[-8.293,-4.713]	[-8.232,-4.936]	[-10.744,-5.653]	[-8.031,-7.577]	
Interactions						
$\delta_{\text{Variety Destinations}}$				[0.927,1.270]	[1.676,1.864]	
δ_{Distance}				[-0.198,0.127]	[-0.107,0.029]	
δ_{GDP}				[-0.158,0.127]	[-0.011,0.129]	
Competitor-specific variables $\mathbf{Z}_{iIc}$						
Firm Industries$_i$	[-0.026,0.194]	[-0.026,0.224]	[-0.061,0.182]	[-0.008,0.155]	[-0.012,0.083]	[-0.037,0.463]
Variety Rank$_i$	[-0.256,0.025]	[-0.256,0.025]	[-0.256,0.016]	[-0.149,0.075]	[-0.081,0.046]	[-0.347,0.219]
Variety Destinations$_{iIc}$	[0.763,1.044]	[0.697,1.045]	[0.700,0.967]	[1.243,1.650]	[1.763,1.951]	[1.750,2.940]
Market-specific variables $\mathbf{X}_{Ic}$						
Geographical Distance$_c$	[-0.946,-0.615]	[-1.234,-0.692]	[-1.439,-0.596]	[-0.934,-0.540]	[-1.261,-0.981]	[-0.846,-0.333]
GDP$_c$	[0.720,1.076]	[0.708,1.221]	[0.824,1.326]	[1.097,1.476]	[1.911,2.161]	[0.681,1.396]
Industry Size$_I$	[0.080,0.453]	[0.119,0.653]	[0.438,0.842]	[0.000,0.407]	[0.417,0.729]	[-0.440,-0.109]
HHI$_{iIc}$		[-0.625,-0.029]	[-0.436,0.007]	[-0.312,-0.062]	[-0.366,-0.092]	[-0.265,0.236]
Tariff$_{Ic} > 0$			[-3.191,-0.837]	[-2.033,-1.259]	[-2.973,-2.421]	[-2.040,-0.750]
Constant	[4.070,7.584]	[3.798,7.468]	[4.344,7.441]	[4.532,9.205]	[7.251,7.501]	[0.000,0.516]
$\sigma_{variety}$	–	–	–	–	[0.001,0.040]	[1.625,2.896]
σ_{market}	–	–	–	–	[2.351,2.476]	[0.125,0.791]
ρ	–	–	–	–	[0.984,0.990]	[-0.165,0.500]
Function Value	2,453.8	3,036.93	3,449.1	3,315.37	2,731.74	4,495.12
Number Observations	8,938	8,802	8,664	8,664	8,664	8,664

Notes: These set estimates contain the 95% confidence region for the true parameter θ. See Chernozhukov et al. (2007) and Ciliberto & Tamer (2009) for more details on constructing these confidence regions.

of $\mathit{Tariff}_{Ic} > 0$ is estimated to be in [-3.191,-0.837], which confirms that superstars are less likely to export to markets with positive tariffs.

Column (4) investigates whether the competitive effects vary across competitors and/or markets; i.e., we estimate the parameters δ_ℓ and δ_h in Equation (1). Specifically, we test the hypothesis that dominant competitors with a broader destination portfolio have a larger negative effect on the profits of their competitors. We thus allow the competitive effect to change with the number of destinations to which a variety is exported. This effect is measured by the parameter $\delta_{\text{Variety Destinations}}$. Moreover, we test the hypothesis that competitive effects vary across destinations according to the standard gravity forces. We thus also allow for the competitive effects to change with the geographical distance and GDP of the destination country. These effects are measured, respectively, by δ_{Distance} and δ_{GDP}.

We do not find evidence that competitive effects vary across destination markets: δ_{Distance} and δ_{GDP} are estimated to be statistically insignificant. Turning to the variation across competitors, we find $\delta_{\text{Variety Destinations}}$ to be positive. Thus, the larger the number of *other* destinations that a firm serves, the *smaller* (in absolute value) its effect on competitors' profits. There are several potential interpretations for this surprising result. First, firms that serve many export markets may have a high visibility to their competitors. This reasoning implies not only larger negative effects on profits due to strategic interactions but also a larger potential for informational spillovers. The latter may explain why we find $\delta_{\text{Variety Destinations}} > 0$. Second, firms that serve a large number of other export markets may compete less aggressively in a given destination, because each destination has a lower importance for their overall exports.

In column (5), we allow for a more flexible variance-covariance matrix of the unobservables. So far, we have maintained that η_i, η_I, η_c, η_{Ic}, and η_{iIc} are drawn from (five) independent standard normal distributions. We relax this assumption in two ways. First, we allow the idiosyncratic shocks η_{iIc} to be correlated across varieties within the same market, and estimate the corresponding correlation coefficient (denoted by ρ). Second, we estimate the variance of η_i, denoted $\sigma^2_{variety}$, and the variance of the (sum of the) market unobservables $\eta_I + \eta_c + \eta_{Ic}$, denoted σ^2_{market}. We continue to restrict the variance of η_{iIc} to be equal to 1. (Note that one of the variances has to be set equal to 1 because this is a discrete choice model.)

We find that the idiosyncratic shocks are almost perfectly correlated across varieties within a market: $\widehat{\rho}$ is positive and strikingly close to 1. This high correlation indicates that idiosyncratic shocks to profitability are almost indistinguishable from market-specific shocks. The estimate of $\sigma_{variety}$ is very small – essentially zero ([0.001,0.040]) – suggesting that export decisions are not driven by unobservables at the variety level. In contrast, the estimate of σ_{market} is quite large, and equal to [2.351,2.476]. Thus, industry, destination and market unobservables are important determinants of firms' export decisions. The other parameter estimates are similar in magnitude and statistical significance to the ones in column (4).

We conclude our analysis with the specification in column (6), where we assume that all the competitive effects are equal to zero. This is equivalent to estimating a model where firms decide whether to export independently of each other, as assumed in models of monopolistic competition. Results from this specification will be used as a benchmark for comparison to uncover the importance of competitive effects in our counterfactual analysis. We estimate the parameters of the exogenous variables with the same signs as in column (5), although with slightly different magnitudes.

With regard to the parameters ρ, $\sigma_{variety}$ and σ_{market}, we see some interesting differences in column (6) compared to column (5). For example, we now estimate $\sigma_{variety}$ to be in [1.625,2.896], therefore much larger than in column (5). Intuitively, this model has fewer competitor-specific variables, and this may rationalize why it exhibits a larger variation in competitor-specific shocks. Finally, observe that ρ is imprecisely estimated in column (6). We also infer that assuming a model with no strategic interactions biases the estimates of the variances and covariances of the unobservables in a significant way.

Table 7: Fit: Market Structures

	Number of predicted entrants							
Number of potential entrants K_{Ic}	0 %	1 %	2 %	3 %	4 %	5 %	6 %	% Correctly predicted
1	10.32	89.68						79.72
2	5.80	61.27	32.92					51.40
3	3.01	51.58	42.19	3.23				41.31
4	1.97	42.49	49.30	6.13	0.10			34.88
5	1.13	33.51	53.94	11.05	0.37	0.00		29.65
6	0.83	28.14	54.75	15.27	1.01	0.01	0.00	23.28
7	0.58	22.96	52.65	20.80	2.89	0.13	0.00	21.38
Total	1.32	36.39	51.15	10.42	0.70	0.02	0.00	36.66

Notes: This table reports the number of predicted entrants based on estimates in column (5) of Table 6, and compares these predictions with the actual number of entrants observed in the data (cf. Table 2).

5.1 Fit

In the following, we will focus on the specification in column (5) of Table 6. There are three ways to determine how well our model fits the data.

First, we compute the percentage of *market structures* that the model predicts correctly. Empirically, in each market we only observe one equilibrium outcome, but the model potentially predicts multiple market equilibria. In order to construct our first measure of fit, we therefore proceed as follows. We draw 100 new simulations of the random shocks to profitability, η_i, η_{Ic}, η_I, η_c and η_{iIc} in Equation (2), and compute a new ϵ_{iIc} for each firm in each market. Based on these new simulations, we find the equilibria in each market at the value of the parameter where the distance function in Equation (4) is minimized for the specification in column (5) of Table 6, and the values of the exogenous variables. Then, we check if any of the equilibria predicted by the model matches the market structure observed in the data. If one of the predicted equilibria matches the market structure observed in the data, then that is a positive match.

We present our results in the last column of Table 7. In markets with one potential entrant, we correctly predict the market structure observed in the data in 79.72 percent of market-simulations. In markets with two potential entrants, the number of correct predictions is 51.40 percent. The percentage of market structures that we predict correctly declines, until it reaches its lowest value of 21.38 percent for markets with seven potential entrants. Overall, we correctly predict 36.66 percent of the market structures that are observed in the data.

For our second measure of fit, we find the distribution of the *number of firms* predicted by the model for each market-simulation, and for any given number of potential entrants. We again use the predicted equilibria for the 100 simulations we run above. In markets for which our model predicts multiple equilibria, we use all the predicted outcomes to construct the distribution of the number of firms predicted by the model. So, if we predict an equilibrium with 2 firms and another one with 3 firms, we consider both predictions.

We present our results in Table 7. In markets with one potential entrant, our model predicts that the firm will enter in 89.68 percent of market-simulations. In the data, the superstar is observed as entering in 83.6 percent of markets; cf. Table 2. The fit is clearly very satisfactory for markets with only one potential entrant. In markets with two potential entrants, our model predicts that there will only be one entrant in 61.27 percent of the market-simulations (vs. 48.13 percent of markets observed in the data), and two entrants in 32.92 percent of the market-simulations (vs. 38.17 of markets observed in the data). The model does not do as well in predicting the number of firms as we increase the number of potential entrants, but there is an important observation to be made. Because of the existence of multiple equilibria, the sum of the probabilities is no longer equal to 1 in Table 7, and thus the comparison with the values in Table 2 is not as helpful. Overall, we observe that the model does not do well in predicting markets with large number of entrants.

