Information Spillovers for Export Markets*

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Abstract

Information frictions are substantial barriers to firm success in international markets. However, firm-specific evidence for the effect of trade information on exporting across a network of firms is rare. To fill this gap, we exploit a quasinatural experiment in Denmark and employ moment inequality estimation approach to establish that: (i) TC supported firms have better export market information than unsupported firms, (ii) unsupported peers of supported firms indirectly gain export information through firm networks, (iii) information spillovers are strongest among firms in close geographic proximity and/or linked through worker transitions, (iv) information spillovers increase total manufacturing exports from the Danish machinery industry by 1-2 percent per year. In aggregate, public benefits from information spillovers are estimated to cover existing export support program costs, but only found to justify program expansion when firm-level export support is targeted to maximize public spillovers.

(*keywords: export, information, industrial policy, spillover*)

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1 Introduction

Government subsidized export support is often justified on the basis that greater export participation is socially desirable and industrial policy is needed to remedy potential market failure. Yet, there is a dearth of evidence supporting the claim that export oriented industrial policy generates public surplus, justifying government intervention. This paper provides primary evidence that government support programs generate informational spillovers through firm networks, highlighting the public good nature of export support programs. In aggregate, informational spillovers originating from the Danish Trade Council (TC) boost exports by 1 to 2 percent per year in the Danish machinery industry.

It is well-established that information frictions are important impediments to firm and industry exports (Allen, 2014; Atkin et al., 2017; Dickstein and Morales, 2018; Steinwender, 2018). Yet, if information frictions were purely private in nature, that in itself would not necessarily justify public intervention. Rather, researchers confirm that information networks have a large impact on wider firm (Fernandes and Tang, 2014; Mion and Opromolla, 2014; Kamal and Sundaram, 2016; Cai and Szeidl, 2017; Bisztray et al., 2018) and aggregate (Head and Ries, 1998; Rauch, 1999; Rauch, 2001; Rauch and Trindade, 2002; Freund and Weinhold, 2004; Portes and Rey, 2005; Fink et al., 2005) trade, suggesting that at least some features of trade-relevant information are potentially non-excludable and public (Fernandes and Tang, 2014; Wei et al., 2021). The importance of networks for firm performance in export markets begs a series of fundamental questions: Does export support, a common form of industrial policy (Juhász et al., 2022), create an informational public good? If so, how does information spread across firms? What do firms learn about export markets through industrial policy-induced spillovers? Are the economic gains from informational spillovers large enough to justify the costs of public intervention?

To make progress, this study establishes three novel results regarding the nature of informational spillovers in export markets. First, we document that export-oriented information flows between the Danish Trade Council (TC) and manufacturers improve the information set of supported manufacturers on export markets. Informational benefits are in addition to the gains accrued from boosting demand or reducing export costs. Second, export information spills over to unsupported, peer manufacturers of supported firms. Peers of supported firms are found to have (at least partial) knowledge of export market conditions, while firms without supported peers often do not. In this sense, our results confirm that export support programs create a public good and potentially address market failure in settings where too few firms enter export markets. Third, informational spillovers are, in aggregate, economically substantive. Using the model's structural parameters, we disentangle the public gains from TC support programs from the private benefits enjoyed by supported firms. In our sample, we find that information spillovers alone increase aggregate exports by 1-2 percent per year among *unsupported* firms. Each finding is established through the combination of a unique empirical setting, partial identification econometric methods, and a structurally identified quantitative trade model.

Figure 2 provides a simple, intuitive illustration of potential network benefits of export-oriented industrial policy taken from the firm-level network data we investigate. It focuses exclusively on unsupported firms; that is, firms that are not directly supported by the TC. Plotting the export propensity among firms that are indirectly linked to the TC through employee or geographic networks (treated) relative to those which are completely unconnected to the TC (untreated) reveals a striking pattern: indirectly TC-linked firms are more likely to export. Moreover, the relative differences are often largest for small firms and unpopular export destinations, where information frictions are likely to prevail. Yet, we may be naturally concerned that, rather than informational differences, these patterns may alternatively reflect selection by firms, policy targeting by forward-looking policy-makers, or demand or cost differences, among other explanations.

To address these concerns, we take advantage of a natural experiment to characterize the nature and diffusion of policy-relevant trade information. As documented in Buus et al., 2025, the Danish TC approaches individual firms with offers of export support in a quasi-random fashion. In this sense, this paper contributes to the branch of empirical research that exploits natural experiments to quantify the impact of information barriers international trade (Steinwender, 2018; Criscuolo et al., 2019). Unique to our setting, the Danish Trade Council outreach program provides an exogenous source of new, industrial policy-driven, export market information. However, because outreach activities are firm-specific we can precisely identify firms that receive an initial endowment of new export market information. Following Fernandes and Tang, 2014 and Bisztray et al., 2018, we build firm-level peer networks to investigate *indirect* benefits of TC support programs.[1] We find that firms which are only connected to the TC through their peers benefit from TC export information even though they do not have any direct relationship with the TC itself.

While the unique data features are essential to our study, they only yield the above insight when used in combination with recent advances in moment inequality estimation (Ciliberto and Tamer, 2009; Pakes, 2010; Pakes et al., 2015; Dickstein and Morales, 2018; Morales et al., 2019). Standard approaches require taking a strong, ex-ante stand on the particular information held by different producers and how it may diffuse across firms. In contrast, a key advantage of the moment inequality approach is that we are able to recover model parameters while remaining agnostic about the export market information held by any firm or the firm network governing its diffusion.

In the spirit of Dickstein and Morales, 2018 we proceed to conduct a series of information tests to characterize the public nature of export support industrial policy. First, we establish that standard information tests confirm that firms directly supported by the TC are better informed than those unsupported by the TC, consistent with broad historical documentation. Specifically, we propose alternative versions of our moment inequality model, each of which holds model structure fixed but varies the information set we presume the firm uses to forecast export revenues. Employing moment inequality specification tests described in Bugni et al., 2015 we consistently reject the hypothesis that unsupported, unconnected firms know more than a minimal set of export market characteristics, such as past aggregate exports, the distance from Denmark, and the firm's own past domestic sales.[2] In contrast, the same information tests sug-

[1]Analogously to the market failure problem studied in Wei et al., 2021, we use the unique empirical setting to identify the firm-level source of information and estimate its downstream impact on peers through firm networks.

[2]There are, important exceptions to our benchmark finding. Among unsupported firms we cannot reject the hypothesis that large firms and past exporters generally know export market demand conditions, as in Dickstein and Morales, 2018. The impact of firm information on firm

gest that TC support programs remedy export informational gaps among supported firms. These initial findings are broadly in line with modern understanding of trade support[3] (Bernard and Jensen, 2004; Görg et al., 2008; Volpe Martincus and Carballo, 2008; Volpe Martincus and Carballo, 2010a; Volpe Martincus and Carballo, 2010b; Volpe Martincus and Carballo, 2010c; Volpe Martincus and Carballo, 2012; Munch and Schaur, 2018) and received wisdom from the trade and information literature (Allen, 2014; Atkin et al., 2017; Dickstein and Morales, 2018; Steinwender, 2018), but demonstrate that informational externalities can be addressed by industrial policy (Juhász et al., 2024a).

Our primary empirical findings build on this benchmark result. Constructing firm-level networks to characterize the nature of information spillovers, we proceed to study whether unsupported firms which are linked to supported firms through firm networks are better informed of export market conditions. Our data permit the development of two distinct types of firm-networks, firms linked by worker mobility and geography. For employment networks, we consider an unsupported firm indirectly linked to the TC if it hires an employee which previously worked for a supported firm during a period of TC support. A key advantage of employment networks are that they provide insight into *how* information spills over across firms in the same industry. For geographic networks, we consider two firms linked if they are located in the same region. An important benefit of geographic networks is that we can test the nature of informational decay over space.[4] In this sense, we contribute to the literature aimed at understanding the value of industrial policy in a network setting (Liu, 2019).

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entry decisions is likewise reminiscent to differences in the bidding behaviour across large and small producers in wholesale electricity markets (Hortaçsu and Puller, 2008; Hortaçsu et al., 2019).

[3]In related work Carballo et al., 2023 study how *investment* support encourages firms to establish new multi-national subsidiaries in foreign countries by reducing information frictions. They do not examine spillovers across firms.

[4]The nature of informational decay in our context is similar to the notion of economic dispersion in Feyrer et al., 2017, where firms located further from center of an informational shock are potentially less likely to learn from it.

We find consistent evidence of information spillovers from directly supported firms to unsupported peers in the same network. We cannot reject the hypothesis that firms indirectly supported by the TC through employment networks know export demand shifters. The informational differences between indirectly supported firms and their unsupported counterparts are particularly salient for less popular export markets, such China, India and Turkey.

A similar pattern is revealed across geographic firm networks, but holds most strongly among unsupported firms in the same zip code as a supported peer. Similar to the findings in Bisztray et al., 2018, we confirm that informational spillovers tend to be *localized*. That is, firms most closely linked to TC supported firms return the strongest evidence of informational spillovers, while the least connected firms provide the weakest evidence. Nonetheless, even weakly connected firms are often found to have some additional knowledge export market conditions.

We further characterize the strength and content of informational spillovers across firm networks. Disaggregating market demand conditions into a component measuring buyer quality in a given location and another component capturing the number of buyers in export markets, we test what *type* of information spills over from supported to unsupported firms. Unsupported firms most closely linked to supported firms know both the number of buyers in an export market and a measure of buyer quality. Among weakly-linked firms, we find evidence that they may learn the typical number of buyers in a given export, but do not find compelling evidence of knowledge of typical buyer quality in export markets. While we find that information spills over across firms, it is far from complete.

We quantify the aggregate economic value of TC driven informational spillovers through a series of counterfactual experiments. We find that informational spillovers alone increase aggregate exports by 1-2 percent annually. The informational gains do not, in general, induce rapid entry into export markets. Rather, information spillovers gains accrue through improved sorting. Improved information encourages profitable exporters to expand into foreign markets, while firms that would otherwise be unprofitable refrain from costly entries abroad. In this sense, informational spillovers help justify TC support programs even at a cost to Danish taxpayers. Our results both confirm key findings from the literature studying the role of networks on aggregate trade flows (Head and Ries, 1998; Rauch, 1999; Rauch, 2001; Rauch and Trindade, 2002; Freund and Weinhold, 2004; Portes and Rey, 2005; Fink et al., 2005) but also shed further light on the impact of industrial policy on aggregate trade (Lawrence and Weinstein, 1999; Blonigen, 2015; Hanlon, 2019; Lashkaripour and Lugovskyy, 2023) and economic performance (**Lane:2022**; Aghion et al., 2015; Juhász, 2018; Liu, 2019; Bai et al., 2022; Choi and Levchenko, 2021; Juhász et al., 2024b).

We proceed to investigate whether program targeting would maximize the public benefits to the Danish Trade Council. In particular, we consider the impact of a purely random assignment of export support, a program which targets the firms with the highest private returns, and one that targets the *most connected* Danish firms. We find that targeting connected firms always yields the greatest public benefits in the presence of informational spillovers.

The above policy findings contribute to a rich branch of research aimed at understanding firm-level trade policy and, in particular, export support programs. Early firm-level studies, such as Bernard and Jensen, 2004 and Görg et al., 2008 find little impact of state-level export support expenditures on export activity. In contrast, a number studies use highly disaggregated support data, similar to that used here, to demonstrate that firm-level trade policies are clearly associated with improved firm-level export outcomes (Volpe Martincus and Carballo, 2008; Volpe Martincus and Carballo, 2010a; Volpe Martincus and Carballo, 2010b; Volpe Martincus and Carballo, 2010c; Van Biesebroeck et al., 2015; Buus et al., 2025). Munch and Schaur, 2018 provide compelling evidence that support services are indeed causal determinants of improved export success, while Buus et al., 2025 show that, among Danish exporters, support primarily drives increases in quantity sold while leaving export prices, production costs and product characteristics largely unchanged. Our model leans heavily on these findings, but quantifies the value of the information spillovers to unsupported firms in export markets and characterizes the nature of information spillovers across firms. In this sense, our research contributes to the growing body of work answering the call in Goldberg and Pavcnik, 2016 to better understand the nature of pervasive, non-tariff trade barriers.

The remainder of the paper is structured as follows. Section 2 briefly describes the TC support programs and firm networks. Section 3 presents the empirical model, while Section 4 introduces the data and documents the key differences across supported and unsupported firms. Section 5 describes the corresponding estimation procedure and Section 6 summarizes the empirical estimates, conducts a series of statistical tests to characterize the nature of information spillovers across Danish exporters and counterfactually quantifies the impact of support driven information spillovers across Danish producers. Section 7 concludes.

2 The Trade Council

All Danish export support programs are organized by the Trade Council. Support services are tailored to individual firms and administered through Danish embassies and consulates abroad. Firms must purchase individual services from the TC, though it is well known that prices are heavily subsidized.

For our purposes, TC export support programs have three key features. First, the most common export support services specifically target some form of informational frictions, though they may also affect overall demand or entry costs.[5] In particular, the most frequently purchased services are partner search, foreign marketing or market intelligence. Partner search includes direct matchmaking, meeting facilitation, and network integration intended to help Danish firms to match with foreign partners and avoid supply chain challenges, such as hold-up problems. Foreign marketing includes services aimed at facilitating participation in fairs, exhibitions, public relations events, conferences, workshops, or seminars. Market intelligence includes providing firms with formal market analysis, access to publications, monitoring market conditions, or assistance with customs, export, and import regulations. In each case, the TC's role is largely informative in nature.

Second, TC support is firm, industry and destination specific. The TC works with individual firms selling individual products produced for target destinations. In this sense, the information

[5] Buus et al., 2025 investigate whether TC support affects firm-level marginal costs, markups, prices or product quality. They do not find evidence that TC support affects any of these margins of firm performance. Section 6 documents benchmark evidence of TC support on firm-level demand and entry costs, with further evidence documented in the appendix.

is highly specialized and the delivery of the information from the TC to the firm is private in nature. As such, by identifying supported firms, we are able to identify the origin of new, industry-and-export destination relevant information within a firm network.

Third, the TC actively contacts individual firms to offer their services. Outreach for any export destination is conducted by the individual embassies and consulates. There is no official strategy for contacting firms and there is no coordination across embassies and consulates. Instead, each embassy and consulate approaches firms solely based on information about industry-specific conditions in the target destination market. As documented by Buus et al., 2025 and Section 4, within a industry-target destination pair, individual firms are approached *quasi-randomly.*

Our data distinguishes firms which were approached by the TC for export support services in target destinations, firms which purchased support services in export markets, or both. This allows us to distinguish between two groups of supported firms, those which sought out this information themselves and found the TC programs and those which were endowed with the information about these programs through a quasi-random TC call.

Variation in support and call status across *firms* allows us to explore the nature of policy-relevant information frictions. For example, a non-trivial number of firms are contacted by the TC but turn down their offer of export support services. We explore whether these TC support *decliners* are more likely to have export information sets like supported relative to unsupported firms.

Variation in support and TC calls across *firm networks* sheds further light on information diffusion. In particular, we distinguish two groups of unsupported firms: (i) unsupported firms in a network of entirely unsupported firms and (ii) unsupported firms connected to supported firms. Leveraging quasi-exogenous variation in the information sets of a firm-peers, we test whether better informed peers leads to information spillovers across firm networks.

3 Empirical Model

Firms located in network location l of home market h decide whether to sell in each export market $j = 1, ..., J$ at time $t = 1, ..., \mathcal{T}$. As in Dickstein and Morales, 2018 we focus on a model in which firms first choose which countries they want to export to while incurring a fixed export cost in each market.[6] Next, conditional upon entry, all firms set prices optimally to maximize export profits. Information and uncertainty regarding future profits may arbitrarily differ across firms when choosing among export destinations, but do not differ across firms after entry.

3.1 Demand, Costs, Information

In each country firms face an isoelastic demand curve $x_{ijt} = \xi_{ijt}^{\eta-1} p_{ijt}^{-\eta} P_{jt}^{\eta-1} Y_{jt}$ where ξ_{ijt} is an idiosyncratic demand shifter and η is the demand elasticity. We allow export demand to differ across firms supported (S) by the TC and unsupported firms (U); we distinguish firm types by $T \in \{S, U\}$. Likewise, let the indicator variable, s_{ijt}, take the value one for supported firms and is zero otherwise. Specifically, we propose that the total firm-level demand shifter, ξ_{ijt}, can be written as a CES composite of a demand shifter the firm would receive without support, ξ_{ijt}^U, and an additional demand premium they would receive with support,[7] ξ_{ijt}^S:

$$\xi_{ijt} = [(\xi_{ijt}^U)^{\eta-1} + s_{ijt}(\xi_{ijt}^S)^{\eta-1}]^{\frac{1}{\eta-1}}$$

Each unit of output is produced with constant marginal costs, c_{it}. To export, firms must pay iceberg trade cost τ_{ijt} and fixed export cost f_{ijt}^T, where the superscript T again indicates that fixed export costs may differ across supported and unsupported firms.[8] Specifically, exporting

[6] We later relax this assumption to consider a dynamic setting with first time (sunk) entry costs and fixed continuation export costs.

[7] As demonstrated in Appendix B.2, this specification can be rationalized through TC programs which affect the number of buyers that firm i reaches in destination j, the quality of buyers firm i reaches in destination j, or both.

[8] We could also allow variable trade costs to vary across supported and unsupported firms

firm i pays fixed export costs f_{ijt} in market j:

$$f_{ijt} = (1 - s_{ijt})(\beta_0^U + \beta_1^U dist_j + \nu_{ijt}^U) + s_{ijt}(\beta_0^S + \beta_1^S dist_j + \nu_{ijt}^S) \tag{1}$$

$dist_j$ is the distance between country h and country j and the firm-specific fixed cost component ν_{ijt}^T represents all fixed cost determinants which the researcher does not observe.

A firm's potential sales revenue in market j and year t is denoted $r_{ijt} = p_{ijt}x_{ijt}$, while $\mathcal{J}_{ijlt}$ represents the information firm i has about market j. We maintain standard Dickstein and Morales, 2018 assumptions: *some* determinants of r_{ijt} and *all* of the determinants of fixed costs f_{ijt} are part of firm i's information set $\mathcal{J}_{ijlt}$ when deciding whether to export to country j. Leveraging evidence from Buus et al., 2025, unsupported firms do not benefit from additional TC driven demand, even if they enjoy additional knowledge of demand conditions through peer networks (as embedded in $\mathcal{J}_{ijlt}$); the (redundant) network subscript l is included only to highlight that information may systematically vary across firm networks. In this sense, *knowledge* of demand conditions and their level are separate objects, a feature of our analysis which we return to below.

3.2 Export Revenue

Upon entry into market j the firm observes η and τ_{ijt}. It then chooses the profit maximizing price, $p_{ijt} = \frac{\eta}{\eta-1}\tau_{ijt}c_{it}$, and earns revenue

$$r_{ijt} = \left[\frac{\eta - 1}{\eta}\frac{\xi_{ijt}P_{jt}}{\tau_{ijt}c_{it}}\right]^{\eta-1} Y_{jt} = (\alpha_{ijt}^U + \alpha_{ijt}^S s_{ijt})r_{iht} \tag{2}$$

where r_{iht} is firm i's domestic sales in year t and

$$\alpha_{ijt}^U \equiv \left(\frac{\xi_{ijt}^U \tau_{iht}P_{jt}}{\xi_{iht}\tau_{ijt}P_{ht}}\right)^{\eta-1}\frac{Y_{jt}}{Y_{ht}} \text{ and } \alpha_{ijt}^S \equiv \left(\frac{\xi_{ijt}^S \tau_{iht}P_{jt}}{\xi_{iht}\tau_{ijt}P_{ht}}\right)^{\eta-1}\frac{Y_{jt}}{Y_{ht}}$$

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through τ_{ijt}. We abstract from this possibility since variable trade cost shocks are (i) isomorphic to demand shocks in the revenue function and (ii) existing evidence for Denmark (e.g. Buus et al., 2025) suggests that TC support primarily operates through demand channels.

are demand shifters among unsupported and supported firms, respectively. We distinguish a component of equation (2) common to all firms in a given market-year pair, α^U_{jt}, a component common to supported firms in the same market-year pair, α^S_{jt}, and a component that varies across firms, e_{ijt},

$$r_{ijt} = (\alpha^U_{jt} + \alpha^S_{jt} s_{ijt}) r_{iht} + e_{ijt} \text{ where } \alpha^T_{jt} = \mathbb{E}_{jt}[\alpha^T_{ijt}] \tag{3}$$

such that $e_{ijt} = e^U_{ijt} + e^S_{ijt}$ accounts for unexpected, relative, firm-, market-, and year specific revenue shocks:

$$\mathbb{E}_{jt}[e_{ijt}|\mathcal{J}_{ijlt}, r_{iht}, f_{ijt}] = 0. \tag{4}$$

Although e_{ijt} is unknown prior to entry, we do not restrict the relationship between the information set $\mathcal{J}_{ijlt}$ and the predictable component of revenue, $(\alpha^U_{ijt} + \alpha^S_{ijt} s_{ijt}) r_{iht}$. That is, it is entirely possible for some firms - large firms, incumbent exporters, firms contacted by the TC, or firms indirectly linked to the TC through firm networks - to have systematically better information about any given market. Likewise, regardless of contact with the TC information sets $\mathcal{J}_{ijlt}$ and $\mathcal{J}_{i'jl't}$ may differ arbitrarily across firms i and i' depending on their particular firm network, among other firm-level mechanisms through which information may be transmitted or spillovers may manifest.

3.3 Export Profits and the Decision to Export

Firm i earns export profits $\pi_{ijt} = \eta^{-1} r_{ijt} - f_{ijt}$ if it exports to market j in year t. A firm exports to any country in any year where expected profits are positive, $\mathbb{E}[\pi_{ijt}|\mathcal{J}_{ijlt}, s_{ijt}, dist_j, \nu^T_{ijt}] \geq 0$. Letting D_{ijt} be an export indicator variable, the probability that unsupported firm i exports to market j in year t is represented by the probit model

$$\begin{aligned}
\mathcal{P}(D_{ijt} = 1|\mathcal{J}_{ijt}, dist_j, s_{ijt} = 0) &= \int_{\nu^U} \left(\mathbb{1}\{\eta^{-1}\mathbb{E}[\alpha^U_{jt} r_{iht}|\mathcal{J}_{ijt}] - \beta^U_0 - \beta^U_1 dist_j - \nu^U \geq 0\} \frac{1}{\sigma_U} \right. \\
&\quad \left. \times\, \phi\left(\frac{\nu^U}{\sigma_U}\right) d\nu^U \right) \\
&= \Phi(\sigma_U^{-1}(\eta^{-1}\mathbb{E}[\alpha^U_{jt} r_{iht}|\mathcal{J}_{ijt}] - \beta^U_0 - \beta^U_1 dist_j)),
\end{aligned} \tag{5}$$

where ϕ and Φ are the standard normal probability density function and cumulative distribution function, respectively, and $\mathbb{1}\{\cdot\}$ is an indicator function. For supported firms, the decision to export is analogous, with the exceptions that supported firms enjoy larger expected demand, $\alpha^U_{jt} + \alpha^S_{jt}$, and potentially lower fixed costs, $\beta^S_0 + \beta^S_1 dist_j + \nu^S_{ijt}$.

Specification (5) highlights four identification challenges. First, as common, data on export choices will not identify the value of $(\sigma_T, \beta^T_0, \beta^T_1)$ separately from η. As such, fix $\eta = 5$, a mid-range value common to the literature (Anderson and Wincoop, 2004; Parro, 2013; Simonovska and Waugh, 2014). Second, integrating over ν^T_{ijt} in equation (5) depends on the firm's expectation of revenue in market j in year t, and, as such, its information set for the same country and year. Researchers rarely observe firm expectations or their information set. We apply a moment inequality estimation approach to relax standard informational assumptions in estimation. Third, firms may endogenously self-select into TC support, potentially biasing in the fixed cost estimates. We employ a quasi-random outreach program from the Danish TC to instrument for prior contact with the TC and recover unbiased fixed cost estimates. Fourth, TC services plausibly bundle both informational, cost and demand features of support. For example, TC agents will likely both improve firm information and increase the number (or quality) of buyers the supported firm has access to in export markets. By structurally estimating the model parameters we can distinguish each of these features in the firm's export decision, including firms which only indirectly receive the benefits TC support through informational spillovers.

3.4 Discussion and Extensions

The benchmark model permits rich variation in demand, cost and information across firms, markets and time. There remains concern that the model is nonetheless overly parsimonious. Among other simplifications, it abstracts from dynamic entry costs (Das et al., 2007; Alessandria and Choi, 2007; Alessandria and Choi, 2014; Alessandria et al., 2021) or differences in demand across firm networks, albeit allowing for demand differences between supported and unsupported firms.

There are important trade-offs with respect to model parsimony to consider in our context. The confidence bands for the model parameters are tighter in a parsimonious model specification. Model-specification based information tests (Bugni et al., 2015; Dickstein and Morales, 2018) accordingly have greater power to reject a given null hypothesis regarding the information firms (or a subset of firms) have when making export decisions. However, if the model is insufficiently rich, we may erroneously reject a null hypothesis due to model-imposed restrictions.

While our benchmark specification draws on Dickstein and Morales, 2018 as a natural starting point, we note that we do not impose any parameter restrictions across directly supported and unsupported firms. We address concerns associated with the structure of entry costs by later estimating a model with differential entry costs across firm export histories and reconsidering the benchmark information tests through the lens of the augmented model. Last, the model imposes the assumption that there are no systematic differences in export demand arising from differences in firm network location. While it would be straightforward to accommodate demand differences across network position, we do not find evidence of systematic differences in export demand across indirectly supported and unsupported firms and, for notational parsimony, abstract from this possibility in the model exposition.

4 Data

We estimate the model using a balanced sample of Danish machinery manufacturers (NACE 28) between 2010 and 2015. We focus on the machinery industry for two reasons. First, machinery was the largest 2-digit NACE industry within manufacturing in terms of export value throughout our sample period, constituting 27 % of total manufacturing exports in 2010. Second, machinery firms have been relatively frequent buyers of export support services. We restrict attention to the period 2010-2015 to mitigate the influence of the Great Recession.

The data set is constructed by merging several sources of register data. First, we obtain firm level characteristics from the Firm Statistics Register and Firm Accounts Statistics, both provided by Statistics Denmark. These data sets cover the population of private Danish firms. We construct the sample by requiring firms to meet the following two requirements in all years from 2010-2015: (i) the firm belongs to the industry "Manufacture of machinery and equipment n.e.c." (NACE 28) and (ii) the firm has registered positive values for all variables needed in the estimation procedure outlined below (such as domestic sales and capital). The resulting sample consists of a balanced panel of 532 firms. Second, we obtain data on export support from the Trade Council (TC) in Denmark. For each firm in our sample we observe purchases of support by destination and year, whether TC contact was initiated by the firm or a TC employee, and whether the firm was approached but no service was taken up. Third, we obtain firm-destination level export data from the statistics for International Trade in Goods, also provided by Statistics Denmark. For each Danish exporter we also observe their counterparty buyers; that is, we observe the value of exports shipped to each distinct importer by in each destination market and year.

The TC does not offer export support services to all destinations. Moreover, the export data does not allow us to observe buyers in EU markets. Accordingly, we construct two estimation samples which use to estimate the model. The first sample includes 8 of the largest export destinations outside of EU which have at least 50 Danish exporters in all years and are regular targets countries for export support. On the one hand, given the high degree of integration across EU countries, the benchmark estimation sample is composed of a set of countries where there is greater potential for trade to suffer from meaningful informational frictions. On the other hand, Danish are heavily skewed towards the EU, resulting in a relatively small number of destination-market-year observations among directly supported firms. While our primary interest rests on the larger set of *indirectly* supported firms within the benchmark sample of countries, the second EU-inclusive sample allows us to investigate and validate the informational content of export support programs among *directly* supported firms.

Table 1 presents summary statistics for the propensity to export or receive support, along with differences in domestic and export sales across firms and countries. The first three columns document that while exporting is common, particularly to larger and closer destinations, TC support is not. Indeed, in the first sample, only 216 firms receive TC support for the most commonly supported destinations.

Columns (4)-(5) of Table 1 confirm that exporters tend to be large firms, and that export sales from any destination are a small fraction of those earned on the domestic market. Likewise, consistent with existing evidence, column (6) documents that supported firms are generally larger than the average Danish producer. The first pair of bars in Figure 3a confirm that domestic sales among supported firms are nearly twice as large as the domestic sales among unsupported firms even though support does not target domestic market performance. Buus et al., 2025 highlight that the observed differences in domestic sales reflect differences in which firms select into TC export support programs and which firms receive TC outreach. The first pair of bars in Figure 3b illustrate that the differences in export sales are, proportionally, even greater than the differences in domestic sales. Indeed, Buus et al., 2025 document that the primary effect of TC support is a large, destination-specific, increase in export demand.