Thirdly, we can compare the values of the distance function at the parameter where it is minimized across columns that use the same exogenous variables to determine the best specification.[22] The distance function is equal to 3315.37 in column (4) and to 3449.1 in column (3), which implies that column (4) provides a better fit to the data than column 3. This is not surprising since the specification in column (4) has more free parameters than the one in column (3). Similarly, the function value is lower in column (5) than in column (4), so the specification with free variances and correlations also fits the data better. The

[22]Because columns (1) and (2) are based on different sets of exogenous variables, a direct comparison of the distance functions is not meaningful.

distance function in column (6) is much higher than in columns (3)–(5), implying that not including the competitive effects leads to a much worse fit.

5.2 Occurrence of Multiple Equilibria

We analyze the occurrence of multiple equilibria as follows. We use the 100 new simulations of the random shocks η_i, η_{Ic}, η_I, η_c, and η_{iIc} from the analysis in Section 5.1 and determine the equilibria for each market-simulation draw at the value of the parameter where the distance function in Equation (4) is minimized for the specification in column (5) of Table 6. We can then identify the market-simulation draws with multiple equilibria, both in the identity and number of competitors. Finally, we compute the fraction of market-simulation draws with multiple equilibria. Table 8 presents the results of this exercise.

In markets with two potential entrants, we predict on average 1.39 equilibria. Notably, these multiple equilibria are only in terms of the identity of the firms; i.e., with two firms there are markets where either of the firms being an exporter will be an equilibrium outcome. If there were informational spillovers and other positive externalities in exporting, we would also expect there to be multiple equilibria in the number of firms; i.e., equilibria where either both firms export or no firm exports. In contrast, Table 8 shows that the equilibria are always unique in the number of firms.

Next, we look at markets with three potential entrants, and find that on average there are 2.33 equilibria (out of eight possible market structures). Moreover, in 6.87 percent of the simulation-market draws (here equal to 100×1502) there are multiple equilibria in the number of firms. For example, these could be equilibria where either one large competitor or two smaller competitors export.

The results for the other configurations with more potential entrants are analogous to the case just analyzed with three potential entrants. For example, when there are seven potential entrants, on average there are 11.02 equilibria, and 27.94 percent of the market-simulations with seven potential entrants have equilibria with different numbers

Table 8: Evidence of Multiple Equilibria in the Identity and Number of Firms

Number of potential entrants	Number of possible market structures	Average number of market equilibria[a]	Multiple equilibria in number of firms (%)[b]	Number of markets
$K_{Ic} = 1$	2	1	–	484
$K_{Ic} = 2$	4	1.39	–	1,057
$K_{Ic} = 3$	8	2.33	6.87	1,502
$K_{Ic} = 4$	16	3.62	17.85	2,097
$K_{Ic} = 5$	32	5.44	21.62	1,443
$K_{Ic} = 6$	64	7.84	28.54	1,196
$K_{Ic} = 7$	128	11.02	27.94	885
Mean	–	7.89	24.51	8,664

Notes: This table is based on estimates in column (5) of Table 6. Markets with one potential entrants are excluded from the Table because there cannot be multiple equilibria in those markets.
[a] This is the average across market-simulation draws with the same number of potential entrants.
[b] Gives the percent of simulation-market-draws for which there are multiple equilibria in the number of firms.

of firms. These results confirm the necessity to use a flexible approach as in Ciliberto & Tamer (2009) to study strategic interactions in export markets.

6 Propensity to Export and Comparative Statics

In this section, we compare the propensities to export predicted by our model with the ones observed in the data and present comparative statics that focus on the individual export propensity. The propensity is computed by taking the ratio of the predicted number of entrants divided by the number of potential entrants.

Recall that the outcome of the equilibrium model is a market structure, or a vector of export decisions by multiple firms. Following Ciliberto & Tamer (2009), marginal effects are then to be computed for the market structures, as one would do when studying the marginal effects in a multinomial logit estimation. Here, instead, we focus on the response of individual firms. Our focus on the export propensity facilitates comparison with the marginal effects from the single-equation probit analysis in Table 5, as well as comparison with the mainstream literature in international trade.

To this aim, in Table 9 export propensities are calculated *(i)* for the observed values of the exogenous variables and the value of the parameter where the distance function in Equation (4) is minimized for the specification in column (5) of Table 6; and *(ii)* for the observed values of the exogenous variables and the value of the parameter where the distance function is minimized for the specification in column (6) of Table 6 (i.e., the model without competitive effects). Note how comparison of the export propensities in *(i)* and *(ii)* will allow us to quantify the importance of competitive effects in determining export decisions. Finally, we also compute export propensities *(iii)* for a one standard deviation increase in each of the exogenous variables, holding other variables at their observed values. (This last exercise again uses the estimated parameters in column (5) of Table 6.)

6.1 Propensity to Export

We first compare the propensities to export predicted by our model in column (5) of Table 6 with the ones observed in the data. In particular, we determine the equilibria for each of the markets and each of the simulations at the observed values of the exogenous variables $\mathbf{X}_{Ic}$ and $\mathbf{Z}_{iIc}$ and the estimated parameters. (This is an analogous exercise to the one we did in the previous section when we computed the percentage of multiple equilibria in the data.) To compute the propensity to export, we compute the ratio of firms exporting over the number of potential entrants. Thus, the propensity to export is an average propensity and it will vary by the number of potential entrants.

The first row of Table 9 presents the propensities to export that are computed in this fashion, separately for markets with $K_{Ic} = 1, \ldots, K_{Ic} = 7$ entrants. We can compare these numbers with those observed in the data (reported in the third row of Table 9). We find that the predicted export propensity is 0.897 in markets with one potential entrant, compared to 0.836 in the data. In markets with two potential entrants, the predicted export propensity is 0.636, which is again very close to the actual propensity of 0.624 in the data. Thus, we again conclude that the model does a good job at fitting the data. Both the predicted and the actual export propensity decline with the number of potential entrants. Averaging across all markets, the export propensity predicted by our model stands at 0.340 (compared with 0.439 in the data).

Table 9: Comparative Statics in the Equilibrium Model

	Propensity to export by number of potential entrants							All markets	
	$K_{Ic} = 1$	$K_{Ic} = 2$	$K_{Ic} = 3$	$K_{Ic} = 4$	$K_{Ic} = 5$	$K_{Ic} = 6$	$K_{Ic} = 7$	Propensity to export	Comparative statics
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Model									
Original values ($\delta \neq 0$)[a]	0.897	0.636	0.485	0.400	0.352	0.312	0.290	0.340	
Original values ($\delta = 0$)[b]	0.896	0.893	0.874	0.865	0.872	0.873	0.871	0.872	0.532
Data	0.836	0.624	0.497	0.428	0.409	0.402	0.394	0.439	
Market-specific variables $\mathbf{Z}_{Ic}$[c]									
Geographical Distance$_c$	0.855	0.594	0.455	0.374	0.331	0.294	0.273	0.321	-0.019
GDP_c	0.950	0.713	0.541	0.445	0.391	0.346	0.320	0.372	0.032
Industry Size$_I$	0.912	0.654	0.498	0.410	0.361	0.320	0.297	0.347	0.007
HHI_{Ic}	0.890	0.628	0.480	0.395	0.348	0.309	0.287	0.336	-0.004
Competitor-specific variables $\mathbf{X}_{iIc}$[c]									
Firm Industries$_i$	0.897	0.636	0.486	0.400	0.352	0.313	0.290	0.340	0.000
Variety Destinations$_{iIc}$	0.947	0.706	0.526	0.427	0.373	0.329	0.304	0.359	0.019
Variety Rank$_i$	0.896	0.635	0.485	0.400	0.352	0.312	0.290	0.340	0.000
Number Observations	484	1,057	1,502	2,097	1,443	1,196	885	8,664	

Notes: This table is based on estimates in column (5) of Table 6, unless noted otherwise. In columns (1) to (7), the propensity to export is calculated for all markets with $K_{Ic} = 1, \ldots K_{Ic} = 7$ potential entrants. In column (8), the overall effect is calculated as the weighted average of the effects in columns (1) to (7), with weights equal to the number of markets with a given number of potential entrants. In column (9), the marginal effect is calculated as the change in predicted probability.

[a] Predicted export propensity, based on estimates from column (5) of Table 6. [b] Predicted export propensity, based on estimates from column (6) of Table 6.

[c] Predicted export propensity as the explanatory variables are individually increased by one standard deviation; based on estimates from column (5) of Table 6.

6.2 Comparative Statics: Competitive Effects

We begin our comparative statics exercise by investigating the role of competition as a determinant of superstar firms' export decisions. The second row of Table 9 shows the predicted export propensities in the model where all the competitive effects (δ_1, δ_{Distance}, δ_{GDP}, and $\delta_{\text{Variety Destinations}}$) are set equal to zero; i.e., using the parameter estimates in column (6) of Table 6. Using the same simulations of the error components which we used for the first row of Table 9, we compute the equilibria for each market-simulation.

In markets with one potential entrant this exercise obviously does not make any difference. With more than one potential entrant, however, we find that the competitive effects are very important. With two potential entrants, the predicted export propensity increases from 0.636 in the model with competitive effects to 0.893, in the model without competitive effects, which is a dramatic increase.[23] Competitive effects are crucial also in markets with more than two potential entrants. For example, if we set all competitive effects equal to zero, the export propensity increases from 0.485 to 0.874 in markets with three potential entrants; and from 0.393 to 0.877 in markets with four potential entrants.

Overall, without the competitive effects firms are predicted to be 53.2 percentage points more likely to export to a given market. Clearly, competition in export markets is an important determinant of export decisions. This number can be compared with the marginal effect of 20.4 percentage points in the probit model of Table 5. The effect that we find in the equilibrium model with strategic interactions is thus more than twice as large as in the single agent probit model.

6.3 Comparative Statics: Exogenous Profit Determinants

Next, to measure the economic effect of changes in the exogenous variables (except for tariffs, which are investigated in Section 7) we consider a one standard deviation increase in each variable, holding all other variables at their original values. For the individual variables, we have to change the variable for each firm at a time, and then take the average

[23]Notice that the new propensity to export is very close to the one we measure when there is only one potential entrant, which is a helpful cross-check on our methodological approach.

effect across all the potential firms in the market. We repeat the simulation exercise above and determine the new export propensities at the original parameter estimates. Results are presented in Table 9.

Consider a one standard increase in the distance from Denmark. We now find that the export propensity with one potential entrant is 0.855, with two potential entrants it is 0.594, and with seven potential entrants it is 0.273. When averaging across all markets the propensity to export is now 0.321. The difference between 0.340 and 0.321 is -0.019, which means that if distance increases by a one standard deviation, the propensity to export decreases, for each firm, by 1.9 percentage points.