4.1 TC outreach across firms

Table 1 further documents summary statistics for firms which receive calls from the TC. As documented in Buus et al., 2025, TC calls are *quasi-random* across firms: while TC employees may have a broad sense of the size or importance of various Danish producers, their outreach is otherwise as good as random.[9] The randomness of TC outreach is a useful feature both for guarding against bias in parameter identification and later testing the informational nature of TC support.

We add to the existing evidence of the quasi-random nature of TC outreach through a series of experiments on our estimation sample. Specifically, we classify firms into four size groups (small, small-medium, medium-large, large) based on their prior ($t-1$) revenues so that each group contains one quarter of the firm-year observations. We then compare the domestic and export revenues of called producers relative to the firms that are not solicited by the TC. Figures 3c and 3d document that, although large firms are more likely to get TC calls than small firms, within a given size bin there is no evidence that there is any significant difference in observed sales outcomes.

The right-most bars of Figures 3a and 3b repeat this experiment, but instead of distinguishing firms by call status, we compare outcomes across supported and unsupported firms. We

[9]In particular, Buus et al., 2025 document that firms with names starting with a letter at the beginning of the alphabet are significantly more likely to receive TC outreach calls.

observe larger differences across support status, particularly with respect to export sales, arguably reflecting that roughly half of the supported firms self select into TC support programs. That said, the gap between supported and unsupported export sales is only statistically different for the smallest firms, for which the absolute sales gap is also smallest.

4.2 Firm networks

We construct two sets of firm networks based on firm geography or worker mobility across firms.[10]

4.2.1 Employment Networks

Using employer-employee matched data we proceed to build employment networks. Specifically, we consider an unsupported firm-destination-year observation indirectly linked to a TC firm if at least one of their current employees was previously employed by a different firm during a period where the previous employer received TC support for the same destination.[11] Implicitly, we are assuming that the employee which transitions from a supported firm to an unsupported does not forget what she learned from working in the supported firm. Using this definition of firm peers, we find that 2.2 percent of firm-year-destination observations are indirectly supported by the TC.

4.2.2 Geographic networks

We alternatively build firm networks by treating any two firms as linked if they co-exist in the same geographic unit. As a benchmark case, we group firms by zip codes and treat any two firms as peers if they are co-located in the same zip code and non-peers otherwise. A supported zip code is a zip code where at least one firm is supported by the TC in the previous year. We

[10]Further potential network definitions, such as strategic partnerships or common buyers, yielded samples that were too small for statistical testing.

[11]Specifically, consider an employee who worked in firm i' during year t' when i' received support for destination d. If the employee transitions from i' to $i \neq i'$ in $t > t'$, we consider i' indirectly supported in destination d in years t and $t + 1$.

expand our investigation of geographic spillovers by broadening the definition of a spillover region. Repeating the same tests we investigate whether there is evidence of informational spillovers across firms located in the same wider municipality.[12]

Expanding the regional definition of a spillover network has two important advantages. First, it allows us to investigate the nature of information decay across geographic units; we intuitively expect that information differences should be clearest among the tightly linked firms. Second, it allows us to guard against misleading conclusions driven by small sample sizes. Indeed, although many zip codes are supported at least once, this does not necessarily imply that many of the unsupported firms have a supported peer. The fraction of firm-destination-year observations in a supported zip code is 632, slightly less than 3 percent of the total number of firm-destination-year observations. In comparison, of Denmark's 98 municipalities, at least one firm receives support in 42 municipalities in at least one sample year. This network definition implies that 8 percent of firm-destination-year observations among unsupported firms belong to a supported (destination-year) municipality, roughly tripling the size of the indirectly supported sample.

On the one hand, we have over 21,000 unsupported firm-destination-year observations for our information tests; even 3 percent represents nearly 1000 observations. On the other hand, the number of observations among unsupported firms in unsupported locations are much larger raising the concern that differential results may yet reflect differences in testing power despite large samples. To address this concern we take a two pronged approach. First, we leverage the EU-inclusive sample which increases both the number of all types of firms, though it does so for markets where information frictions are likely less binding. Second, we consider random

[12]Unlike employment networks, our measure of geographic networks inherently omits a clear mechanism through which information is transferred from one firm to another. Nonetheless, existing empirical evidence confirms the importance of geographic proximity to successful exporters for export entry (Fernandes and Tang, 2014), among other contexts. Information spillovers through firm networks can be rationalized through information spillovers over local, unobserved buyer-seller networks, such as that posited in Eaton et al., 2022. The data do not provide information on buyer-seller purchasing networks.

assingment placebo tests across informational network structure to further establish the presence of informational spillovers.

4.3 TC outreach across firm networks

If the TC is aware that support programs create informational spillovers, they may intentionally target well connected firms for TC programming. There is no evidence of this type of targeting in the TC outreach mandate. We also find no statistical evidence of this concern either.

Panel (a) of Figure 4 compares the size of unsupported firms located in municipalities where at least one firm receives a TC call to those located in municipalities that do not receive any TC outreach. The differences are miniscule, both on average and conditional on firm size. Panel (b) documents the same information for municipalities that receive support and those that do not. Again, there is no difference in the size of indirectly supported firms across municipalities.

In general, Figure 4 suggests that the arrival of TC generated export information is quasi-exogenous to unsupported firms located in municipalities where one of their peers receives TC support. Similar patterns exist for each of our firm networks.

5 Empirical Approach

5.1 Empirical Model

The observable component of export revenue, $r^o_{ijt} = (\alpha^U_{jt} + \alpha^S_{jt} s_{ijt}) r_{iht}$, captures year and market specific demand conditions for both supported and unsupported firms. Because receiving TC support is relatively rare, we cannot confidently identify market-year specific demand shifters for supported firms and, as such, we restrict the observable component of the model to be $r^o_{ijt} = (\alpha^U_{jt} + \alpha^S_{j} s_{ijt}) r_{iht}$, where α^S_j varies over markets, but not time.

Given the above structure, we assume $\mathbb{E}[e^S_{ijlt} | \mathcal{J}_{ijlt}] = 0$, $\mathbb{E}[e^U_{ijlt} | \mathcal{J}_{ijlt}] = 0$ and $\mathbb{E}[e_{ijt} | \mathcal{J}_{ijlt}] = 0$ ensuring that $\mathbb{E}[r_{ijt} | \mathcal{J}_{ijlt}] = \mathbb{E}[r^o_{ijt} | \mathcal{J}_{ijlt}]$. Although this structure holds across all informational settings, identifying the impact of TC support requires additional assumptions on the relationship between firm-level information $\mathcal{J}_{ijlt}$ and observable revenues r^o_{ijt}.

We consider a setting where the firm has a partial information set which includes at least a minimal information set, but may also include other firm or country-specific information, such as market demand conditions. Building on Dickstein and Morales, 2018 we assume that firms employ (i) their own domestic revenues in the previous year, r_{iht-1}, (ii) sectoral aggregate exports to country j in the previous year, R_{jt-1}, and (iii) distance to the export market, $dist_j$, when considering whether to export to market j in year t. We also allow that firms know whether they receive TC support or not (potentially instrumented by TC outreach).

The information possessed by any firm may arbitrarily differ by TC support, firm size, location, peer networks or otherwise. While each firm decides whether to export based on their expectation of potential export revenues conditional on their firm-specific information set, $\mathbb{E}[r_{ijt}|\mathcal{J}_{ijlt}]$, identifying model parameters and performing counterfactual experiments nonetheless requires modest restrictions on firm information, $\mathcal{J}_{ijlt}$ (Manski, 1993).

5.2 Information and Identification

Despite known estimation bias induced from informational misspecification (Yatchew and Griliches, 1985; Dickstein and Morales, 2018), strong informational assumptions remain common.[13] Yet, if information is not entirely excludable or differentially spills over across firm networks, these assumptions are unlikely to hold in practice. In settings with multiple overlapping (or unknown) information networks researchers would rarely observe the co-variates that form the basis of the firm's information set. However, under the assumption that each firm has access to at the least the minimal information set, $Z_{ijt} \subseteq \mathcal{J}_{ijt}$, to forecast export revenues it is possible to partially identify model parameters.

Following Dickstein and Morales, 2018 we employ both (i) odds-based and (ii) revealed preference moment inequalities to achieve tighter confidence bounds on the estimated fixed

[13] A typical set of starting assumptions for the empirical characterization of the firm-level decision to export are that (i) all firms have the *same* co-variates when making export decisions and (ii) the researcher observes the information which firms use to make export decisions, up to a structural error term. Key advantages include the point identification of model parameters, straightforward comparisons with established findings and unambiguous policy analysis.

cost parameters. Below we briefly describe each moment inequality, noting the full set of moment inequalities is employed twice: once each for supported and unsupported firms alike.[14] Letting Z denote an arbitrary co-variate in the firm's information set $Z \subseteq \mathcal{J}_{ijlt}$, we define the conditional odds-based ($m_{ob}^{l,T}$ and $m_{ob}^{u,T}$) and revealed preference[15] moment inequalities ($m_{rp}^{l,T}$ and $m_{rp}^{u,T}$) as

$$\mathcal{M}^T(Z_{ijt};\theta^T) = \mathbb{E}\left[\begin{array}{c|c} m_{ob}^{l,T}(D_{ijt}, r_{ijt}^o, dist_j, s_{ijt});\theta^T & \\ m_{ob}^{u,T}(D_{ijt}, r_{ijt}^o, dist_j, s_{ijt});\theta^T & \\ m_{rp}^{l,T}(D_{ijt}, r_{ijt}^o, dist_j, s_{ijt});\theta^T & Z_{ijt} \\ m_{rp}^{u,T}(D_{ijt}, r_{ijt}^o, dist_j, s_{ijt});\theta^T & \end{array}\right] \geq 0, \tag{6}$$

where θ^T either denotes $\theta^S = (\beta_0^S, \beta_1^S, \sigma_S)$ for supported firms or $\theta^U = (\beta_0^U, \beta_1^U, \sigma_U)$ for unsupported firms so that the lower and upper bounds can be generally expressed

$$m_{ob}^{l,T}(\cdot) = D_{ijt}\frac{1-\Phi((\theta_2^T)^{-1}(\eta^{-1}r_{ijt}^o - \theta_0^T - \theta_1^T dist_j))}{\Phi((\theta_2^T)^{-1}(\eta^{-1}r_{ijt}^o - \theta_0^T - \theta_1^T dist_j))} - (1-D_{ijt}) \tag{7}$$

$$m_{ob}^{u,T}(\cdot) = (1-D_{ijt})\frac{\Phi((\theta_2^T)^{-1}(\eta^{-1}r_{ijt}^o - \theta_0^T - \theta_1^T dist_j))}{1-\Phi((\theta_2^T)^{-1}(\eta^{-1}r_{ijt}^o - \theta_0^T - \theta_1^T dist_j))} - D_{ijt} \tag{8}$$

$$\begin{aligned} m_{rp}^{l,T}(\cdot) &= -(1-D_{ijt})(\eta^{-1}r_{ijt}^o - \theta_0^T - \theta_1^T dist_j) \\ &\quad + D_{ijt}\theta_2^T\frac{\phi((\theta_2^T)^{-1}(\eta^{-1}r_{ijt}^o - \theta_0^T - \theta_1^T dist_j))}{\Phi((\theta_2^T)^{-1}(\eta^{-1}r_{ijt}^o - \theta_0^T - \theta_1^T dist_j))} \end{aligned} \tag{9}$$

$$\begin{aligned} m_{rp}^{u,T}(\cdot) &= D_{ijt}(\eta^{-1}r_{ijt}^o - \theta_0^T - \theta_1^T dist_j) \\ &\quad + (1-D_{ijt})\theta_2^T\frac{\phi((\theta_2^T)^{-1}(\eta^{-1}r_{ijt}^o - \theta_0^T - \theta_1^T dist_j))}{1-\Phi((\theta_2^T)^{-1}(\eta^{-1}r_{ijt}^o - \theta_0^T - \theta_1^T dist_j))}. \end{aligned} \tag{10}$$

Consider equation (8), the upper bound of the odds-based moment condition, $m_{ob}^{u,T}$, for an unsupported exporter, $s_{ijt} = 0$ and $D_{ijt} = 1$. Intuitively, if $D_{ijt} = 1$ then firm i must expect to

[14] Further discussion of each type of moment inequality is relegated to Appendix B.2.

[15] We maintain the standard assumption that the ν_{ijt}^T are structural errors that vary across the triplet (i, j, t) with unbounded support. Operationalizing revealed preference moment inequalities (9) and (10) requires assuming a distribution for ν_{ijt}^T up to a scale parameter, σ_T.

earn positive profits, $\eta^{-1}\mathbb{E}[r_{ijt}|\mathcal{J}_{ijlt}] - \beta_0^U - \beta_1^U dist_j - \nu_{ijt}^U \geq 0$. Expectations, conditional on $(D_{ijt}, \mathcal{J}_{ijlt}, dist_j, s_{ijt})$, yields

$$\mathbb{E}\left[(1-D_{ijt})\frac{\Phi(\sigma_U^{-1}(\eta^{-1}\mathbb{E}[r_{ijt}|\mathcal{J}_{ijlt}] - \beta_0^U - \beta_1^U dist_j))}{1-\Phi(\sigma_U^{-1}(\eta^{-1}\mathbb{E}[r_{ijt}|\mathcal{J}_{ijlt}] - \beta_0^U - \beta_1^U dist_{ijt}))} - D_{ijt}\middle|\mathcal{J}_{ijlt}\right] \geq 0. \tag{11}$$

Although condition (11) holds at the true parameter vector, $\theta = \theta^*$, for any arbitrary firm information set it cannot be used for identification precisely because we do not observe $\mathcal{J}_{ijlt}$. Employing Jensen's inequality Dickstein and Morales, 2018 derive weaker, but feasible moment inequalities that hold at $\theta = \theta^*$

$$\mathbb{E}\left[(1-D_{ijt})\frac{\Phi(\sigma_U^{-1}(\eta^{-1}\mathbb{E}[r_{ijt}|Z_{ijt}] - \beta_0^U - \beta_1^U dist_j))}{1-\Phi(\sigma_T^{-1}(\eta^{-1}\mathbb{E}[r_{ijt}|Z_{ijt}] - \beta_0^U - \beta_1^U dist_{ijt}))} - D_{ijt}\middle|Z_{ijt}\right] \geq 0 \tag{12}$$

where the observable values of $\mathbb{E}[r_{ijt}|Z_{ijt}]$ takes the place of the unobserved $\mathbb{E}[r_{ijt}|\mathcal{J}_{ijlt}]$ and the moment inequalities are conditioned on the instrument vector Z_{ijt} instead of the unobserved information set $\mathcal{J}_{ijlt}$. Similar, well-established, arguments justify each of the above moments conditions used for identification.

5.3 Estimation and Selection

For computational purposes, we focus on a fixed set of unconditional moment inequalities to estimate parameter estimates, each of which is defined by a positive-valued instrument function, $g^T(\cdot)$:

$$\mathbb{E}\left[\left\{\begin{array}{c} m_{ob}^{l,T}(D_{ijt}, r_{ijt}, s_{ijt}, dist_j; \theta^T) \\ \\ m_{ob}^{u,T}(d_{ijt}, r_{ijt}, s_{ijt}, dist_j; \theta^T) \\ \\ m_{rp}^{l,T}(D_{ijt}, r_{ijt}, s_{ijt}, dist_j; \theta^T) \\ \\ m_{rp}^{u,T}(D_{ijt}, r_{ijt}, s_{ijt}, dist_j; \theta^T) \end{array}\right\} \times g^T(Z_{ijt})\right] \geq 0. \tag{13}$$

In each case, the inequalities are conditioned on the instrument vector, Z_{ijt}, and we estimate fixed costs separately for supported and unsupported firms so that model parameters can vary flexibly across support status.

Estimating the unconditional moment inequalities (13) by support status inherently raises two estimation concerns. First, firms may endogenously select into TC support. Second, firm information may systematically differ across firms and markets. Indeed, as documented in Section 4.1 the likelihood of a random TC calls differs by firm size. Accordingly, the instrument used to estimate model parameters, $g^T(Z_{ijt})$, are decomposed by firm-size, lagged aggregate export revenue, and distance to market. Employing quasi-random TC calls as instrument for support further allows us to then validate the degree of self-selection bias in the fixed cost estimates.[16]

6 Results

Results are presented in the following order. We first document the estimated model parameters. Next, we use model specification tests from Bugni et al., 2015 to establish that TC supported firms have systematically more information than their unsupported counterparts. Third, we document that (unsupported) peers of supported firms are better informed of export demand relative to the unsupported firms without any supported peers. Finally, we quantify the impact of informational spillovers on Danish export growth.

6.1 TC Demand Premia

The export demand shifters are recovered by the OLS estimation of equation (3). Table **??** reports the demand shifters for each destination country. The first column documents annual average values of market demand for unsupported firms, α^U_{jt}, while the middle column presents the additional demand premium enjoyed by firms directly supported by the TC, α^S_j. The unsupported demand shifters are almost always estimated to be statistically significant, while supported demand shifters are statistically significantly among popular export markets. In unpopular export markets, the estimated support premium is estimated to be small and insignificantly different from zero.

Two empirical patterns are immediately evident. First, on average, supported firms enjoy

[16] See Appendix B.3 for details.

much larger export market demand than unsupported firms even among firms with similar domestic sales. Indeed, Table **??** indicates that export market demand among supported firms is nearly twice as large as that among unsupported firms in Norway, roughly three times as large in India and Japan, four times as large in China and the USA, and five times as large in Australia.[17] While these differences suggest that supported firms benefit from a large increase in demand in export markets, the increase in demand is not universal: on average, TC support has no estimated impact in either Russia or Turkey.

Second, differences in estimated market demand across export destinations are broadly consistent with differences in economic size across regions. China and the US represent particularly large export markets for both supported and unsupported firms and the export demand for these markets are multiples of that from smaller export markets, regardless of support status. Given differences in export market size and the influence of support, it is plausible firms would have differing levels of information across potential export destinations.

A natural concern with these estimates is that they omit the possibility that support-driven demand premia spills over across firms or markets. Buus et al., 2025 investigate the hypothesis that TC programming generates *demand* (rather than information) spillovers across firms, but do not find evidence of demand spillovers across firms or markets.

We further investigate whether demand spills overs to firms indirectly linked to the TC through firm networks. Specifically, we re-estimate equation (3) but distinguish a demand premium among indirectly supported firms differentially from those unsupported by the TC. The estimated demand premia among indirectly supported firms is reported in Table 3 for each network. In 22 out of 23 cases, the network demand premium is estimated insignificantly different from zero.[18] In 17 of 23 cases the premium is smaller than 2 percent; in over half of cases, the estimated coefficient is small and negative.[19] Given that both existing evidence and our model-

[17]The estimated support premia are consistent with evidence reported in Buus et al., 2025.

[18]The single statistically significant estimate is negative network demand premium for Japan through employee networks.

[19]The only country that reports consistently positive network demand spillover premia is China and these coefficients are always insignificantly different from zero. Table 3 reports a

consistent estimates do not find strong evidence of widespread demand spillovers, we conclude that the assumption that network *demand* spillovers are small and insignificantly different from zero is broadly supported by the data.

6.2 Fixed Export Costs

Table 4 reports moment inequality estimates of the fixed cost parameters (β_0^U, β_1^U, σ_U, β_0^S, β_1^S, σ_S), while Table 5 documents the implied fixed costs for exporters to Norway, the United States and China. In each table the first three columns of the top panel report results for unsupported firms, while the last three columns document analogous estimates for supported firms. Likewise, in each table the top row presents fixed cost estimates recovered by the moment inequality approach, but ignoring endogenous selection into TC support. The bottom row documents the same estimates recovered from an approach which uses TC calls as an instrument for TC support.

For both supported and unsupported firms fixed costs are estimated to be substantive, increasing in distance, and vary little across firms. Across destinations export entry costs represent roughly 12 to 24 percent of the typical exporter's annual export revenue to an arbitrary export destination. Intuitively, entering distant locations requires that exporters incur larger fixed entry costs. Among unsupported exporters, we recover average fixed cost estimates that range between 336 to 493 thousand DKK (60 to 88 thousand USD) for Norway, 450 to 648 thousand DKK (80 to 115 thousand USD) for the United States, and 454 to 655 thousand DKK (81 to 117 thousand USD) for China.

By comparison, Das et al., 2007 estimate that average export-entry costs in Colombia to range between 344 and 430 thousand USD employing a maximum likelihood (ML) estimator. Castro et al., 2016 document that export-specific fixed cost expenditures potentially imply much smaller estimates. Our benchmark fixed cost estimates among unsupported firms are closest to the moment inequality fixed cost estimates from Dickstein and Morales, 2018, which

large estimated demand spillover for Norway in the zip code-based network. This is due to a single zip code. Removing this one zip code from estimation returns a statistically insignificant coefficient near zero.

documents that ML fixed cost estimates suffer from significant bias in informationally opaque export markets.[20]

The last three columns of Tables 4 and 5 report fixed export cost parameters for supported firms, which, as expected, are much smaller than those for their unsupported counterparts. We expect that supported firms are more likely to use TC support for distant, and informationally opaque, export markets, while common, neighbouring export markets are less likely to suffer from export-relevant informational frictions. Indeed, not only do we observe a smaller fixed cost intercept, but we also observe an intuitive decline in the estimated coefficient on distance. Comparing the midpoint of the confidence sets across destinations we observe that fixed costs among supported firms are 43 percent (USA, China) to 46 percent (Norway) smaller than that estimated for their unsupported counterparts.

Roughly half of the supported firms contact the TC for export support and, as such, we might expect that these firms may be disproportionately likely to export, possess better export market knowledge, or benefit from lower entry costs. To guard against estimation bias arising from endogenous selection into export support services, we follow Buus et al., 2025 and repeat our estimation procedure using calls from the TC as an instrument for support. Fixed cost estimates are documented in the last row of Tables 4 and 5.

The fixed cost estimates returned by the moment inequality approach using calls as an instrument for TC support are generally similar to the benchmark moment inequality estimates. Among supported firms the confidence set is modestly wider but generally covers the same range, providing confidence that the benchmark confidence regions are not overly sensitive to endogenous selection. Moreover, the estimates maintain their modest size and intuitive ranking across countries, affirming that the moment inequality approach returns plausible fixed cost estimates for both supported and unsupported firms. It might seem surprising that the IV has a small impact on the range of fixed cost estimates. We caution that in either case the moment conditions account for firm size differences. As documented in Figure 3, within a size bin there

[20]Standard maximum likelihood estimates for unsupported firms are presented Appendix C. Because Dickstein and Morales, 2018 already highlights the significant impact that informational assumptions have on estimated fixed export costs we omit further discussion hereafter.

remains only modest differences across supported and unsupported firms, none of which are statistically significant. Although these differences are further reduced by using TC outreach calls, the outreach instrument only has a small impact on estimated fixed costs.

6.3 Information, Networks and TC Support

Rational expectations implies that any variable in the firm's information set serves as an instrument in our moment inequalities. We accordingly test whether any set of variables included in Z_{ijt} belong to the firm's information set using the model specification test in Bugni et al., 2015. In practice, the null hypothesis tests whether expectational error from the firm's revenue forecast, ε_{ijt}, satisfies the moment condition $\mathbb{E}[\varepsilon_{ijt}|Z_{ijt}] = 0$, where $\varepsilon_{ijt} \equiv r^o_{ijt} - \mathbb{E}[r^o_{ijt}|\mathcal{J}_{ijt}]$. If we reject the null hypothesis, we conclude that the estimated model implies that variable Z_{ijt} was not part of the firm's information set when deciding whether to export to market j.[21]

Consider, for example, the moment inequalities used to identify model parameters for unsupported firms, $\bar{\mathcal{M}}^U(X_{ijt}, Z_{ijt}, \theta^U; \hat{\alpha}^U)$ where $\hat{\alpha}^U \equiv \{\hat{\alpha}^U_{jt}; \forall j, t\}$ and $X_{ijlt} = (D_{ijt}, dist_j, r^o_{ijlt})$. The identified set Θ_0 includes all values of θ^U consistent with $\bar{\mathcal{M}}^U(X_{ijt}, Z_{ijt}, \theta^U; \hat{\alpha}^U) \geq 0$. The model defined by moment inequalities $\bar{\mathcal{M}}^U(X_{ijt}, Z_{ijt}, \theta^U; \hat{\alpha}^U) \geq 0$ is correctly specified when Θ_0 is non-empty:

$$H_0 : \Theta_0 \neq \emptyset \quad \text{vs} \quad H_1 : \Theta_0 = \emptyset.$$

By systematically varying the content Z_{ijt} we conduct a wide of set hypothesis tests to characterize the nature of information differences across firms and networks.

In particular, we start by separately testing what supported and unsupported firms know about export markets, documenting differences along firm and market characteristics. These tests are only used to confirm the widely held narrative that supported firms have systematically better export market information than their unsupported counterparts. Given this benchmark we proceed to whether unsupported peers of supported firms plausibly gain export market information from indirect network connections to TC programs.

[21] See Appendix E for a detailed description of the tests and their computation.

6.3.1 Are TC supported firms better informed?

This section document hypothesis tests aimed at (i) validating the claim that supported firms are better informed than their unsupported counterparts and (ii) characterizing information differences across heterogeneous producers.

Table 6 documents p-values for each information test. We first investigate whether firm-level information sets contain the minimal set of information: aggregate exports to destination j in the previous year, $R_{j,t-1}$, distance to export market j, $dist_j$, and the firm's domestic sales in the previous year, r_{iht-1}. Each column reports whether the specification test rejects the null hypothesis that these covariates are plausibly in firm-level information sets.

Panel A indicates that we cannot reject the hypothesis that firms know the minimal set of information, for either supported or unsupported firms. In Panel B, investigate whether firm information sets are sufficiently rich allow firms to perfectly predict observed profits from exporting. Specifically, we test whether firm information sets include the minimum information set, $\{R_{j,t-1}, dist_j, r_{iht-1}\}$ and the observable component of revenues $r^o_{ijt} = \alpha_{jt} r_{iht}$. For each sample, we clearly reject, at conventional significance levels, that firms have perfect foresight regardless of TC support. Rejecting the null hypothesis that firms have perfect foresight highlights the fact that, for an inappropriate perturbation of the minimal information set, the Bugni et al., 2015 test has statistical power in our context.

In Panel C, we test whether firms have knowledge of the relevant export market demand shifters, lagged one year, in addition to the minimal information set in the previous year. For unsupported firms, the demand shifter is $\alpha^U_{j,t-1}$ in export market j; for supported firms the demand shifter is $\alpha^U_{j,t-1} + \alpha^S_j$. We reject the hypothesis that the country demand shifters are part of firm-level information sets among unsupported firms. In contrast, we fail to reject the same hypothesis for supported firms, suggesting that supported firms are aware of export market demand conditions, as measured by $\alpha^U_{j,t-1} + \alpha^S_j$, when making export decisions.

The careful reader will notice that by virtue of TC program size, there is a much larger sample of unsupported firms relative to supported firms. Expanding our sample to include EU destinations has no impact on the information test conclusions in panels A-C; see Appendix D for details for (and complications) with respect to) the incorporation of EU export destinations.

Indeed, Table A7 is qualitatively identical to Table 6.

We next consider the same information test, whether a firm knows the minimal information set and the export demand shifter, but disaggregate our sample across firm size, export history and export destination popularity.[22] To be clear, in the first column and first row of panel D the null hypothesis we test is whether large unsupported firms know the export market conditions in popular destinations, while all other unsupported firms know the minimal information set for each market. The third column of the same row tests the null hypothesis among supported firms. Each of the subsequent rows consider analogous tests for various subsets of firm-market combinations. For each test we report both individual p-values and adjusted p-values which account for multiple hypotheses, though this is only relevant in lower panels.

Two clear patterns immediately emerge from Panel D. First, we rarely fail to reject the hypothesis that unsupported firms know export market conditions. The sole exception is large Danish firms deciding whether to export to popular destination markets.[23] Second, we almost always fail to reject that supported firms know export market conditions. Again, there is a single exception: large firms without previous export experience. It is also informative, however, to consider *why* a specification test of the type in Bugni et al., 2015 rejects the null hypothesis in this case, but not others. Large non-exporters are firms which have large domestic sales, r_{iht}. Our model suggests that large, supported firms will earn particularly large export revenues, $(\alpha^U_{jt} + \alpha^S_j)r_{iht}$, and pay modest fixed export costs, f^S_{ijt}. Thus, in light of the model, the specification test effectively rationalizes lower current export propensities among previous non-exporters *despite favorable conditions*, as evidence that these firms do not know of their export demand conditions.

Alternatively, it might also suggest model misspecification, at least for this subset of firms.

[22]A firm is large (small) if domestic revenue was above (below) the median in the previous year. Popular destinations include Norway, USA, Japan and Australia.

[23]It is somewhat surprising that large firms which have exported in the past are not likewise found to have strong knowledge of export market conditions. However, we note that this test requires that they have a good sense of export market conditions in *all* potential destinations, not just the few they have exported to in the past.