This effect is considerably smaller than the 13.52 percentage point drop that we found in the simple probit model; cf. column (5) of Table 5. The effect of a change in an exogenous variable in the context of our equilibrium model can be quite different than if we consider the same effect in a model where each firm is making its entry decision independently. In particular, the effect of a change in the exogenous variable is larger when compounded over all the potential entrants. For example, the effect is -0.017 ($= 0.273 - 0.290$) in markets with seven potential entrants. When compounded over all the seven potential entrants, this would imply that there is a 11.9 percentage point higher probability that *at least one* of the firms will not export to a market if distance increases by one standard deviation. Note how this compounded effect is very similar in magnitude to the marginal effect in Table 5. We will return to this comparison shortly.

We find that one standard deviation increase in the GDP of the destination country is associated with a 3.2 percentage point increase in the propensity to export. For industry size, the same effect amounts to 0.7 percentage points. For the HHI, we find that a one standard deviation increase in the HHI is associated with a 0.4 percentage point decrease in the propensity to export.

We conclude the analysis of exogenous changes in the market-specific variables by computing the probability that at least one firm will export after a one standard deviation increase in the geographical distance, the GDP, the industry size, and the HHI. Those changes in the probabilities are equal to, respectively, −0.077, 0.129, 0.028, and −0.016.[24] These numbers are largely comparable to the ones in column (5) of Table 5, where we found the marginal effects of geographical distance, GDP, industry size, and the HHI, equal to, respectively, −0.135, 0.193, −0.002, and −0.020. Some of the differences may be explained by the different specification that we are running, since GDP and geographical distance are also interacting with the competitive effects in column (5) of Table 6.

Finally, we study changes in the export propensity for a one standard deviation increase in each of the competitor-specific variables. In contrast to the changes in the market-specific variables which affect the profits of all the potential firms in a market, changes in the competitor-specific variables only affect one firm at the time. We find that a one standard deviation increase in $\textit{Variety Destinations}_{iIc}$ increases the propensity to export by 1.9 percentage points. Recall that the other two competitor-specific variables were not statistically significant in the equilibrium model.

7 Policy Experiments

Table 10 presents the results from two policy experiments. The first policy experiment consists of setting the binary variable $\textit{Tariffs}_{Ic}$ equal to zero in all markets with positive tariffs and recomputing the equilibria to see how the propensity to export is affected. The results of this counterfactual exercise are presented in the top panel of Table 10. The second policy experiment consists of setting the binary variable $\textit{Tariffs}_{Ic}$ equal to one in those markets that do not have tariffs. The results for this counterfactual exercise are presented in the bottom panel of Table 10.

For both policy experiments, we are particularly interested in how the strategic interactions between superstar exporters affect firms' export decisions after a trade policy change. For example, consider the case where trade is liberalized. If firms interact strategically, positive effects on profits due to trade liberalization are counter-balanced by negative

[24] These numbers are derived by multiplying the ones in the last column of Table 9 by 4.03, which is the weighted average number of potential entrants in the sample used in Table 9.

effects due to competitor entry. Thus, a model without strategic interactions (which does not take into account the effects of competitor entry) would overestimate the export entry response of superstar exporters. Similarly, when new trade barriers are being imposed, reduced competition from competitors who exit will mitigate the negative direct effect on firms' export profits. A model without strategic interactions would therefore overstate firm's export exit response.

In our simulations, we quantify these biases. In particular, for each policy experiment, we first simulate the change in export propensities using the parameter where the distance function in Equation (4) is minimized for the specification in column (5) of Table 6. Next, we compare these results to those from simulations using the parameter where the distance function is minimized for the specification in column (6) of Table 6. The latter set of simulations does not allow for competitive effects, and can thus serve as a useful benchmark for comparison.

7.1 Eliminating Tariffs in Markets with Positive Tariffs

Consider first the case of markets with positive tariffs. Out of the 3,601 export markets with positive tariffs, there are 199 markets with one potential entrant, 386 with two potential entrants, and so on. The first row of Table 10 shows the export propensity at the estimated parameters and the original values of the exogenous variables. We compute these propensities in the same fashion as we did in Table 9, except that we now take the average only across markets with positive tariffs. For example, before the policy change, the predicted propensity to export is 0.520 in markets with two potential entrants.

Next, consider the counterfactual scenario where tariffs are eliminated. The second row of Table 10 reports the new propensities to export. In markets with three potential entrants, the propensity increases from 0.396 to 0.505 as trade becomes duty free. Similarly, in markets with seven potential entrants the propensity is now 0.302, compared to 0.243 in the original situation with positive tariffs. If we consider the probability that *at least* one firm exports in markets with seven potential entrants, this increases by 41.3

percentage points.[25] When averaging across all markets, we find that the propensity to export increases from 0.283 to 0.348 if tariffs are eliminated. The difference is 6.5 percentage points, which is a sizable effect. Across all market structures, the probability that *at least* one firm exports increases by 27.6 percentage points.[26]

Next, we ask by how much we overestimate the entry response due to trade liberalization if the strategic interaction between superstar exporters is not taken into account. To address this line of inquiry, we perform the same counterfactual exercise using estimates from column (6) of Table 6. We first compute the propensities to export at the original values of the exogenous variables, i.e., with positive tariffs. The results are presented in the third row of Table 10. Consider now what happens to the export propensities if we eliminate tariffs. We compute the new equilibria in each market and we find that the average propensity to export increases from 0.373 to 0.512; i.e., by 13.9 percentage points. This is a much larger effect than the 6.5 percentage point effect we find when accounting for competitive effects (cf. above). Thus, the increase in export propensity is overestimated by a factor of two when strategic interactions are not taken into account.

7.2 Introducing Tariffs in Markets without Tariffs

Our second policy experiment introduces tariffs in markets which currently have no tariffs. The exercise is similar to the one that we just described, except that now we look at a different set of markets. Thus, now we change the binary variable $Tariffs_{Ic}$ from 0 to 1 before recomputing the equilibria in each market-simulation.

The results of this counterfactual exercise are presented in the bottom panel of Table 10. They show, for example, that introducing a tariff decreases the propensity to export from 0.403 to 0.370 in markets with four potential entrants. On average, the propensity to export drops from 0.342 to 0.318, or by 2.4 percentage points. If we repeat this last exercise using the estimates from column (6) of Table 6, we find that the average

[25] (0.302-0.243) $\times$ 7, which is equal to 0.413.

[26] This is calculated as the comparative statics effect across all markets (0.065) times the weighted average number of potential entrants in markets with positive tariffs, which is equal to 4.24.

Table 10: Policy Experiment

	Propensity to export by number of potential entrants							All markets	
	$K_{Ic} = 1$	$K_{Ic} = 2$	$K_{Ic} = 3$	$K_{Ic} = 4$	$K_{Ic} = 5$	$K_{Ic} = 6$	$K_{Ic} = 7$	Propensity to export	Comparative statics
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Markets with positive tariffs									
– with competitive effects[a]									
original values	0.757	0.520	0.396	0.327	0.288	0.256	0.243	0.283	
all tariffs zero	0.928	0.673	0.505	0.416	0.364	0.322	0.302	0.348	0.065
– without competitive effects[b]									
original values	0.661	0.481	0.408	0.360	0.355	0.344	0.371	0.373	
all tariffs zero	0.798	0.632	0.545	0.500	0.497	0.487	0.516	0.512	0.139
Number of observations	199	386	596	893	616	549	372	3,611	
Panel B: Markets with zero tariffs									
– with competitive effects[a]									
original values	0.924	0.637	0.489	0.403	0.354	0.315	0.288	0.342	
all tariffs > 0	0.872	0.581	0.448	0.370	0.326	0.291	0.267	0.318	-0.024
– without competitive effects[b]									
original values	0.802	0.638	0.586	0.538	0.530	0.529	0.530	0.550	
all tariffs > 0	0.677	0.499	0.451	0.404	0.394	0.393	0.396	0.415	-0.135
Number of observations	285	671	906	1,204	827	647	513	5,053	

Notes: This table reports results from our policy analysis. We run two policy experiments, both of which consist of computing equilibria with simulated unobservables as we change the tariffs. The upper panel of the table focuses on markets with positive tariffs; the lower panel on markets with zero tariffs. Rows labeled "original values" report the propensity to export at the original values of the variables and at the estimated parameters. Rows labeled "all tariffs = 0" report the predicted propensity to export after the tariff indicator is set equal to zero for all markets with positive tariffs. Rows labeled "all tariffs > 0" report the predicted propensity to export after the tariff indicator is set equal to one for all markets with zero tariffs. [a] Uses estimates from column (5) of Table 6. [b] Uses estimates from column (6) of Table 6.

propensity to export would be predicted to drop by 13.5 percentage points (now the average number of potential entrants is 4.11). Again, the change in export propensity is grossly overestimated when strategic interactions are not taken into account.

In sum, the strategic interaction between superstar exporters implies that changes in tariffs have a less dramatic effect than what we would predict in single-firm models, where each firm acts independently of the other firms. Our simulations show that the bias in single-firm models can be very large, overstating the entry or exit response due to changes in tariffs by a factor of two to more than five.

8 Conclusion

We study the determinants of export decisions by superstar firms, defined as firms with a share in industry-level exports of at least five percent. We model their export decisions as the result of a strategic game of entry, which we estimate adapting the methodology in Ciliberto & Tamer (2009) to an international trade framework. We find that competitive effects have a large impact on firms' export decisions: in the absence of strategic interactions, superstar exporters would be 53.2 percentage points more like to export to a given market.

We also employ our model to analyze implications for trade policy. We show that failing to account for the strategic interaction among superstar exporters leads to: *(i)* overstating the increase in export propensity if tariffs were liberalized by a factor of two; and, *(ii)* overstating the drop in export propensity if tariffs were imposed by a factor of more than five.

Finally, we find that the competitive effects vary across firms. Negative competitive effects are smaller for firms with a larger export portfolio in terms of the export destinations. These heterogeneous competitive effects imply that there exist multiple equilibria, both in the identity and in the number of firms.

There are some limitations to our analysis. To begin with, we have modeled the strategic interaction among the firms as a static game. Our static model allows us to incorporate very general forms of heterogeneity among firms as well as multiple equilibria. To our knowledge, these are features that have not yet been modeled in dynamic games. We think of our approach as complementary to one where firms are modeled as playing a dynamic game, but where most of the heterogeneity across firms is necessarily assumed away.

Secondly, we have assumed that export decisions are independent across markets. For example, a Danish firms that is deciding whether to export to the Netherlands does not take into account its decision on whether to export to Belgium. This assumption is clearly at odds with the empirical evidence (see, e.g., Albornoz et al. (2012) and Morales et al. (2019)), but relaxing it is very difficult because it would require us to model firms' decisions as if they were building a network rather than one single link. We leave this challenging task to future work.

Finally, we have maintained that the Herfindahl-Hirschman Index (HHI) captures the role of non-Danish exporters in the import markets. Arguably, we would expect that the strategic interaction between non-Danish and Danish firms is more complex and nuanced than the one that can be captured by a single aggregate measure like the HHI. We think that there is a lot to benefit from merging firm-product level data from different countries, and we hope to see that direction pursued in future empirical work.

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Superstar Exporters: An Empirical Investigation of Strategic Interactions in Danish Export Markets

Online Appendix

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This document contains supplementary material for the paper "Superstar Exporters: An Empirical Investigation of Strategic Interactions in Danish Export Markets" by Federico Ciliberto and Ina C. Jäkel. Section A contains details on the construction of our sample and the discretization of variables. Section B provides a detailed robustness analysis for our empirical findings, based on the simple probit model. In Section C, we present details for the falsification test discussed in Section 4.2 of the main text. In Section D, we discuss the likely direction and size of bias in our estimated competitive effects if firms have the option to export *indirectly* to foreign markets. We adapt the "balls and bins" framework of Armenter & Koren (2014) to our data in Section E, and use this framework as a benchmark to evaluate the fit of our empirical model of strategic interactions. In Section F, we show that results from our equilibrium model are upheld in specifications with different specifications of the non-idiosyncratic errors. Finally, Section G provides information for the estimation of the equilibrium model.

A Data Appendix

A.1 Construction of Sample

Our starting point is the universe of export transactions by firm, destination and product. We aggregate products up to the NACE four-digit industry level in order to account for competition between firms producing products that are close substitutes. We focus on a cross section for the year 2007.

We define superstar firms based on their share in industry-wide exports, and purely domestic firms are therefore by definition excluded from the sample. This choice is not very restrictive since firms that only sell their output domestically are typically smaller firms. In Appendix B.3 below, we show that our results are robust to an alternative superstar definition based on a firm's share in total industry revenue.

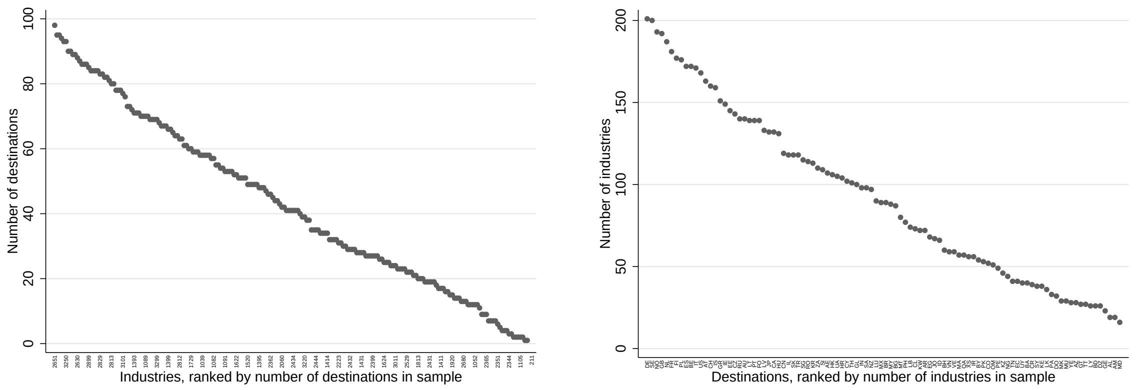
We also exclude wholesalers, retailers and other non-manufacturing firms, since these firms' exporting behavior differs significantly from the one of manufacturing firms; see, e.g., Bernard et al. (2015). In Appendix B.1 we discuss results where we *(i)* account for competition from non-manufacturing firms, or *(ii)* restrict the sample to industries where manufacturing firms dominate overall exports.

Selection of Markets

As discussed in the main text, we focus on the top-100 destinations for Danish exporters and further restrict the sample to markets which could potentially be served by the firms in our sample. Hence, we keep only markets that were served at least twice over the last five years. Our final sample covers 72 percent of overall Danish manufacturing exports.

Figure A.1 further describes the sample composition in terms of destinations and industries. In some of the most export intensive industries – such as NACE 2651 ("Manufacture of instruments and appliances for measuring, testing and navigation") and NACE 2110 ("Manufacture of basic pharmaceutical products") – almost all destinations are judged to be attractive (according to the criteria mentioned above), and hence included in the sample; see

Figure A.1: Sample Composition: Destinations and Industries



(a) Number of Destinations by Industry

(b) Number of Industries by Destination

Figure A.1(a). Some other industries – such as NACE 2363 ("Manufacture of ready-mixed concrete") – are little export-oriented, and our sample selection criteria lead us to exclude many destination markets. Similarly, in the most popular destinations (Germany and Sweden), we observe more than 200 industries; see Figure A.1(b). However, on average, we only include 92 industries per destination.

Superstar Definition and Persistence in Superstar Status

Varieties are included in the sample of superstar exporters if they have a share in industry-wide exports in 2007 of at least 5 percent. In the following, we document that a variety's status as "superstar" is very persistent over time.

Table A.1: Persistence in Superstar Status

	New Superstars		Incumbent Superstars		Total	
	%	No.	%	No.	%	No.
$K_{Ic} = 1$	0	0	100	14	100	14
$K_{Ic} = 2$	20	14	80	56	100	70
$K_{Ic} = 3$	21.7	26	78.3	94	100	120
$K_{Ic} = 4$	20.2	38	79.8	150	100	188
$K_{Ic} = 5$	20.6	32	79.4	123	100	155
$K_{Ic} = 6$	26.5	35	73.5	97	100	132
$K_{Ic} = 7$	26.9	32	73.1	87	100	119
Total	*22.2*	*177*	*77.8*	*621*	*100*	*798*

Notes: The table considers all varieties i that are classified as export superstars in 2007, and asks whether they were superstars already in 2006. The columns labeled "New Superstars" report the percent and number of superstars in 2007 that were not classified as superstars in 2006. The columns labeled "Incumbent Superstars" report the percent and number of superstars in 2007 that were already classified as superstars in 2006.

Table A.1 shows that the overwhelming majority of superstars in 2007 were already superstars in 2006. The table splits the sample of superstar varieties in 2007 into *(i)* "incumbent superstars", defined as varieties that had a share in industry-wide exports of at least 5 percent in both 2006 and 2007; and *(ii)* "new superstars", defined as varieties that passed the 5-percent threshold from 2006 to 2007. Across all industries, 621 out of 798 superstars in 2007 (approx. 78 percent) were superstars already in 2006. This persistence in the identities of the superstars varies somewhat across industries depending on the number of potential entrants: for example, in industries with only one superstar firm, all superstars included in our sample were already superstars in 2006. In industries with six or seven superstars, however, only approx. 73 percent of superstars in 2007 were already superstars in 2006. These latter numbers reflect the circumstance that in industries with more potential entrants K_{Ic} there are more superstar varieties that are close to the five-percent threshold.

In Section B.2 below, we report results from the simple probit model where we apply a stricter superstar definition: there, a variety is defined to be a superstar within its industry if it has a share in total industry-wide exports of at least 10 percent. The aim of this robustness check is two-fold: first, varieties with a larger share in exports are more likely able to influence market outcomes (which is a prerequisite for finding evidence of strategic interactions between firms). Second, with a few exceptions, varieties with a share in industry exports in 2007 of 10 percent or more had a significant market share already in 2006. Thus, we here are even less concerned with "shooting stars"; i.e., firms which had a negligible share in overall exports in the pre-sample period.

Persistence in Market-Specific Export Decisions

Table A.2 shows that the market entry decisions of superstar firms also tend to be persistent. For example, out of the 16,254 observations where a superstar i is serving a given market Ic in 2007 ($y_{iIc,2007}=1$), 85 percent recorded positive exports already in 2006. Similarly, out of the 21,002 observations where a superstar i is not serving a given market Ic in 2007 ($y_{iIc,2007}=0$), almost 90 percent recorded zero exports also in 2006. Out of 37,256 observations, we see

Table A.2: Persistence in Superstars' Export Decisions

	$y_{iIc,2006}$=0		$y_{iIc,2006}$=1		Total	
	%	No.	%	No.	%	No.
$y_{iIc,2007}$=0	89.8	18,860	10.2	2,142	100	21,002
$y_{iIc,2007}$=1	14.9	2,422	85.1	13,832	100	16,254
Total	*57.12*	*21,282*	*42.88*	*15,974*	*100*	*37,256*

Notes: $y_{iIc,t}$ is an indicator variable, which is equal to one if variety i was exported to market Ic in year t, and zero otherwise; $t = 2006, 2007$

switching into or out of a given market only for 4,564[1] observations; i.e., 12 percent. These patterns are confirmed when we dis-aggregate industries by the number of potential entrants, K_{Ic}. For example, the probability of switching in or out of specific export markets is 14.8 percent in markets with one potential entrant, 11.8 percent in markets with four potential entrants, and 12.4 percent in markets with seven potential entrants.

A.2 Discretization

In order to estimate the equilibrium model in Section 5 in the main text, we need to discretize each of our control variables. We do so by first standardizing the variable; i.e., subtracting the respective mean and dividing by the standard deviation. Subsequently, we divide the standardized variable into unit intervals. We then represent values that fall into a specific interval by the mid-point of this interval. We check the plausibility of the discretization procedure by comparing probit results for the standardized and the discretized variables, and find that estimated effects are qualitatively and quantitatively unaffected by the discretization.

B Robustness Analysis

This section reports several sets of robustness checks. In Section B.1, we extend our empirical model to include additional control variables, and account for competition from other competitors besides the "'superstars". In Section B.2, we analyze the robustness of our

[1] 2,422 + 2,142.

findings to different ways of constructing the sample. In Section B.3, we consider alternative definitions of the "superstars". Finally, in Section B.4 we show how the effects of competitor entry vary across industries depending on the number of potential entrants K_{Ic}.