Numerous studies (c.f. Das et al., 2007) suggest that new exporters face larger entry costs than incumbent exporters. Ignoring the differences in entry costs across incumbents and new entrants may lead to spurious rejections. In unreported preliminary tests, a fully dynamic model with with both sunk (first-time) and fixed (continuation) entry costs suggests that model misspecification of this form is *not* the reason for the rejection of the null hypothesis.[24]

Panel E reports a similar series of tests where we consider each destination market separately. We cannot reject the hypothesis that Danish firms know export market conditions in Australia, Norway, Japan and the USA. Intuitively, the p-values are largest for nearby, popular markets. Likewise, we consistently the reject the hypothesis that unsupported firms know export market conditions in China, India, Russia and Turkey. Unlike their unsupported counterparts, we can never reject the hypothesis that supported firms know export market conditions regardless of the destination market.

Panel F characterizes the role that self-selection plays in determining export market knowledge. It also further validates the informational nature of TC programming. Although the preceding analysis distinguishes supported and unsupported firms, in our hypothesis we have not distinguished firms that receive at outreach call from those that do not receive an outreach call at all. For roughly 50 percent of supported firms, the TC initiates contact with individual producers through a quasi-random outreach process, as documented in Section 4.1.

Accordingly, the first row of Panel F distinguishes firms which receive a random call and proceed with acquiring TC support services and those which receive the same call, but decline TC support services. For both supported and unsupported firms, we fail to reject the hypothesis that firms which receive a TC call know destination market export conditions. Notably, unsupported firms which received a call are firms which chose to decline an offer of, on average, highly profitable export support services. Given high rates of subsidization, declining support services suggests that either firms already know information contained in TC support services or do not believe they can make use of it.

[24]Appendix Tables A3 and A4 confirm that allowing dynamic costs results in substantially larger (first time) entry costs and smaller fixed continuation costs. Preliminary information tests for the fully dynamic model are in progress.

The last row of Panel F documents the findings among firms that are not called by the TC. We again reject the hypothesis that unsupported firms know export market conditions, and fail to reject the hypothesis that firms that self-select into TC support know export market conditions. Remarkably, the individual p-value for supported firms that receive a call from the TC is very close that from supported firms that self-select into TC support. This suggests that, post-support, there is little difference in the export market knowledge between supported firms that self-select into support and those which are first contacted by the TC.

In sum, the information tests across all panels reinforce the common narrative that TC support improves the firm-level information of export market conditions. With few exception we consistently reject the hypothesis that most unsupported firms know export market conditions in most export markets. In contrast, rarely do we reject the analogous hypothesis tests among our sample of supported firms.[25] It is encouraging that the first-stage information tests return economically reasonable findings, confirming the existing narrative and historical evidence. However, substantive benefits to supported firms do not in itself imply market failure or suggest that the nature of TC information is public in nature. To further investigate these features of export support programs, we leverage these first-stage findings to characterize the nature of information spillovers across firm networks.

6.4 Does export market information spillover to unsupported firms?

An advantage of allowing each firm to have its own arbitrary information set is that we need not specify firm information networks for model estimation. Moreover, we recall that there is no evidence of fundamental differences across firms in supported networks and those in unsupported networks. With the recovered model parameters in hand we proceed to test the nature information spillovers across each firm network.

We proceed to test whether unsupported firms in supported locations have better information than unsupported firms in unsupported locations. The first column in Panel A of Table

[25] Qualitatively, the same pattern of findings are documented in both the smaller benchmark sample and the expanded EU-inclusive sample. See Appendix D for further discussion of EU-inclusive results.

7 reproduces the p-value for the null-hypothesis that all uninformed firms know demand conditions in export destination markets. This hypothesis is clearly rejected. Columns 2 and 3 repeat the same test but restrict the fraction to indirectly informed firms to include only those in smaller and smaller firm networks; in column 2 indirectly supported firm are those that share the same municipality; in column 4, the same zip codes. In each case, we fail to reject the same null hypothesis for unsupported firms in indirectly supported locations regardless of the region over which we test for the presence of informational spillovers. The difference between these findings in columns 2-3 and the benchmark result in column 1 is consistent with the presence of informational spillovers across geographic firm networks.

While geographic networks provide a natural starting point for linking firms, they do not provide a strong sense of a mechanism by which information spills over from one firm to another. To provide evidence for an important informational mechanism, the last column of Panel A repeats the same statistical test across a firm-level network based on employment transitions. We again fail to reject the null that unsupported firms indirectly linked to the TC through employee networks know export market conditions. This finding indicates that that employee turnover is a potentially important mechanism through which industrial policy yields broader economic benefits.[26]

In Panel B we check that these benchmark findings do not reflect firms that have other contact with the TC, confounding those firms without any links to the TC and those with such connections. In particular, we again appeal to the data which allows us to distinguish firms which receive quasi-random outreach calls from the TC and those that do not. This distinction ensures that the set of unsupported firms we consider in our tests genuinely have no direct contact with the TC itself. The first row again reports that we never reject the null hypothesis that called firms are well informed of export market conditions. The second row considers the same hypothesis for the group of uncalled firms and each firm network. We again find that

[26]This result is reminiscent of Hastings et al., 2017 which finds that sales force intensity reducing demand sensitivity and increasing firm profits. In contrast, we do not find significant evidence that employment transitions from TC supported firms affects demand conditions, but do find that employment transitions influence firm export decisions.

although we clearly reject the null hypothesis that uncalled unsupported firms are informed of export market conditions (column 1), we cannot reject the same hypothesis for any network of the indirectly supported firms (columns 2-4). Indeed, the p-values in the second row of Panel B are nearly identical to those in Panel A.

An additional concern naturally arises because p-values appear to rise as network scope declines. On the one hand, this may reflect that informational spillovers decay as network links weaken. For instance, we intuitively expect that connections between firms in the same zip code are plausibly stronger than those in wider municipalities. On the other hand, this difference may reflect the fact that the fraction of informed firms must decline as we consider increasingly narrow definitions of geographic firm networks. In this sense, failing to reject the null hypothesis may be indicative of a lack of statistical power.

Table 7 provides two pieces of evidence to counter this interpretation. First, even when we consider the widest definition of firm networks we continue to fail to reject the null hypothesis. Second, in Panel C we consider a placebo test for the two sparsest definitions of firm networks, supported zip codes and worker transitions. In the first experiment, we randomly draw zip codes until we reach sample sizes of placebo firms of the same size as the number of indirectly supported firms in the benchmark sample.[27] Specifically, we ensure that in each placebo the number of artificially treated is the same as that in the actual data sample. If the information tests lack statistical power we should expect to always fail to reject the null hypothesis even if firms are poorly informed of export market demand conditions.

In the second exercise we likewise placebo samples by drawing employment transitions nodes and counterfactually categorizing firms in the selected networks as informed. Again, the number of informed firms of the placebo sample is set to match that in the actual data.

The fourth and fifth columns of Panel C document the mean value of 50 separate placebo tests for each firm network. In each case, we observe that, on average, we would clearly reject the same null hypothesis for either zip codes or employment networks.[28] In this sense, Panel C

[27]Since roughly 5 percent of firms are actually located in supported zip codes, each random sample of placebo largely contain firms which do not have a supported peer in practice.

[28]Indeed, for each network specification and each placebo we always individually reject the

suggests that if firms in supported zip codes or supported employment networks did not have knowledge of export market conditions there is sufficient statistical power to reject that null hypothesis. Yet, in contrast to all placebo samples, we never reject the null hypothesis for the true sample of indirectly supported firms.

6.4.1 Export market information spillovers across firms and geography

To further characterize the nature of information spillovers Table 8 distinguishes unsupported firms by firm and market characteristics (small vs large firms, popular vs unpopular markets), while each column distinguishes each null hypothesis by firm network. The first column of Panels A and B in Table 8 correspond to the case where we test whether all unsupported firms know export market conditions against the alternative that they only know the minimal information set; it is identical to Panel D and E of Table 6. The null hypothesis is strongly rejected with few plausible exceptions: large firms or popular markets such as the US, Japan or Norway.[29]

In Panel A, we find that we cannot reject the hypothesis that large, unsupported firms know export demand conditions in unpopular markets if they have a supported peer exporting to unpopular export markets in the same zip code. Disaggregating this result to specific destinations in Panel B, we confirm that we cannot reject that unsupported firms know export demand conditions in Australia, China, India and Turkey if they have a supported peer in same zip code exporting to the same country.

By comparison, we reject the hypothesis that large firms know export market conditions across unpopular markets if they are indirectly connected to the TC through a firm sharing the municipality (column 2). That said, Panel C indicates that should a supported firm in a municipality receive TC support for Australia, China or India this information would spillover to unsupported firms within municipality-level networks. Overall, these findings are broadly

null hypothesis.

[29] A full set of results can be found in each table. For parsimony the text focuses exclusively on pairs of tests where there were meaningful differences across subgroups. Likewise, Table A10 which documents p-values adjusted for multiple testing within each panel is relegated to the appendix.

consistent with stronger informational spillovers, particularly for larger export markets and in more narrowly defined firm networks.

The last column of Table 8 repeats the same set of informational tests across employment networks. We again find that we cannot reject the hypothesis that firms with indirectly supported workers broadly know export market conditions, while firms without workers with past TC connections do not. Informational spillovers are found to be particularly relevant for unpopular markets, regardless of firm size, suggesting that informational frictions are particularly relevant in distant, less familiar markets. Indeed, Panel B confirms informational spillovers in all less popular, distant or informationally opaque export destinations (Australia, China, India, Russia, and Turkey).

Likewise, we cannot reject the hypothesis that large exporters with employment links to the TC know export market conditions. The p-values in Panel A are consistent with evidence from Labanca et al., 2024, which highlights that Brazilian firms with a greater share of workers with export experience in previous employment are more likely to start exporting. Our results build on their evidence to suggest that worker employment transitions transmit export-relevant information, including information originating from government lead policy institutions, such as the TC.

Relative to our regional network tests, the worker-network tests return stronger and more consistent evidence of informational spillovers. This is suggestive that although export-relevant information is non-exclusive, it remains rival or at least partially unobservable without some past contact with the TC. This inherently raises the questions as to the type of export-relevant information that diffuses across firm networks, a question we address next.

6.5 What do firms learn through information networks?

Our benchmark model collects all export relevant information into a limited number of covariates, the most important of which is the export market demand shifters. While model consistent, the demand shifters provide little intuition as to their fundamental composition. To make progress we appeal to data that records the number of buyers each firm has in export market each year. Appendix A highlights that the demand shifter can be decomposed into additively separable components capturing the number of buyers a firm has in a particular destination market and the average quality of the buyers in that location, measured by average sales per buyer.

Table 9 reports findings across network types. We again find no evidence that unsupported firms broadly know either component of export demand. Among regional networks, we find evidence that information about the number of buyers and buyer quality spills over from supported to unsupported firms. However, the evidence in favor of information regarding the number of buyers spilling over to unsupported firms is stronger than the evidence of information regarding buyer quality spilling over to unsupported firms. Indeed, we only find that buyer quality spills over to unsupported firms if they are located in the same zip code as a supported firms. Turning to worker-networks, the same finding presents itself: firms learn both the number of buyers and buyer quality.

Relative to our existing results, we find two results that merit particular comment. First, unsupported firms which are related to supported firms, either through geography or worker history, learn both buyer quality and the number of buyers in a typical destination market. This is in contrast to both unsupported firms at large, where we individually reject the hypotheses that either component is known, and supported firms at higher levels of aggregation, where we reject the hypothesis that buyer quality is known to indirectly supported firms.

Second, focusing on buyer quality based information spillovers across regional networks, we find evidence of informational decay. For example, we cannot reject that indirectly supported firms in the same zip code as a directly supported firm know the typical buyer quality in destination markets. We reject each of the above hypotheses at higher levels of regional aggregation, consistent with informational decay. This difference is substantive: while differences in the (log) number of buyers explains roughly two thirds (68%) of the total variation in the export demand shifter, with variation in buyer quality explaining the remaining third. As such, information spillovers in less connected networks are far from complete.

6.6 Are information spillovers economically important?

Employing the model and estimates we conduct a series of counterfactual experiments to evaluate the value of *information* spillovers in export markets. We start by considering a setting without informational spillovers. That is, holding demand and costs fixed, how does firm and industry performance change if we remove knowledge of export demand shifters from firms in supported networks. We then compare firm and industry performance where firms in supported networks receive information spillovers, but firms in unsupported networks do not. Panels A-D repeat the counterfactual for each network structure and document results in Table 10.

Panel A of Table 10 considers information spillovers among employee networks. We do not observe any significant change in average export propensity. This does not imply that there is no change in which firms export; indeed, mean export profits increase, indicating that information spillovers effectively improve sorting into export markets as less profitable firms refrain from entry, while more profitable firms grow into export markets.

Small changes in the propensity to export and mean export profits might suggest that information spillovers are of little economic consequence. In aggregate we find that these spillovers increase aggregate exports to non-EU countries by 0.2-0.6 percent. While the percentage increase in aggregate exports appears small, it is important to recognize that information spillovers alone account for additional export profits of 1.6-2.5 million DKK (0.22-0.35 million USD) even in this very narrow case.

Using information from the TC on the approximate cost and subsidy rate for each supported firm, inclusive of the outreach program, we compute the aggregate existing subsidy to the Danish machinery industry by multiplying the per firm subsidy by the number of supported firms. The total subsidy cost of supplying directly supported firms with TC support amounted to 0.32 million DKK, a fifth of the aggregate gain in profits (0.32/1.6=0.2). Given a corporate tax rate of 22 percent the taxes earned on the additional profits approximate 0.35-0.55 million DKK, which themselves are sufficient to cover the cost of the public subsidy.

In Panel B we find that the transfer of information to unsupported firms in supported zip codes increases export participation by as much as 0.2-0.3 percent, though it is largely concentrated among large firms and firms exporting to large, popular markets. Mean exports increase modestly. Across all firms and all markets mean export profits are expected to rise by 0.1 to 0.2 percent. The modest increase is not surprising; improved information induces entry among marginal exporters pushing down average firms exports.[30] Despite a relatively small number for indirectly supported firms, aggregate exports among indirectly supported firms are predicted to rise by 0.6-1.3 percent a year. Again, back-of-the-envelope calculations suggest the gain in export profits from indirect information spillovers alone are greater than the aggregate value of the subsidies enjoyed by firms directly supported by the TC.