Ideally, all robustness checks should be performed using the equilibrium model, but this proves computationally burdensome. We thus resort to the (single equation) probit model in this section. All tables report parameter estimates and standard errors for the variables included in the model. At the bottom of each table, we additionally report the marginal effect of competitor entry. Recall that these effects are calculated as the change in the predicted probability of exporting if a firm does not face any competition in the foreign market (i.e., if the count of competitors active in market Ic is set equal to zero). Importantly, we find that all robustness checks substantiate our results in the main text.

B.1 Additional Control Variables

Additional Firm Controls

We first extend the set of variables included in the vector $\mathbf{Z}_{iIc}$. In particular, we allow export participation to be related to firm size and labor productivity, as measured by the number of employees and value added per employee, respectively. Firm size and productivity are standard controls in the empirical trade literature; see, e.g., Roberts & Tybout (1997) and Bernard & Jensen (2004). In fact, models with heterogeneous firms (e.g., Melitz (2003)) predict that larger, more productive firms are more likely to export to a given market.

Column (1) of Table B.1 broadly confirms these predictions. Firm size (as measured by the number of employees) enters positively as expected. Firm productivity is the main driver of export participation in empirical studies building on Melitz (2003). However, we find that productivity does not affect the probability to export. On closer inspection, this result is driven by a high correlation of productivity with a firm's industry scope (i.e., a high correlation with the variable *Firm Industries*$_i$).

Table B.1: Additional Control Variables and Competition from Non-Superstars

	Dependent Variable: Variety Export Status, by Market				
	Additional Control Variables			Restricted Sample	
	(1)	(2)	(3)	(4)	(5)
δ_{probit}	-0.585***	-0.733***	-0.707***	-0.555***	-0.499***
	(0.012)	(0.013)	(0.013)	(0.014)	(0.018)
Potential K_{Ic}	0.110***	0.150***	0.140***	0.100***	0.125***
	(0.011)	(0.011)	(0.011)	(0.012)	(0.016)
Firm Industries$_i$	0.003	0.016	0.020	0.031**	0.017
	(0.014)	(0.013)	(0.013)	(0.015)	(0.019)
Variety Rank$_i$	-0.044***	0.002	-0.020	-0.009	-0.018
	(0.013)	(0.012)	(0.012)	(0.016)	(0.024)
Variety Destinations$_{iIc}$	1.181***	1.183***	1.211***	1.253***	1.352***
	(0.016)	(0.016)	(0.016)	(0.018)	(0.025)
GDP_c	0.850***	0.583***	0.658***	0.871***	0.889***
	(0.016)	(0.018)	(0.017)	(0.019)	(0.024)
Geographical Distance$_c$	-0.611***	-0.445***	-0.390***	-0.634***	-0.560***
	(0.021)	(0.021)	(0.022)	(0.024)	(0.030)
Industry Size$_I$	-0.020	-0.429***	-0.256***	-0.006	-0.027
	(0.016)	(0.020)	(0.018)	(0.019)	(0.022)
HHI_{iIc}	-0.089***	-0.075***	-0.063***	-0.088***	-0.074***
	(0.015)	(0.015)	(0.015)	(0.017)	(0.021)
$Tariff_{iIc} > 0$	-0.680***	-0.455***	-0.512***	-0.663***	-0.696***
	(0.041)	(0.041)	(0.041)	(0.046)	(0.058)
Labour Productivity$_i$	0.013				
	(0.010)				
Firm Size$_i$	0.087***				
	(0.015)				
Fringe Competitors$_{Ic}$		0.819***			
		(0.023)			
Non-Manuf. Competitors$_{Ic}$			0.549***		
			(0.016)		
Observations	35,681	36,078	36,078	27,121	16,197
Number of markets	8,664	8,664	8,664	6,371	4,050
Market random effects	Yes	Yes	Yes	Yes	Yes
Marginal effect of competitor entry[a]	0.202	0.226	0.223	0.194	0.177

Notes: The table gives coefficient estimates from a probit model for the firm-industry-destination specific export status. All specifications include market (industry-destination) random effects. Column (4) restricts the sample to industries where manufacturing firms account for 50 percent or more of overall exports. Column (5) restricts the sample to industries where manufacturing firms account for 75 percent or more of overall exports. δ_{probit} is the coefficient on the count of other competitors that are active in a market. All other variables (except for $Tariff_{Ic} > 0$ and *Potential* K_{Ic}) are standardized. Standard errors in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

[a] Marginal effect calculated as the change in the predicted probability to export as competition in a market goes to zero.

Accounting for Competition from Fringe Firms

Next, we add further variables to the vector of market-specific determinants of profits, $\mathbf{X}_{Ic}$. While our focus in this paper is on the behavior of superstar firms, we might be concerned that not accounting for competition from fringe firms might bias our results. We therefore define a variable $\textit{Fringe Competitors}_{Ic}$ as the number of fringe firms entering a given market Ic.[2] Column (2) of Table B.1 shows that the coefficient on this variable is positive. Thus, in contrast to the negative effect of superstar competitors, fringe competitors actually have a *positive* effect on the export decisions of the superstars. This finding is interesting because it confirms that negative effects of competitor entry are only relevant for large firms which have the capability of affecting the market outcome. Moreover, it is consistent with the results on positive informational spill-overs in the trade literature; see, e.g., Aitken et al. (1997), Koenig et al. (2010) and Choquette & Meinen (2015). The estimate of δ_{probit} is, however, largely unaffected by the inclusion of $\textit{Fringe Competitors}_{Ic}$.

Accounting for Competition from Non-Manufacturing Firms

Recall that we restrict our analysis of export superstars to the set of manufacturing firms. In columns (3) to (5) of Table B.1, we investigate the effects of competition from non-manufacturing firms. First, we define the variable $\textit{Non-Manuf. Competitors}_{Ic}$ as the number of non-manufacturing firms entering a given market Ic.[3] In column (3), $\textit{Non-Manuf. Competitors}_{Ic}$ is estimated with a positive coefficient, implying that the presence of non-manufacturing firms in an export market has a positive effect on the export probability of the superstars. Again, this is consistent with informational spillovers across firms.

Second, we estimate regressions where we restrict the sample to industries where manufacturing firms account for the majority of exports (defined as 50 percent or 75 percent); see columns (4) and (5) of Table B.1 respectively. Both the parameter estimate of δ_{probit}, as well as the corresponding marginal effect, are largely unaffected by these sample restrictions.

[2] This variable is included in logs in the empirical model.

[3] This variable is included in logs in the empirical model.

B.2 Alternative Sample Definitions

In this section, we report a number of robustness checks regarding the construction of the sample.

Robustness to Alternative Years

Our sample is a cross-section for the year 2007. The choice of year is mainly driven by data availability regarding the tariff data. Specifically, the CEPII (Guimbard et al., 2012) provides custom-made information on applied, preferential tariffs for the year 2007 for a large number of importing countries. Importantly, non-ad valorem tariffs have already been transformed into ad-valorem equivalents by these authors. Nevertheless, it is important to establish that our results are not specific to the (pre-crisis) year 2007.

We thus estimate the probit model on data from different years. Columns (1) and (2) of Table B.2 report results for the years 2005 and 2006, respectively. Note that specifications do not include tariffs and the HHI, since these variables were not readily available for those years. For both years, the parameter estimates of δ_{probit}, as well as the corresponding marginal effects, are comparable in magnitude to those reported in Tables 4 and 5 in the main text.

Including All Destinations

In the main text, we have restricted the sample to the top 100 destinations. In column (3) of Table B.2 we show results where all destinations are included, as long as the criterion regarding a market being 'attractive' (i.e. having been served at least twice over the last five years) is still fulfilled. As can be seen, the sample size only increases slightly, implying that the restriction to the top 100 destinations is not very strict. Moreover, results on the sign and size of the effects of competitor entry are again confirmed.

Excluding EU/Euro Countries

Throughout the analysis, we have assumed that a firm's export decisions are independent across markets. This assumption may be particularly restrictive when considering the EU,

Table B.2: Alternative Samples

	Dependent Variable: Variety Export Status, by Market							
	Year 2005	Year 2006	All Destinations	Drop EU	Drop EMU	World Regions	Homogeneous goods	Differentiated goods
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
δ_{probit}	-0.542***	-0.582***	-0.548***	-0.621***	-0.586***	-0.550***	-0.661***	-0.586***
	(0.012)	(0.012)	(0.011)	(0.017)	(0.015)	(0.026)	(0.031)	(0.013)
Potential K_{Ic}	0.085***	0.083***	0.081***	0.048***	0.073***	0.069***	0.018	0.125***
	(0.010)	(0.011)	(0.010)	(0.014)	(0.012)	(0.023)	(0.026)	(0.012)
Firm Industries$_i$	0.057***	0.057***	0.054***	0.082***	0.062***	0.152***	0.050*	0.043***
	(0.012)	(0.013)	(0.012)	(0.018)	(0.016)	(0.026)	(0.026)	(0.016)
Variety Rank$_i$	0.004	-0.017	-0.024**	0.013	-0.001	-0.047*	-0.038	-0.023*
	(0.012)	(0.012)	(0.011)	(0.016)	(0.015)	(0.025)	(0.035)	(0.013)
Variety Destinations$_{iIc}$[a]	1.143***	1.103***	1.112***	1.189***	1.178***	0.984***	1.112***	1.202***
	(0.015)	(0.015)	(0.014)	(0.021)	(0.018)	(0.030)	(0.037)	(0.017)
GDP_c[a]	0.738***	0.717***	0.822***	0.745***	0.809***	1.148***	0.752***	0.872***
	(0.015)	(0.015)	(0.015)	(0.021)	(0.019)	(0.045)	(0.036)	(0.018)
Geographical Distance$_c$[a]	-0.793***	-0.769***	-0.801***	-0.460***	-0.579***	-0.662***	-0.850***	-0.552***
	(0.015)	(0.015)	(0.015)	(0.027)	(0.023)	(0.040)	(0.048)	(0.023)
Industry Size$_I$	-0.050***	-0.056***	-0.048***	-0.056**	-0.026	-0.134***	0.055	-0.008
	(0.015)	(0.015)	(0.015)	(0.022)	(0.019)	(0.033)	(0.037)	(0.018)
HHI_{Ic}				-0.091***	-0.076***		-0.054*	-0.099***
				(0.018)	(0.017)		(0.031)	(0.017)
$Tariff_{Ic} > 0$				-0.780***	-0.716***		-0.422***	-0.749***
				(0.048)	(0.044)		(0.090)	(0.045)
Observations	37,893	35,566	40,311	20,295	24,909	9,062	6,582	29,496
Number of markets	9,183	8,985	9,685	4,803	5,933	2,237	1,727	6,937
Market random effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Marginal effect of competitor entry[b]	0.197	0.205	0.189	0.194	0.194	0.181	0.203	0.207

Notes: Columns (1)–(5) and (7)–(8) give coefficient estimates from a probit model for the firm-industry-destination specific export status. In column (6), export status is instead defined at the firm-industry-region level. All regressions include market (industry-destination or industry-region) random effects. δ_{probit} is the coefficient on the count of other competitors that are active in a market. All other variables (except for $Tariff_{Ic} > 0$ and *Potential* K_{IC}) are standardized. Standard errors in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

[a] In column (6), these variables are defined at the region level rather than the country level.