Increasing the scope for information spillovers across geographical space increases aggregate gains by construction, since more unsupported firms benefit from information spillovers but the costs of support do not change. Moving from zip codes (Panel A) to municipalities (Panel B) increases the growth in export propensities, doubles the impact on mean export profits and leads to aggregate export growth that is a full 1-2 percent larger than baseline through information spillovers alone.

Last, Panel D considers a setting with informational decay in both quality and quantity. Specifically, we assume, consistent with our information tests, that unsupported firms in supported zip codes receive a full informational spillovers, while those in wider municipalities only learn the number of buyers in supported export markets. Unsupported firms in supported districts that are not part of a supported zip code or municipality are assumed to receive no informational spillover.

Not surprisingly, the quantitative implications from the experiment reported in Panel D fall between the findings reported in Panels B and C. On average, we observe a total change in export propensity which relatively modest; indeed, the overall change in export propensities overlaps

[30]Luco, 2019, studying retail gasoline markets, finds that information disclosure has a disproportionately large impact on profit margins in smaller markets with fewer existing firms. Ater and Rigbi, 2023 finds information disclosure has a larger impact on prices and price dispersion among premium grocery chains. Our findings suggest that large firms disproportionately benefit from information disclosure and the gains are largest in large export markets, confirming that both firm and market fundamentals matter for the evaluation of information disclosure on firm behaviour and profits.

with the zip code policy experiment closely. In contrast, mean export growth is relatively strong, as in Panel B, where municipalities enjoy full information spillovers. Accordingly, aggregate gains from information spillovers are substantive even when less connected firms only receive partial information.

6.7 Do information spillovers justify expansion of TC outreach?

We next consider how policy outreach shapes the benefits TC support. Focusing on presently unsupported firms (firm-destination-year observations), we counterfactually provide export demand information to an additional 216 firms, effectively doubling the program size in the machinery industry. Each counterfactual exercise varies the nature of information spillovers and the outreach strategy pursued by the TC. For each experiment, we restrict attention to employment networks where information is transmitted by employee transitions between firms.

In panel A of Table 11, we assume that the firms that receive TC outreach become informed about the demand conditions $\alpha^{U}_{j,t-1}$ for a particular export destination, but none of this information spills over to connected peer firms. In panel B the firms contacted by the TC receive full information regarding demand shifter $\alpha^{U}_{j,t-1}$, while indirectly supported firms only learn information pertaining to the number of buyers in the export market. Finally, panel C we explore informational gains from full information provision to both the firms directly contacted by the TC and their connected peers under the assumption of full information spillovers. We continue to abstract from TC driven demand premia or fixed cost reductions to focus exclusively on the economic gains from information provision. In all settings we impose the extreme assumption that all firms contacted by the TC accept their offer of support.

For each assumption regarding the nature of information diffusion across firm networks, we consider four different outreach strategies the TC could pursue. For the first strategy we assume that the TC draws firms randomly for contact. This approach serves as a lower bound relative to targeted alternatives. The second strategy approximates the actual TC approach by categorizing firms by past revenues and randomly selecting firms within size bins to match the outreach call distribution illustrated in Figure 3c. This strategy captures the gains from targeting large firms, where additional profits from exporting are expected to be greatest.[31] The third strategy refines the second by exclusively targeting the largest firms, disregarding any attention to small and medium producers. This strategy effectively creates a size-based pecking order for TC outreach.

While large firms are inherently well connected by virtue of the fact that they employ large numbers of workers, the correlation between employment transitions and size is far from perfect. Our last counterfactual experiment instead targets the most connected firms; that is, firms that have the highest number of employment links to other firms in the data. On the one hand, because these firms are smaller than those targeted by the TC in the experiment which exclusively targets firm size, the direct benefits to TC outreach will also be smaller. On the other hand, the public benefits rise with a greater number of network linkages.

Table 11 reports the impact of broad or targeted TC outreach. The first column again reports the percentage change in the number of exporters due to TC outreach. Perhaps surprisingly, in almost every case the experiments find that the number of exporters declines with further TC outreach. Again, this result reflects a change in selection into export markets: firms are more likely to refrain from entering unprofitable export markets, while profitable firm-market pairs are more likely to see new entry. On net, the change export propensities are negative.[32]

Improved sorting into export markets is likewise reflected in column 2, where we document mean export profits across all machinery exporters. Intuitively, higher rates of net exit are correlated with greater mean export profits across experiments, as greater information leads firms to refrain from entering unprofitable export markets. This feature is most clearly demonstrated in the first three rows of panel A. When outreach is targeted to the largest firms, the gains from learning which markets are most likely to be profitable are largest. Maximal profits are achieved by when the most productive firms enter markets with the largest potential export sales. Providing the largest firms with this information yields the largest increase in profits in an environment without informational spillovers.

[31] The additional profits from exporting are largest among large since the absolute gains from support, $\alpha_j^S r_{iht}$, are proportional to domestic revenues.

[32] Dickstein and Morales, 2018 likewise find that adding information reduced the propensity to export.

Allowing for spillovers in panels B and C reinforce the export market selection mechanism whenever the TC pursues random, binned random (actual), or size-targeted (largest) outreach strategies. However, the *change* in the selection effects are similar across outreach strategies. For example, Panels A and C indicate that adding full spillovers to the random approach strategy causes the (midpoint) percentage change in the number of exporters declines from -0.35 to -4.55 percent, an additional decline of 4.2 percentage points. When the TC targets the largest firms, the (midpoint) percentage change in the number of exporters declines from -6.7 to -9.9 percent, an additional decline of 3.2 percentage points. Likewise, the absolute growth in (midpoint) mean exports after adding full spillovers is 4850 thousand DKK when pursuing the random outreach approach, but 5300 thousand DKK when targeting the largest firms.

Targeting the most connected firms yields substantially different findings. In the absence of network spillovers, targeting connected firms induces substantial net exit and a large rise in mean export profits. However, these changes are smaller in magnitude than a program targeting the largest firms by size, confirming that the largest firms are not necessarily the most connected firms. Unlike the other outreach strategies, adding spillovers in panels B and C has a very small impact on either the propensity to export or mean export profits relative to Panel A for an outreach approach targeting connected firms. This difference is substantive as the largest number of firms are receiving TC information indirectly in the outreach strategy targeting the most connected firms.

Column 3 of Table 11 documents the change in aggregate exports for the machinery industry. Strikingly, we find little evidence of significant growth in aggregate exports from expansion of the TC programs when the TC pursues random, binned random (actual), or size-targeted (largest) outreach strategies. Regardless of the network spillover assumption, the predicted impact of TC expansion is always small or even slightly negative. In this case, any aggregate gains are largely achieved by saving fixed export costs among firms which refrain from export markets.[33]

This result is reminiscent of Atalay et al., 2023 and Bartelme et al., 2025 where gains to

[33]Relaxing the assumption that all firms that receive outreach agree to support would modestly reduce the aggregate gains even further.

industrial policy are modest at best, though it is important to recall that we are omitting the direct demand boost or fixed cost savings to supported firms. In this sense, our experiment cannot fully determine whether the benefits to expansion outweigh the costs. It can, however, clearly conclude that expansion is not justified on the basis of public benefits alone. In the absence of said justification, it is prudent to question the appropriate degree of public subsidy to these widespread programs.

The same is true when the TC targets the most connected firms, but network spillovers are omitted or incomplete. However, with full spillovers and network targeting, the gains are always positive and economically substantive. Indeed, even at the lower-bound the gains in export growth are sufficient to justify the full costs of program expansion based on the informational benefits alone. This last experiment, in contrast to all preceding experiments, indicates that both program design and the nature of network connections are necessary to maximize the public benefits of export-oriented industrial policy.

7 Concluding Remarks

This paper develops and estimates a model of firm-level export decisions under (i) entry costs, (ii) demand shocks and (iii) information spillovers. Employing variation in firm-level export support from the Danish Trade Council (TC) and a partial identification estimation approach, we find that information originating from TC export support programs spills over to unsupported firms through firm networks. Across regional and employment-based firm networks, we find evidence that information spillovers are salient for large firms in unpopular export destinations, small firms in popular export destinations, exporting firms, and in China, India and Turkey.

Yet, even when information spillovers occur we find evidence that they are incomplete. Our estimates suggest that information pertaining to the number of buyers in foreign markets spills over through peer networks, but provide mixed results for information pertaining to the typical quality of foreign buyers.

Finally, we quantify the aggregate gains from policy driven information spillovers. We find that information spillovers alone increase aggregate exports from the Danish machinery industry by 1-2 percent per year. This tax revenue generated by additional profits through information spillovers to *unsupported* firms is greater than the total value of subsidies enjoyed by TC *supported* exporters. In this sense, our findings suggest that the current program is self-financing.

Nonetheless, we find little evidence that *further expansion* of TC programs can be justified on the basis of the informational benefits alone, unless both spillovers are complete and the policy is targeted to firms with the greatest number of connections in the machinery industry.

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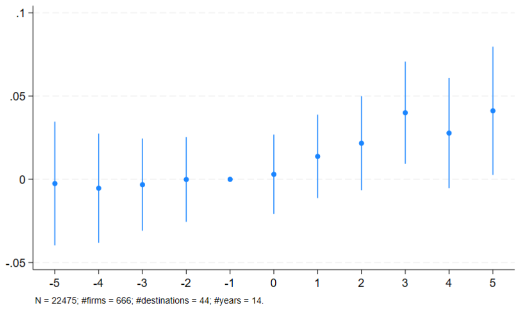
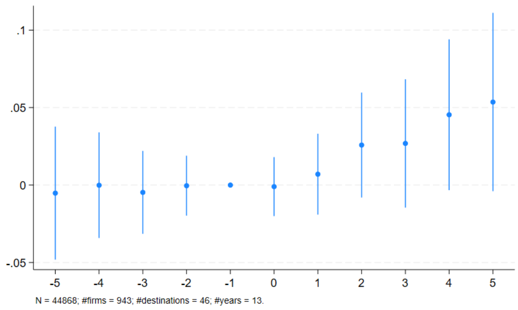
8 Figures

Figure 1: Export Share Event Study Across Firm Networks

(a) Zipcode Networks



(b) Worker Transition Network



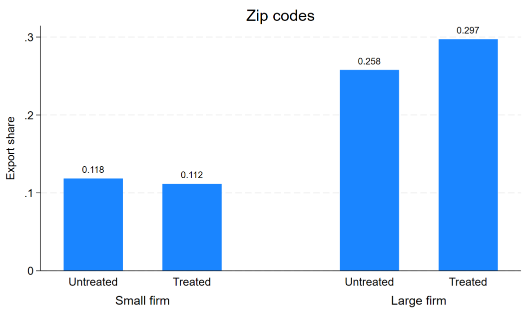
Notes: Panel (a) reports an event study-type regression:

$$d_{ijt} = \alpha_{ij} + \delta_{js(i)t} + \eta_{g(i)t} + \gamma \log(\#\text{employees}_{it}) + \sum_{k=-5,\ldots,-2,0,\ldots,5} \beta_k \mathbf{1}\{\text{event time}_{ijt} = k\} + e_{ijt}$$

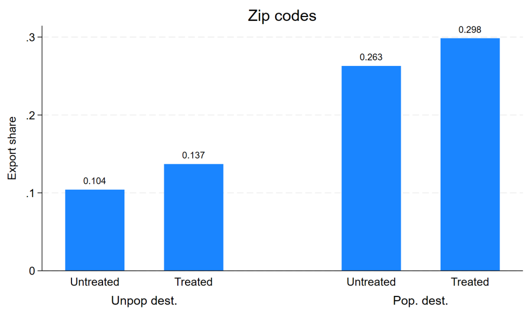
where d_{ijt} is export status of firm i in destination j in year t, s is industry and g is zipcode. Event time is zero for ij in the year t where $i' \neq i$ from the same zipcode ($g(i) = g(i')$) received promotion for j. If an ij pair experienced multiple events over the sample period, we restrict attention to the first event. Event time is binned/winsorized at -5 and 5. An analogous event study exercise is documented in Panel (b) for the network of worker transitions.

Figure 2: Export Share Across TC Firm Networks

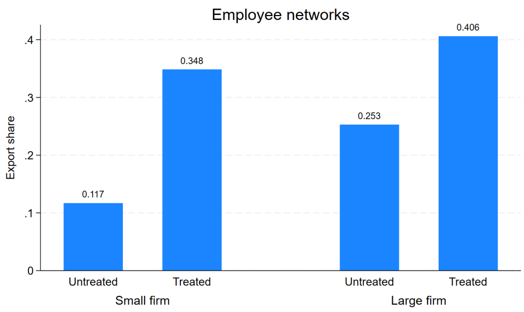
(a) Firm Size & Zipcode



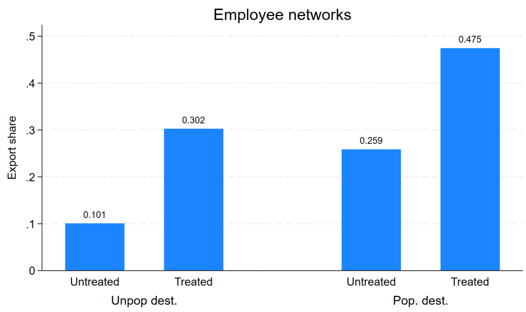
(b) Dest. Popularity & Zipcode



(c) Firm Size & Emp. Network



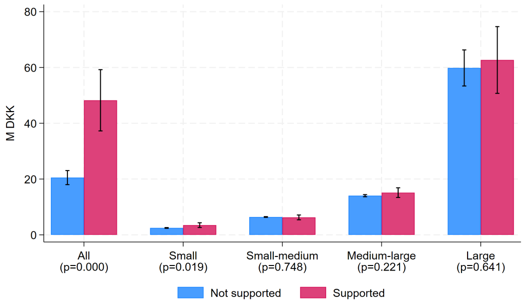
(d) Dest. Popularity & Emp. Network



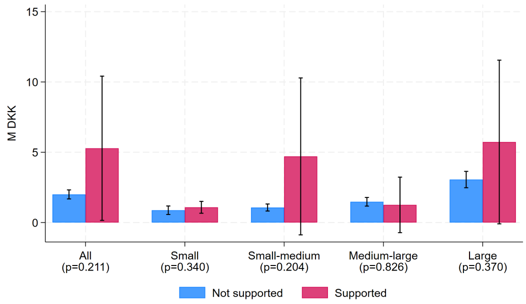
Notes: The above figures report the fraction of exporting firms unsupported by the Danish Trade Council. We separately document export share across firm size and export destination popularity for firms that have a supported neighbour in the same zipcode (panels (i) and (ii)) and firms which have hired an employee who was previously employed by a TC supported firm (panels (iii) and (iv)). Large (small) firms are firms with domestic revenue above (below) the median domestic revenue for the industry. Popular export destinations include the USA, Japan and Norway. Unpopular export destinations include China, India, Russia and Turkey.