[b] Marginal effect calculated as the change in the predicted probability to export as competition in a market goes to zero.

where countries are highly integrated. For example, a superstar's decision of whether to export to Belgium may not be independent of its decision of whether to export to the Netherlands. As a robustness check, we therefore confirm that our results are robust to dropping EU countries in general, or countries that are members of the European Monetary Union (EMU) in particular; see columns (4) and (5) of Table B.2.

Defining Markets based on World Regions

Morales et al. (2019) and related work highlight how export decisions are correlated across geographically proximate destinations. Dropping EU/EMU countries from the sample may not be sufficient to address this correlation of export decisions across markets. In particular, we could imagine a broader strategic game, where – for example – one superstar firm exports to France and Belgium, and the other exports to Japan and China. In order to mitigate the concern that this correlation in export decisions could impact our findings, we divide the countries in our sample into 18 distinct world regions.[4]

We can then estimate the probit model on a sample where the export decisions of superstar varieties are aggregated into regional clusters. Thus, a market is now defined as a combination of an industry I and a world region g; and the dependent variable is an indicator variable y_{iIg} for whether variety $i \in I$ is exported to region g. The main explanatory variable of interest is the count of other superstars exporting to market Ig. The definition of some of the control variables also changes slightly because the unit of analysis is different: *GDP* now reflects the aggregate GDP of a world region, *Geographical distance* refers to the regional average distance from Denmark, and *Variety destinations* refers to the number of other regions (not countries) that a variety is exported to.

Results, reported in column (6) of Table B.2, show an estimate of δ_{probit} which is negative and highly statistically significant. Moreover, based on the marginal effect of competitor entry, we predict the probability of exporting to increase by 18.1 percentage points as the number of competitors faced in a regional export market is reduced to zero. This effect is

[4]For example, countries on the American continent are divided into three regions: North America, Central America and South America.

strikingly similar to the marginal effect of roughly 20 percentage points reported in the main text.

Homogeneous vs. Differentiated Products

Finally, we ask whether the effects of competitor entry vary across industries depending on the extent of product differentiation. We revert to Rauch (1999)'s classification of SITC industries into organized exchange, reference-priced, and differentiated. We use a conversion table to link four-digit SITC industries to six-digit HS codes, and another conversion table to link the HS codes to our four-digit NACE industries. We next calculate the share of six-digit HS products within an industry that are classified as differentiated.

In column (7) of Table B.2, we estimate the single equation probit model on the sample of homogeneous-goods industries (defined as industries where 50 percent or more of all six-digit HS codes are reference-priced or organized exchange goods according to Rauch's classification). Column (8) shows equivalent results for the sample of heterogeneous-goods industries (i.e., industries where more than 50 percent of all six-digit HS codes are classified as differentiated goods). We find that the effects of competitor entry do not vary significantly across homogeneous-goods and differentiated-goods industries: both parameter estimates and marginal effects are very similar across the two sets of industries.

How can we rationalize this finding? On the one hand, price competition between firms might be fiercer for homogeneous goods than for differentiated goods, which should result in larger effects of competitor entry. On the other hand, if products are (partly) differentiated by country of origin, competition between *Danish* superstar exporters may indeed be fiercer for differentiated products than for homogeneous products. This second, opposing effect may explain why we do not find δ_{probit} to be significantly smaller in column (8) compared to column (7).

B.3 Alternative Superstar Definitions

Defining Superstars based on Overall Sales

Our sample of superstars employed in the main text only includes firms that export to at least one destination. Thus, large firms that are superstars only on the domestic market exist are ignored in our analysis. Such 'domestic superstar' firms do not export anywhere (yet) but could potentially export. In that sense, modelling their decision of *not* to export might be relevant, because this decision could be influenced by the strategic interaction with the set of superstar exporters.

Our next robustness check therefore involves looking at a firm's overall revenues (including both domestic and export sales) to determine superstar status. We obtain information on firm revenue the balance-sheet data. In this data set, firms are allocated to four-digit NACE Revision 1.1 industries[5] according to their *main activity.* We classify firms as 'superstars' if they have a share in total industry revenue of at least 5 percent. We end up with a sample of 722 firms in 199 industries. 102 of these 722 firms produce only for the domestic market. Importantly, firms are now classified as 'superstars' only for the industry of their main activity (recall that in the main text, a firm could be a superstar in potentially more than one industry). Accordingly, there is no variation in the two variables $\textit{Variety Rank}_i$ and $\textit{Firm Industries}_i$, and we drop them from the model.[6]

Estimating the simple probit model for this alternative set of superstar firms confirms the negative effects of competitor entry highlighted throughout the paper. With a 16.3 percent increase in the likelihood of exporting if the number of competitors faced in a market is reduced to zero, the marginal effect is somewhat lower than the ones presented in the main text. Note, however, that these effects are not strictly comparable, since they are based on different samples with a different overall probability to export. In particular, because the sample of column (1) includes domestic superstars that do not export anywhere but

[5]The analysis here thus differs slightly from the approach used in the main text where we use the more recent NACE Revision 2 classification.

[6]We also resort to the simple model without the variables $\textit{HHI}_{Ic}$ and $\textit{Tariff}_{Ic} > 0$. Recall, however, that adding those variables to the specification had a negligible impact on the estimate of δ_{probit}.

Table B.3: Alternative Superstar Definitions

	Dependent Variable: Variety Export Status, by Market	
	Superstars Overall Sales	Superstar 10 percent
	(1)	(2)
δ_{probit}	-0.492***	-0.629***
	(0.014)	(0.020)
Potential K_{Ic}	0.055***	-0.044***
	(0.012)	(0.012)
Firm Industries$_i$		0.010
		(0.018)
Variety Rank$_i$		0.005
		(0.017)
Variety Destinations$_{iIc}$	1.344***	1.248***
	(0.018)	(0.021)
GDP$_c$	0.540***	0.708***
	(0.016)	(0.018)
Geographical Distance$_c$	-0.736***	-0.522***
	(0.017)	(0.024)
Industry Size$_I$	-0.012	-0.116***
	(0.018)	(0.019)
HHI$_{iIc}$		-0.089***
		(0.018)
Tariff$_{iIc} > 0$		-0.562***
		(0.047)
Observations	28,721	19,897
Number of markets	7,702	8,462
Market random effects	Yes	Yes
Marginal effect of competitor entry[a]	0.163	0.116
Marginal effect of competitor entry[b]	0.189	0.251

Notes: The table gives coefficient estimates from a probit model for the firm-industry-destination specific export status. All regressions include market (industry-destination) random effects. δ_{probit} is the coefficient on the count of other competitors that are active in a market. All other variables (except for *Tariff*$_{Ic} > 0$ and *Potential* K_{IC}) are standardized. Standard errors in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

[a] Marginal effect calculated as the change in the predicted probability to export as competition in a market goes to zero.

[b] Marginal effect calculated as the change in the predicted probability to export due to a unit decrease in the number of competitors exporting to a market.

may exclude some export superstars that have negligible sales at home, the overall export probability (and, thus, the average number of competitors faced on an export market) is substantially lower than in the sample used throughout the main text.

Applying a Stricter Superstar Definition

Throughout the paper, we define superstars as firms that within an industry account for 5 percent or more of overall exports. In fact, only sufficiently large firms have the market power to influence market outcomes. The 5 percent threshold might still be low in this respect. As a robustness check, we therefore further constrain the set of superstars to firms with a share in overall industry-wide exports of at least 10 percent. Results, reported in column (2) of Table B.2, confirm that the estimated effect of competitor entry remains negative, highly statistically significant, and economically large with this alternative superstar definition.

Again, the marginal effect – calculated as the change in the predicted export probability as the number of competitors faced in a market is reduced to zero – is not directly comparable to the one from our benchmark estimations in the main text. To facilitate comparison, we also ask how the export probability changes if only *one* competitor stops exporting to a given destination market. Based on column (2) of Table B.2, this marginal effect stands at 0.251. The same marginal effect calculated based on estimates in column (2) of Table 4 in the main text, is equal to 0.211. Thus, when we restrict the sample to larger superstars with a share in industry-wide exports of at least 10 percent, we also find somewhat larger effects of competitor entry on export probabilities.

B.4 Variation Across Industries

In Section B.2, we have considered differences in the effects of competitor entry across homogenous and differentiated goods industries, but found these differences to be negligible. In Table B.4, we instead ask how effects vary across industries depending on the number of Danish superstars; i.e., the number of potential entrants K_{Ic}. We estimate our simple probit model separately for the subset of industries with $K_{Ic} = 2, \ldots 7$. Our hypothesis is that competition between any two individuals firms is fiercer in industries with fewer export superstars.

Consider, first, the marginal effect calculated as the change in the predicted export probability as the number of competitors that export to a given destination is reduced to zero. Recall that this corresponds to our approach in the main text. We find that the predicted changes in export probability are strikingly similar across all columns of Table B.4.