Figure 3: TC Calls Across Firms and Randomization

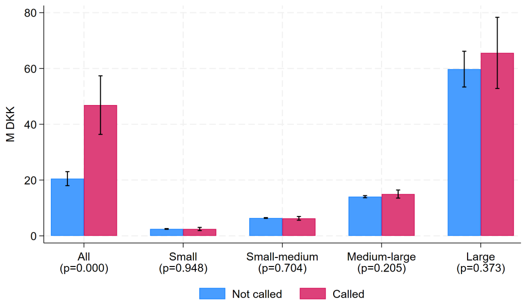
(a) Dom. Sales by Support Status



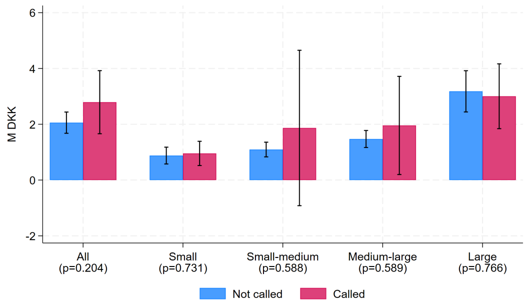
(b) Exp. Sales by Support Status



(c) Dom. Sales by Call Status



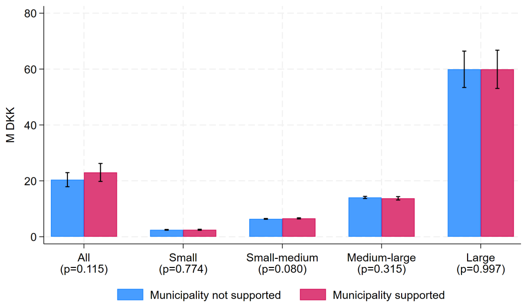
(d) Exp. Sales by Call Status



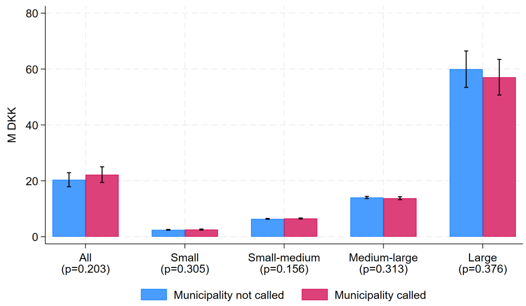
Notes: The above figures report the results from a randomization experiment where we first divide firms into four distinct groups based on lagged firm size, measured by domestic sales. We then report average domestic and export sales, along with corresponding confidence intervals, across firms supported by the TC and those not supported by the TC in panels (a) and (b). Panels (c) and (d) report analogous findings for firms which receive a TC outreach call and those that do not.

Figure 4: TC Calls Across Municipalities and Randomization

(a) Dom. Sales by Support Status



(b) Dom. Sales by Call Status



Notes: The above figures report the results from a randomization experiment where we first divide unsupported firms into four distinct groups based on lagged firm size, measured by domestic sales. We then report average domestic sales, along with corresponding confidence intervals, across municipalities where at least one firm was supported by the TC and those where no firms were supported by the TC in panel (a). Panel (b) reports analogous findings for municipalities where at least one firm is called by the TC and those where no firms are called by the TC.

9 Tables

Table 1: Summary statistics across destinations (2010-2015 annual averages)

	Export	Support	Support cond. on export	Call	Call cond. on export	Exp. rev. cond. on export	Dom. rev. cond. on export	Dom. rev. cond. on support	Dom. rev. cond. on call
Australia	75.5	0.83	-	1.67	0.83	1.18	33.6	60.3	42.4
China	89.5	6.33	4.00	4.50	3.00	3.07	38.8	62.9	58.5
India	53.5	3.67	2.83	4.00	2.50	1.35	40.2	83.7	76.0
Japan	61.5	1.00	1.00	1.33	1.33	1.15	41.0	68.7	64.5
Norway	262	1.33	-	0.83	-	2.02	27.0	22.3	33.4
Russia	60.1	5.67	3.67	8.00	3.83	2.45	37.9	54.7	78.0
Turkey	51.2	1.83	0.83	0.83	-	0.96	39.6	66.8	60.9
US	137	5.50	4.33	7.83	5.50	3.71	34.8	44.9	41.3

Notes: Columns (1) and (2) report the average number of exporters and number of supported firms in each country, while column (3) reports the fraction of exporters who receive TC support. Columns (4)-(5) report the average number of firms called by the TC for a particular destination country and the the fraction of exporters who received TC outreach calls. Columns (6)-(7) report average export and domestic revenue conditional on exporting to a particular destination, while columns (8)-(9) document average domestic revenue conditional on TC support or calls to a particular destination. All values in million DKK. Average domestic revenues across all firms is 21.2 million DKK across all 532 firms in the estimation sample. "-" indicates that the cell value is based on too few firms to comply with Statistics Denmark's rules on data confidentiality.

Table 2: Country shifters

Country	Unsupported Demand α^U_{jt}			Supported Premium α^S_j		
	Coef.	S.E.	P-val.	Coef.	S.E.	P-val.
Australia	0.021	0.007	0.002	0.081	0.051	0.112
China	0.062	0.019	0.001	0.094	0.090	0.296
India	0.019	0.004	0.000	0.035	0.035	0.326
Japan	0.016	0.003	0.000	0.042	0.010	0.000
Norway	0.036	0.006	0.000	0.023	0.007	0.001
Russia	0.056	0.023	0.015	0.001	0.022	0.964
Turkey	0.013	0.003	0.000	-0.005	0.006	0.408
US	0.072	0.016	0.000	0.239	0.142	0.093

Notes: This table reports the results from the OLS estimation of equation 3. Note that α^S_j carries a j subscript, not a jt subscript; α^S_j varies across destinations, but not across years.

Table 3: Network Demand Spillover Country Shifters

Country	Municipality			Zip code			Employee network		
	Coef.	S.E.	P-val.	Coef.	S.E.	P-val.	Coef.	S.E.	P-val.
Australia	0.004	0.015	0.776	-0.018	0.020	0.356	0.014	0.013	0.281
China	0.070	0.044	0.110	0.040	0.020	0.050	0.062	0.041	0.131
India	-0.008	0.005	0.091	-0.009	0.005	0.060	-0.009	0.011	0.428
Japan	-0.012	0.007	0.091	—	—	—	-0.016	0.005	0.001
Norway	-0.014	0.020	0.471	0.017	0.042	0.686	0.042	0.088	0.633
Russia	-0.044	0.026	0.100	-0.026	0.021	0.209	0.008	0.021	0.719
Turkey	-0.015	0.010	0.148	-0.001	0.008	0.851	0.018	0.012	0.467
US	-0.005	0.026	0.839	-0.020	0.021	0.349	0.040	0.055	0.467

Notes: This table reports the results from the OLS estimation of equation 3 but allowing for potential demand spillovers across networks. The reported coefficients in the above table are only the estimated network demand premia. Standard errors clustered at the firm-level. A single extreme observation was dropped the zip code network for Norway.

Table 4: Fixed Cost Parameter estimates, 1,000 DKK; across support/call status

	Unsupported			Supported		
Estimator	σ_U	β_0^U	β_1^U	σ_S	β_0^S	β_1^S
Moment inequality	[314; 471]	[326; 480]	[146; 243]	[122; 357]	[109; 322]	[48; 278]
Moment inequality, IV	[320; 471]	[330; 471]	[155; 249]	[106; 417]	[105; 346]	[42; 238]

Notes: Distance is measured in 10,000 kilometers. The demand elasticity η is set to 5. Parameter β_0 measures the fixed cost intercept while parameter β_1 reflects the relationship between geographic distance and fixed costs. Likewise, parameters σ_U and σ_S govern the variance of the fixed cost shocks

Table 5: Average fixed export costs, 1,000 DKK; across support status

	Unsupported			Supported		
Estimator	USA	China	Norway	United States	China	Norway
Moment inequality	[450; 648]	[454; 655]	[336; 493]	[193; 433]	[194; 440]	[117; 327]
Moment inequality, IV	[459; 648]	[463; 655]	[340; 484]	[187; 438]	[188; 442]	[113; 353]

Notes: The above table documents average fixed costs by export destination and estimation approach. The demand elasticity η is set to 5. Fixed costs are reported in thousands of Danish Krones.

Table 6: Testing the content of information sets; support status

		Unsupported firms		Supported firms	
Firms	Markets	Ind. p-value	Adj. p-value	Ind. p-value	Adj. p-value
Panel A: Minimal information					
All	All	0.224	—	0.429	—
Panel B: Perfect foresight					
All	All	0.021	—	0.001	—
Panel C: Minimal information & country shifter					
All	All	0.029	—	0.557	—
Panel D: Minimal information & country shifter across firm and destination groups					
Large	Popular	0.318	0.318	0.018	0.126
Large	Unpopular	0.002	0.005	0.538	1
Small	Popular	0	0	0.523	1
Small	Unpopular	0	0	0.737	1
Large exporter	All	0.009	0.018	0.134	0.804
Large non-exporter	All	0	0	0.001	0.004
Small exporter	All	0	0	0.291	1
Small non-exporter	All	0	0	0.512	1
Panel E: Minimal information & country shifter across destinations					
All	Australia	0.048	0.190	0.358	1
All	China	0.004	0.021	0.620	1
All	India	0.012	0.058	0.189	1
All	Japan	0.342	0.815	0.197	1
All	Norway	0.368	0.815	0.510	1
All	Russia	0	0	0.586	1
All	Turkey	0	0	0.640	1
All	U.S.	0.272	0.815	0.664	1
Panel F: Minimal information & country shifter across call status					
Called	All	0.481	0.481	0.652	1
Not called	All	0.039	0.078	0.645	1
No. of Obs.		21064		216	

Notes: A firm is large (small) if domestic revenue was above (below) the median in the previous year. A destination is popular (unpopular) if the number of exporters was above (below) the median in the previous year. Call status is measured in the same year as support status.

Table 7: Testing the content of information sets across firm networks

Uninformed		None	Unsup. Muni.	Unsup. Zips	Unsup. Wkrs
Informed		All Unsup.	Sup. Muni.	Sup. Zips	Sup. Wkrs
Firms	Markets				
Panel A: Minimal information & country shifter					
All	All	0.029	0.230	0.415	0.345
Panel B: Minimal information & country shifter across call status					
Called	All	0.481	0.541	0.412	0.545
Not called	All	0.039	0.224	0.416	0.373
Panel C: Minimal information & country shifter for Placebo firms					
All	All	—	—	0.039	0.043
No. of Uninformed Obs.		0	19421	20432	20601
No. of Informed Obs.		21064	1643	632	463

Notes: Independent p-values are reported in Panel B. Adjusting p values for multiple testing had little impact reported p-values. The p-values reported in Panel C are the average p-values over 50 placebo samples. The null hypothesis is rejected in each individual placebo sample of supported zip codes. The number of un/informed observations in panel C is the total number in each group multiplied by the fraction that receive a call (or do not receive a call from the TC). Approximately 5.4 percent of firms receive a destination specific call in a typical year.

Table 8: Testing the content of info. sets across firm networks, by firm/market type

Uninformed		None	Unsup. Muni.	Unsup. Zips	Unsup. Wkrs
Informed		All Unsup.	Sup. Muni.	Sup. Zips	Sup. Wkrs
Firms	Markets				
Panel A: Minimal information & country shifter across firm and destination groups					
Large	Popular	0.318	0.425	0.423	0.492
Large	Unpopular	0.002	0.027	0.438	0.422
Small	Popular	0	0.147	0.003	0.008
Small	Unpopular	0	0	0.001	0.503
Large exp.	All	0.009	0.377	0	0.412
Large non-exp.	All	0	0	0.008	0
Small exp.	All	0	0	0	0.001
Small non-exp.	All	0	0	0	0.458
Panel B: Minimal information & country shifter across destinations					
All	Australia	0.048	0.266	0.263	0.518
All	China	0.004	0.420	0.424	0.444
All	India	0.012	0.235	0.136	0.364
All	Japan	0.342	0.435	0.290	0.164
All	Norway	0.368	0.288	0.354	0.302
All	Russia	0	0	0.004	0.381
All	Turkey	0	0.001	0.341	0.526
All	U.S.	0.272	0.418	0.453	0.483

Notes: Independent p-values are reported above; p-values adjusted for multiple testing are reported in Appendix H. A firm is large (small) if domestic revenue was above (below) the median in the previous year. A destination is popular (unpopular) if the number of exporters was above (below) the median in the previous year.

Table 9: Testing the disaggregated content of information sets

Uninformed		None	Unsup. Muni.	Unsup. Zips	Unsup. Wkrs
Informed		All Unsup.	Sup. Muni.	Sup. Zips	Sup. Wkrs
Firms	Markets				
Panel A: Minimal information & no. of buyers					
All	All	0	0.366	0.381	0.345
Panel B: Minimal information & buyer quality					
All	All	0.040	0.016	0.346	0.492
No. of Uninformed Obs.		0	19421	20432	20601
No. of Informed Obs.		21064	1643	632	463

Notes: No. of buyers captures the typical number of buyers in a given destination. Buyer quality measures the typical sales per buyer in each destination markets.

Table 10: Effect of improving info. to unsupported firms, by network

Firms	Markets	Number of exporters	Mean export profits	Aggregate exports
Panel A: Employment networks				
All	All	[0; 0]	[0.2; 0.3]	[0.2; 0.6]
Large	All	[-0.1; 0]	[0.2; 0.4]	[0.1; 0.4]
Small	All	[0; 0]	[0; 0]	[0; 0]
All	Large	[-0.1; 0]	[0; 0.1]	[0; 0]
All	Small	[0; 0]	[0; 0]	[0; 0.1]
Panel B: Zip codes				
All	All	[0.2; 0.3]	[0.1; 0.2]	[0.6; 1.3]
Large	All	[0.2; 0.4]	[0.1; 0.2]	[0.5; 1.1]
Small	All	[0; 0.1]	[-0.1; 0]	[0.1; 0.2]
All	Large	[0.1; 0.1]	[0; 0]	[0.2; 0.3]
All	Small	[0; 0]	[0; 0]	[0.1; 0.2]
Panel C: Municipalities				
All	All	[0.2; 0.5]	[0.3; 0.5]	[1; 2.1]
Large	All	[0.1; 0.6]	[0.3; 0.5]	[0.6; 1.8]
Small	All	[0.1; 0.2]	[-0.2; -0.1]	[0.3; 0.6]
All	Large	[0.2; 0.2]	[0; 0]	[0.3; 0.5]
All	Small	[0; 0]	[0; 0.1]	[0.1; 0.3]
Panel D: Zip codes & partial spillovers within municipalities				
All	All	[0.1; 0.3]	[0.4; 0.6]	[0.8; 1.8]
Large	All	[0.1; 0.4]	[0.4; 0.5]	[0.5; 1.5]
Small	All	[0.1; 0.2]	[-0.1; -0.1]	[0.2; 0.5]
All	Large	[0.2; 0.2]	[0; 0.1]	[0.3; 0.7]
All	Small	[0.1; 0.1]	[-0.1; 0]	[0.5; 0.6]

Notes: All percentages are rounded to one decimal, but due to formatting e.g. ”-3.0” is shown as ”-3”. These numbers reflect averages of a large number of simulations. If an individual simulation shows that the number of exporters does not change, the change in mean export profits is set to zero.