As noted above, effects are not strictly comparable across columns if the sample differs. here, in particular, the number of competitors differs in each column. Again, we therefore also ask how the export probability changes if one competitor stops exporting to a given destination market. In industries with two superstars, we predict the market-specific export probability to increase by 39 to 40 percentage points if the superstar's competitor is not present in that market. A similar prediction holds in industries with three superstars. In contrast, as the number of superstars K_{Ic} increases, the marginal effect drops. For example, in markets with five superstars, any individual firm's export probability only increases by 23 percentage points due to a unit decrease in the number of competitors who export to that market. These results indicate that competition between any two firms is fiercer (in the sense of each firm having a larger (negative) effect on the other firm's export probability) in markets with fewer competitors.

C Falsification Test

In this section, we provide details for the falsification test discussed in Section 4.2 in the main text. Recall that the falsification test asks how the export behavior of superstar firms in industry I depends on the entry decisions of superstar firms from other, unrelated industries $I' \neq I$. Superstar firms interact strategically only if they are competing with each other on output markets, and we would thus expect that negative effects of competitor entry should only be present within industries, but not across industries.

We proceed as follows. For each market Ic, we randomly draw $K_{Ic} - 1$ superstars from

Table B.4: Variation across Industries depending on K_{Ic}

	Dependent Variable: Variety Export Status, by Market					
	$K_{Ic}=2$	$K_{Ic}=3$	$K_{Ic}=4$	$K_{Ic}=5$	$K_{Ic}=6$	$K_{Ic}=7$
	(1)	(2)	(3)	(4)	(5)	(6)
δ_{probit}	-1.285***	-1.014***	-0.915***	-0.636***	-0.528***	-0.459***
	(0.089)	(0.046)	(0.031)	(0.029)	(0.025)	(0.025)
$Tariff_{Ic}$	-0.029	-0.113***	-0.270***	-0.295***	-0.483***	-0.425***
	(0.028)	(0.029)	(0.036)	(0.046)	(0.053)	(0.064)
GDP_c	0.631***	0.835***	0.849***	0.915***	1.000***	0.909***
	(0.052)	(0.040)	(0.032)	(0.037)	(0.041)	(0.046)
Geographical Distance$_c$	-0.558***	-0.582***	-0.856***	-0.897***	-0.725***	-0.884***
	(0.054)	(0.039)	(0.035)	(0.041)	(0.043)	(0.052)
Industry Size$_I$	-0.102**	-0.075**	0.016	0.025	0.046	0.209***
	(0.049)	(0.033)	(0.033)	(0.054)	(0.057)	(0.046)
Variety Rank$_i$	-0.059	-0.043	-0.063**	0.021	-0.012	-0.000
	(0.063)	(0.034)	(0.025)	(0.027)	(0.027)	(0.035)
Variety Destinations$_{iIc}$	1.037***	1.119***	1.105***	1.242***	1.145***	1.213***
	(0.064)	(0.042)	(0.031)	(0.034)	(0.035)	(0.041)
Firm Industries$_i$	0.061	0.038	0.083***	-0.035	0.072**	0.007
	(0.048)	(0.045)	(0.026)	(0.028)	(0.031)	(0.036)
HHI_{Ic}	-0.020	-0.080**	-0.128***	-0.106***	-0.142***	-0.076
	(0.046)	(0.040)	(0.030)	(0.033)	(0.039)	(0.049)
Constant	0.905***	0.802***	0.909***	0.663***	0.637***	0.665***
	(0.082)	(0.060)	(0.050)	(0.056)	(0.061)	(0.070)
Observations	2,114	4,506	8,388	7,215	7,176	6,195
Number of markets	1,057	1,502	2,097	1,443	1,196	885
Market random effects	Yes	Yes	Yes	Yes	Yes	Yes
Marginal effect of competitor entry[a]	0.170	0.223	0.243	0.213	0.223	0.225
Marginal effect of competitor entry[b]	0.392	0.404	0.344	0.230	0.191	0.161

Notes: The table gives coefficient estimates from a probit model for the firm-industry-destination specific export status. All regressions include market (industry-destination) random effects. δ_{probit} is the coefficient on the count of other competitors that are active in a market. All other variables (except for $Tariff_{Ic} > 0$ and *Potential* K_{IC}) are standardized. Standard errors in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively. [a] Marginal effect calculated as the change in the predicted probability to export as competition in a market goes to zero. [b] Marginal effect calculated as the change in the predicted probability to export due to a unit decrease in the number of competitors exporting to a market.

Table C.1: Results from the Falsification Test

	(1) mean	(2) sd	(3) min	(4) max	(5) N
Average "false" competitor entry	1.666	0.012	1.643	1.703	50
$\delta_{unrelated}$					
Parameter estimate	0.116	0.010	0.090	0.130	50
t statistic	7.529	0.669	5.945	8.476	50
Marginal effect[a]	-0.045	0.004	-0.051	-0.036	50

Notes: The table reports results from simulations based on the probit model. 'False' competitive effect ($\delta_{unrelated}$) gives the count of randomly drawn competitors from unrelated industries which are active in destination c. Otherwise, regressions are based on the same set of explanatory variables as in column (5) of Table 4 in the main text. We repeat the analysis for 50 random draws of $K_{Ic} - 1$ firms. [a] Marginal effect calculated as the change in the predicted probability to export as the number of randomly drawn "false competitors" in a market goes to zero.

different industries I'.[7] In the following, we call these randomly drawn superstars from unrelated industries "false competitors". We make two restrictions in order to select firms and industries that are truly unrelated to the set of superstar firms in industry I. First, recall that firms can be active in several industries. We thus exclude a firm's other superstar varieties in industries $I' \neq I$ when making the random draws. Second, there could be a broader game played between firms in different four-digit industries that are loosely related, e.g. due to substitutability in production. As just one example, firms active in "Operation of dairies and cheese making" (Nace 10.51) that are currently not active in "Manufacture of ice cream" (Nace 10.52) could be *potential* entrants in the latter industry if the cheese making equipment could be reemployed for ice-cream production. We thus exclude observations from industries I' that belong to the same two-digit industry as industry I.[8]

Recall that the main explanatory variable of interest in the single equation probit model is the count of the number of competitors active in market Ic. We now similarly count the number of randomly drawn superstars from industries I' which entered destination c. (Note how drawing $K_{Ic} - 1$ superstars from other industries eases comparability of effects.) We denote the parameter on this variable by $\delta_{unrelated}$.

Table C.1 summarizes the estimates of $\delta_{unrelated}$, as well as the corresponding marginal

[7]The set of destinations included in the sample varies across industries. For each market Ic, we thus make random draws only from those industries I' where firms are potential entrants in destination c.

[8]Examples of two-digit industries are "Manufacture of food products", "Manufacture of Textiles", "Manufacture of basic metals", etc.

effects. As in Section 4 in the main text, marginal effects are calculated as the change in the predicted probability of exporting as the count of ("false") competitors entering destination c is set equal to zero. We find that $\widehat{\delta}_{unrelated}$ is greater than zero and statistically significant for all 50 simulations. The associated marginal effects are, however, small: if all "false competitors" exit a destination, we predict the export probability to decrease by 3.6 to 5.1 percentage points.

Importantly, we thus confirm that negative effects of competitor entry are present only *within* industries, substantiating our interpretation that these negative effects are due to strategic interactions between competing firms. How could we rationalize the positive effects that are working *across* across industries? One plausible interpretation is that there are destination-specific informational spillovers due to inter-industry linkages; see for example Choquette & Meinen (2015) for empirical evidence on such spillovers.

D Potential Biases due to Indirect Exports

As acknowledged in Section 2.2 in the main text, we may face measurement error in both the dependent variable and the independent variable of interest because firms can serve a market Ic either directly (via exports) or indirectly (via an intermediary). We have argued that measurement error is expected to be small in our sample of superstar exporters. In the following, we discuss the likely direction of any remaining biases. We first consider measurement error in the dependent variable (y_{iIc}, a firm's export decision) and next turn to measurement error in the independent variable ($\sum_{j\neq i} y_{jIc}$, competitors' export decisions). We focus on the single equation probit model, where we can draw on insights from previous literature.

Since y_{iIc} is binary, any measurement error in the dependent variable is by definition non-classical. Meyer & Mittag (2017) discuss the consequences of misclassification in binary choice models. They derive formulas for the components of the asymptotic bias in both the linear probability and the Probit model. They conclude that "[s]imulations and validation data show that the bias formulas are accurate in finite samples and *in most situations imply* *attenuation*" (emphasis added).[9] Thus, we are likely to underestimate the true competitive effects in our model.

Next, we turn to measurement error in the count of competitors exporting to market Ic, $\sum_{j \neq i} y_{jIc}$. To ease exposition, we reformulate this problem in terms of omitted variables: our estimations do not account for competition that takes place through indirect exporters. (In fact, since the competitive effects of indirect exports may differ from those of direct exports, we prefer the omitted variable representation of this problem.) A superstar firm that employs an intermediary for exporting to market Ic will not serve the market directly. The omitted variable (competition through indirect exports) and the independent variable of interest ($\sum_{j \neq i} y_{jIc}$) are therefore negatively correlated. If competition through indirect exports has a negative effect on firms' profits, the resulting omitted variable bias is positive and we are again likely to *underestimate* the negative competitive effects stemming from direct exports.

To understand the intuition behind this result, consider an industry with two superstars. If variety j is exported to market Ic via an intermediary, we observe $y_{jIc} = 0$. Assume that due to competition from j's indirect exports, variety i is not served to market Ic; i.e., $y_{iIc} = 0$. Thus, firms' observed export decisions in this situation would seem to be positively correlated, even though there is competition between the two firms, and one firm is exporting while the other firm is not.

In sum, we conclude that *(i)* measurement error due to firms' indirect exports is expected to be small in our sample of large exporters (cf. the main text); and *(ii)* any remaining bias is likely to imply that our estimated competitive effects provide a lower bound for the true competitive effects that we would estimate if we were able to account for indirect exports.

[9] In the special case where misclassification is "conditionally random" (i.e., conditional on the "true outcome" misclassification does not depend on the independent variables), the marginal effects in the observed data are proportional to the true marginal effects, with a proportionality factor smaller than one; i.e. there is attenuation bias (see also Hausman et al., 1998). In more general cases, the bias formulas are more involved but imply a tendency for the bias to be in the opposite direction of the sign of the coefficient.

E Comparison with a “Balls and Bins” framework

Armenter & Koren (2014) propose an elegant statistical model to describe the extensive margin of trade. According to the authors, their balls-and-bins model establishes “(...) a benchmark for the quantitative evaluation of structural models in sparse data” (Armenter & Koren (2014, p.2129)). We therefore adapt their framework to our set-up and derive such a benchmark for our empirical model.

Armenter & Koren (2014) depart from the observation that trade data consists of a finite number of shipments which are assigned to categories (e.g., destinations, product codes, and/or firms). Their statistical model then describes the assignment of export shipments to categories as balls falling into bins. Since the number of shipments is typically small relative to the number of possible categories, we could observe markets with only one entrant due to this sparsity of the data.

We base our analysis on the model extension with multiple classifications (pages 2134ff. in Armenter & Koren (2014)), which resembles most closely the structure of our data. Recall that our model makes predictions on market structures conditional on the number of potential entrants. In contrast, market structures are not of interest in Armenter & Koren (2014). We therefore have to amend their statistical model to our set-up.

Let $c = 1, \ldots C$ denote destinations and let $i \in I$ denote firms in industry I. Let k_{Ic} denote the number of non-empty bins (i.e., exporting firms) in market Ic. Finally, s_i is the likelihood that a “ball” belongs to firm i and n_{Ic} is the number of “balls” (shipments) going to market Ic. The expected number of non-empty bins (i.e., exporting firms) in destination c for industry I are given by (Armenter & Koren (2014, Equation 5)):

$$E(k_{Ic}) = \sum_i \left[1 - (1 - s_i)^{n_{Ic}}\right]. \tag{E.1}$$

where s_i is the probability that an export shipment belongs to firm i, $(1 - s_i)$ is the inverse of this probability and $(1 - s_i)^{n_{Ic}}$ is the probability that all n_{Ic} shipments going to market Ic do *not* belong to firm i. Thus, $[1 - (1 - s_i)^{n_{Ic}}]$ is the probability that firm i exports to market Ic, and we sum over firms to arrive at the total number of entrants.

In applying this framework to our set-up, we are challenged by the circumstance that our data does not contain information on the size of export shipments. We therefore rely on information in Armenter & Koren (2014), who report that the average shipment size was 36,000USD in their US data.[10]

The size of each bin, s_i, is equal to the inverse of the number of competitors in the industry (i.e., we assign equal export shares to all firms). We do not use information on exporter size, as exporter size is itself endogenous to the entry behavior of firms. Thus, using the actual relative size of firms in the sample for deriving the Armenter & Koren (2014) predictions would imply using additional information in the statistical model which is not used in the empirical model. Comparing our framework to Armenter & Koren (2014) would then entail comparing models that use different sets of information for deriving predictions.

We next need to calculate the number of balls going to a given market, n_{Ic}. If a market is not served by any Danish superstar, the number of actual shipments observed in the data is zero. The statistical model of Armenter & Koren (2014) would then trivially predict these market structures perfectly. Instead, we proxy the number of balls per market as follows. First, we calculate *(i)* the number of shipments n_c going to a given destination and *(ii)* the share of an industry i in overall shipments. Next, we multiply these two numbers, which amounts to the assumption that each industry accounts for a constant fraction of overall shipments across destinations.

Given s_i and n_{Ic}, we can compute the number of predicted entrants in the statistical model according to Equation (E.1). Importantly, the number of predicted entrants will generally not be an integer, and we round the prediction to the nearest integer. We can then compare the predicted market structure to the one observed in the data.

When we apply these computations to our data, we find the following. First, the "balls and bins" framework, as applied here, correctly predicts 27.95 percent of market structures. The overall fit of the statistical model to the data is therefore lower than the fit of our em-

[10]Given that more firms (including smaller firms) export in Denmark, and that many shipments are to nearby European markets, this assumed shipment size might be too large. On the other hand, our sample includes large superstar firms – and large exporters tend to have larger shipment sizes (Blum et al., 2016).

Table E.1: Armenter & Koren (2014) vs. Ciliberto & Jäkel (2019)

Number of potential	Percent Correctly Predicted	
entrants K_{Ic}	Armenter & Koren (2014)	Ciliberto & Jäkel (2019)
1	83.99	79.72
2	44.02	51.40
3	30.82	41.31
4	21.39	34.88
5	17.96	29.65
6	18.62	23.28
7	17.31	21.38
Total	27.95	36.66

Notes: This table reports the percent of market structures correctly predicted in the "balls and bins" model of Armenter & Koren (2014), as applied to our framework. It also compares these numbers to the percent correctly predicted by our equilibrium model; cf. Table 7 in the main text.

pirical model, which yielded 36.66 percent correct predictions. Second, the percent correctly predicted of "balls and bins" also varies depending on the number of potential entrants. With 83.99 percent correctly predicted, the statistical model performs better than our empirical model for markets with only one superstar; i.e., markets where competitive effects are not relevant. Recall from Table 7 in the main text that our equilibrium model predicted only 79.72 percent of outcomes for these markets. In contrast, our empirical model displays a better performance in predicting market structures for markets with two or more potential entrants. For example, with two potential entrants, our model correctly predicts market outcomes in 51.40 percent of simulations. The statistical model only yields 44.02 percent correct predictions.

F Role of the Non-idiosyncratic Errors

In this section, we investigate the robustness of our results from the equilibrium model to different specifications of the error components of the profit equation (cf. Equation (2) in the main text). In particular, in Table F.1 we exclude each of the four non-idiosyncratic component one at a time, and see how excluding that component changes the results of the estimation.

In the first column we model ϵ_{iIc} as the sum of four components:

$$\epsilon_{iIc} = \eta_i + \eta_I + \eta_c + \eta_{iIc}. \tag{F.1}$$

Thus, in this column we drop the market-specific random effect η_{Ic}. In the following columns, we respectively drop the industry-specific component η_I (cf. Equation (F.2)), the country-specific component η_c (cf. Equation (F.3)), and the variety-specific component η_i (cf. Equation (F.4)):

$$\epsilon_{iIc} = \eta_i + \eta_{Ic} + \eta_c + \eta_{iIc}. \tag{F.2}$$

$$\epsilon_{iIc} = \eta_i + \eta_{Ic} + \eta_I + \eta_{iIc}. \tag{F.3}$$

$$\epsilon_{iIc} = \eta_{Ic} + \eta_I + \eta_c + \eta_{iIc}. \tag{F.4}$$

The estimation results in Table F.1 should be compared with those in column 1 of Table 6 in the main text. We observe that each error component, if dropped separately, is not uniquely determining the estimated values. We reach this conclusion by observing that the confidence intervals of the parameter estimates overlap for the competitive effect across all columns, and for almost all of the other variables.

G Computational Details

Our minimization approach closely follows the one described in Ciliberto et al. (2020), with some tweaks. The tweaks are introduced here because the minimization problem is much simpler than in Ciliberto et al. (2020).

To begin with, the minimization of the distance function (4) in the main text is computationally intensive because we have to use simulation methods to construct lower and upper bounds for the probability of each market structure in each market. To do this, we need to solve for the equilibria for each market-simulation.

In addition, the objective function may be non-smooth and non-convex, and finding the parameter vector that minimizes it is best done by using a flexible approach.

We find the global minimum in the most efficient way if we have good initial guesses on the parameters; and if we use flexible minimization routines that mix different built-in algorithms. We normally find a global minimum after a week of work.

Table F.1: Role of the non-idyosincratic Errors

	(1)	(2)	(3)	(4)
	$\eta_i - \eta_c - \eta_I$	$\eta_i - \eta_m - \eta_c$	$\eta_i - \eta_m - \eta_I$	$\eta_m - \eta_c - \eta_I$
Competitive Effect (δ_1)	[-10.115,-4.679]	[-9.357,-4.826]	[-9.357,-4.848]	[-7.871,-4.355]
Competitor-specific variables $\mathbf{Z}_{iIc}$				
Firm Industries$_i$	[-0.043,0.216]	[-0.011,0.206]	[-0.037,0.203]	[0.002,0.141]
Variety Destinations$_{iIc}$	[0.798,1.140]	[0.810,1.146]	[0.785,1.104]	[0.700,0.931]
Variety Rank$_i$	[-0.261,0.024]	[-0.238,0.228]	[-0.243,0.049]	[-0.207,-0.006]
Market-specific variables $\mathbf{X}_{Ic}$				
Geographical Distance$_c$	[-0.980,-0.658]	[-0.991,-0.665]	[-1.032,-0.632]	[-0.833,-0.564]
GDP$_c$	[0.787,1.185]	[0.800,1.122]	[0.737,1.125]	[0.644,0.908]
Industry Size$_I$	[0.111,0.413]	[0.118,0.401]	[0.082,0.464]	[0.086,0.350]
Constant	[3.923,9.352]	[4.057,8.580]	[4.063,8.549]	[3.660,7.214]
Number Observations	8,938	8,938	8,938	8,938
Function Value	2470,72	2469,2	2473,88	2390,28

Notes: These set estimates contain the 95% confidence region for the true parameter θ. See Chernozhukov (2007) and Ciliberto and Tamer (2009) for more details on constructing these confidence regions.

G.1 Starting Values

The probit regressions provide us with excellent starting values for the parameters of the exogenous variables. We use these, together with different starting values for the competitive effects. Recall that we have standardized all the exogenous variables. As in Ciliberto et al. (2020), this approach stabilizes the search and allows us to limit the parameter search within small intervals for all the exogenous variables. Finally, to ensure that we do not get stuck in a global minimum, we draw up to *50,000* independent random draws from these intervals. Out of these 50,000 starting values, we choose the ones that are associated with the lowest distance function values and compare our estimation results with the ones that we get starting from the parameter guess discussed above.

G.2 Canned Algorithms

We use a variety of canned algorithms in the GLOBAL OPTIMIZATION TOOLBOX in Matlab to minimize the function. We use PATTERNSEARCH and FMINSEARCHOS, a more flexible implementation of Matlab's fminsearch, which can be found on Matlab's FileExchange platform. There are no bounds on the parameters when we run FMINSEARCHOS.

G.3 Confidence Intervals

For inference purposes, we continue the minimization longer in order to collect as many parameters close to the *argmin*. We sample the objective function to get a snapshot of the surface of the function. Then, we proceed as discussed in Ciliberto & Tamer (2009) and Ciliberto et al. (2016) to construct the confidence intervals.

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