Table 11: Impact of doubling TC outreach via information alone; broad vs targeted policy (%)

Firms	Number of exporters (%)	Mean export profits (DKK)	Aggregate exports (%)
Panel A: No spillovers			
Random	[-1.4; 0.7]	[2700; 5500]	[0; 0.1]
Actual	[-2.2; -0.1]	[2600; 6400]	[0; 0.2]
Largest	[-8.6; -4.8]	[2000; 19400]	[-0.6; 0.2]
Most connected	[-5.7; -3.2]	[8600; 15000]	[-0.1; 0.3]
Panel B: Partial spillovers			
Random	[-3.3; -0.9]	[4200; 5400]	[0.1; 0.2]
Actual	[-4.2; -1.9]	[4700; 5800]	[-0.1; 0.2]
Largest	[-11.1; -8.5]	[7500; 14200]	[-2.1; -1.2]
Most connected	[-5.2; -1.9]	[4500; 4900]	[-0.3; 1]
Panel C: Full spillovers			
Random	[-6.5; -2.6]	[8100; 9800]	[0.1; 0.3]
Actual	[-7.1; -3.1]	[10600; 12700]	[0; 0.6]
Largest	[-11; -8.8]	[13300; 18700]	[-1.4; -0.2]
Most connected	[-6.7; -1.8]	[9900; 11700]	[0.5; 2.4]

Notes: "Random": Support allocated randomly. "Actual": Support allocated according to observed size distribution, c.f. Figure 3. "Largest": Support allocated to the largest firms. "Most connected": Support allocated to the firms that provides the most employees to other sample firms. All targeted policy experiments focus exclusively on the existing set of unsupported producers. These numbers reflect averages of a large number of simulations. If an individual simulation shows that the number of exporters does not change, the change in mean export profits is set to zero. Mean export profits and aggregate exports are measured among all firms including those directly supported, indirectly supported and unsupported. Column 2 measured in thousands of DKK.

Online Appendix

Information Frictions in Export Markets

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May 2025

A Buyers and the Export Demand Shifter

This section builds a simple framework which distinguishes a firm-level component of export demand that captures "average buyer quality" from differences in the average number of buyers each firm faces. We abstract from network demand spillovers and for the sake of notational parsimony omit the location index throughout. Specifically, let market-specific demand shocks take the form: $\tilde{\xi}_{ijt} = \left(\sum_{b\in\Omega^T_{ijt}} (\mu^T_b)^{\eta-1}\right)^{\frac{1}{\eta-1}}$ where Ω^T_{ijt} is the set of buyers firm i reaches market j and year t, b indexes individual buyers, and μ^T_b is a buyer-specific demand shock. We assume that TC support may manifest in two possible manners. First, it may enlarge the set of buyers which firm i reaches, $n(\Omega^S_{ijt}) > n(\Omega^U_{ijt})$, where $n(\Omega)$ is the cardinality of set Ω. Second, it may increase the purchase size of any particular buyer, $\mu^S_b > \mu^U_b$.

Suppose firm i reaches n^S_{ijt} buyers in market j with TC support and n^U_{ijt} buyers without TC support, $n^S_{ijt} \geq n^U_{ijt}$. Likewise, assume that for any buyer b the amount purchased if firm i has TC support, μ^S_{bjt} is no smaller than what it would have purchased without TC support, μ^U_{bjt}, $\mu^S_{bjt} \geq \mu^U_{bjt}$. We write firm i's demand shifter $\tilde{\xi}^T_{ijt}$ as

$$\xi^T_{ijt} = \left(\sum_{b\in\Omega^T_{ijt}} (\mu^T_{bjt})^{\eta-1}\right)^{\frac{1}{\eta-1}}$$

Regardless of whether the firm uses TC support, we focus on a symmetric equilibrium where all buyers purchase the same amount so that $\mu^0_{bjt} = \bar{\mu}^U_{jt}\ \forall\ b \in \Omega^U_{ijt}$, $\mu^S_{bjt} = \bar{\mu}^S_{jt}\ \forall\ b \in \Omega^S_{ijt}$ and

$\mu^S_{bjt} \geq \mu^U_{bjt}$. We can then write $\tilde{\xi}^S_{ijt}$ as

$$\begin{aligned}
\xi^S_{ijt} &= \bar{\mu}^S_{jt}(n^S_{ijt})^{\frac{1}{\eta-1}} \\
&= (\bar{\mu}^U_{jt} + \Delta\bar{\mu}_{jt})[(n^U_{ijt})^{\frac{1}{\eta-1}} + \Delta(n^{\frac{1}{\eta-1}}_{ijt})] \\
&= \underbrace{\bar{\mu}^U_{jt}(n^U_{ijt})^{\frac{1}{\eta-1}}}_{\xi^U_{ijt}=\tilde{\xi}^U_{ijt}} + \underbrace{\bar{\mu}^U_{jt}\Delta(n^{\frac{1}{\eta-1}}_{ijt}) + \Delta\bar{\mu}_{jt}(n^U_{ijt})^{\frac{1}{\eta-1}} + \Delta\bar{\mu}_{jt}\Delta(n^{\frac{1}{\eta-1}}_{ijt})}_{\xi^S_{ijt}} \qquad \text{(A1)}
\end{aligned}$$

where $n^T_{ijt} = n(\Omega^T_{ijt})$ and $\Delta x = x^S - x^U$ for any variable x. The first term in equation (A1) is the demand shifter that would apply to firm i in the absence of TC support, ξ^U_{ijt}. The demand shock ξ^U_{ijt} in turn has two components, the number of buyers among unsupported firms in destination j, $(n^U_{ijt})^{\frac{1}{\eta-1}}$, and average buyer quality among supported firms in destination j, $\bar{\mu}^U_{ijt}$, measured as average sales per buyer. These two subcomponents are features of our empirical work

It is also possible to theoretically decompose the TC demand premium, ξ^S_{ijt} into similar subcomponents. The second term in equation (A1) decomposes the TC demand premium into a component that increases demand through a greater number of buyers, $\bar{\mu}^S_{jt}\Delta(n^{\frac{1}{\eta-1}}_{ijt})$, a component that increases demand through larger orders per buyer, $\Delta\bar{\mu}_{jt}(n^U_{ijt})^{\frac{1}{\eta-1}}$, and an interaction term representing the joint gains from having a greater number of high quality buyers, $\Delta\bar{\mu}_{jt}\Delta(n^{\frac{1}{\eta-1}}_{ijt})$.

A.1 From demand to revenues

To map the disaggregated demand shifters to firm revenues, we reformulate equation (3) as

$$\begin{aligned}
r_{ijt} &= \alpha^U_{ijt}(1-s_{ijt})r_{iht} + (\alpha^U_{ijt} + \alpha^S_{ijt})s_{ijt}r_{iht} \\
&= \left(\frac{\xi_{iht}\tau_{ijt}P_{ht}}{\bar{\mu}^U\tau_{iht}P_{jt}}\right)^{1-\eta}\frac{Y_{jt}}{Y_{ht}}n_{ijt}(1-s_{ijt})r_{iht} + \left(\frac{\xi_{iht}\tau_{ijt}P_{ht}}{\bar{\mu}^S\tau_{iht}P_{jt}}\right)^{1-\eta}\frac{Y_{jt}}{Y_{ht}}n_{ijt}s_{ijt}r_{iht}.
\end{aligned}$$

Focusing on a symmetric equilibrium where firm i's buyers all purchase the same amount, $\mu^T_b = \bar{\mu}^T_{ijt} \; \forall \; b \in \Omega^T_{ijt}$, γ^U_{jt} measures the per buyer revenue (buyer quality) among unsupported firms and we can decompose the TC revenue premium, α^S_{ij}, into a component capturing a per buyer TC premium, $\alpha_{ij}^{S,\mu}$ and number of buyers premium, $\alpha_{ij}^{S,n}$

$$\alpha_{ijt}^{S} = \alpha_{ijt}^{S,\mu} + \alpha_{ijt}^{S,n} + \alpha_{ijt}^{S,j} \tag{A2}$$

where $\alpha_{ijt}^{S,\mu} \equiv \alpha_{ijt}^{U}\left[\left(\frac{\bar{\mu}_{ijt}^{S}}{\bar{\mu}_{ijt}^{U}}\right)^{\eta-1} - 1\right]$, $\alpha_{ijt}^{S,n} \equiv \alpha_{ijt}^{U}\left[\frac{n(\Omega_{ijt}^{S})}{n(\Omega_{ijt}^{U})} - 1\right]$, $\alpha_{ijt}^{S,j} \equiv \alpha_{ijt}^{U}\left[\left(\frac{\bar{\mu}_{ijt}^{S}}{\bar{\mu}_{ijt}^{U}}\right)^{\eta-1} - 1\right]\left[\frac{n(\Omega_{ijt}^{S})}{n(\Omega_{ijt}^{U})} - 1\right]$.

We distinguish a common market-year components from those that vary across firms so that we can express revenue function (3) as

$$r_{ijt} = [\alpha_{jt}^{U} + (\alpha_{jt}^{S,\mu} + \alpha_{jt}^{S,n} + \alpha_{jt}^{S,\mu n})s_{ijt}]r_{iht} + e_{ijt} \tag{A3}$$

where $\mathbb{E}[\alpha_{ijt}^{S,\mu}] = \alpha_{jt}^{S,\mu}$, $\mathbb{E}[\alpha_{ijt}^{S,n}] = \alpha_{jt}^{S,n}$ and $\mathbb{E}[\alpha_{ijt}^{S,\mu n}] = \alpha_{jt}^{S,\mu n}$. As such, potential exporters may have information about any subcomponent of α_{jt}^{S}, none, or all of them. Each of these are relevant to understanding the nature of informational frictions and what role the TC plays in alleviating them.

Dividing through by n_{ijt} and collecting like terms yields

$$\begin{aligned}
\frac{r_{ijt}}{n_{ijt}} &= \left(\frac{\xi_{iht}\tau_{ijt}P_{ht}}{\bar{\mu}^{U}\tau_{iht}P_{jt}}\right)^{1-\eta}\frac{Y_{jt}}{Y_{ht}}\left[(1-s_{ijt})r_{iht} + \left(\frac{\bar{\mu}^{S}}{\bar{\mu}^{U}}\right)^{\eta-1} s_{ijt}r_{iht}\right] \\
&= \left(\frac{\xi_{ht}\tau_{jt}P_{ht}}{\bar{\mu}^{U}\tau_{ht}P_{jt}}\right)^{1-\eta}\frac{Y_{jt}}{Y_{ht}}r_{iht}\left[1 + \left[\left(\frac{\bar{\mu}^{S}}{\bar{\mu}^{U}}\right)^{\eta-1} - 1\right]s_{ijt}\right] + e_{ijt}^{n} \\
&= (\gamma_{jt}^{U} + \gamma_{j}^{S}s_{ijt})r_{iht} + e_{ijt}^{n}
\end{aligned} \tag{A4}$$

where the second equality separates unexpected, relative firm-, market-, and year specific per buyer revenue shocks, e_{ijt}^{n}, from the common per buyer demand shifter and the third equality applies the assumption that TC premia are time invariant.

The estimated demand coefficients capture relative buyer quality, $\frac{\gamma_j^S}{\gamma_{jt}^U} = \left(\frac{\bar{\mu}_j^S}{\bar{\mu}_{jt}^U}\right)^{\eta-1} - 1$, and allow us to compute the TC quality premium $\alpha_{jt}^{S,\mu}$, the TC buyers premium $\alpha_{jt}^{S,n}$, and the TC interaction premium $\alpha_{jt}^{S,\mu n}$. Appealing to data on the number of buyers for each exporter in each destination market, we estimate the disaggregated demand components in a simple two-step procedure. First, we recover estimates γ_{jt}^{U} and γ_{j}^{S} from the OLS regression of equation (A4), conditional on $r_{ijt} > 0$). Second, using the estimates of γ_{jt}^{U} and γ_{jt}^{S} along with our previous estimates of α^U_{jt} and α^S_{jt}, we compute $\alpha^{S,\mu}_{jt} = \alpha^U_{jt}\frac{\gamma^S_j}{\gamma^U_{jt}}$, $\alpha^{S,n}_{jt} = \frac{\alpha^S_j - \alpha^{S,\mu}_{jt}}{1+\gamma^S_j/\gamma^U_{jt}}$ and $\alpha^{S,\mu n}_{jt} = \frac{\gamma^S_j}{\gamma^U_{jt}}\frac{\alpha^S_j - \alpha^{S,\mu}_{jt}}{1+\gamma^S_j/\gamma^U_{jt}}$.

A.2 Disaggregated information tests among supported firms

Table A9 documents additional information tests based on the model above for supported firms. In each column the null hypothesis of the test is that unsupported firms (left columns) or supported firms (right columns) know disaggregated demand components (no. of buyers, buyer quality or their interaction).

The columns reporting results for the unsupported firms replicate the findings in Table 9 of the main text. In each case we reject the null hypothesis that unsupported firms know the number of buyers in export markets or buyer quality. The columns reporting results for the supported firms display the exact opposite. Indeed, we can never reject the null hypothesis that supported firms know any individual demand component. Accordingly, we conclude that these findings further support the narrative evidence of a high degree of information among export markets among supported firms.

B Estimation Details

B.1 Perfect knowledge of exporter information sets

Consider a setting where the information set specified by the researcher, $\mathcal{J}^a_{ijt}$ is the same as that used by the firm for its export decision, $\mathbb{E}[r_{ijt}|\mathcal{J}_{ijt}] = \mathbb{E}[r_{ijt}|\mathcal{J}^a_{ijt}]$, including any benefits of export support. In this case, the researcher can estimate the parameter vector θ^* as the value of the unknown parameter vector θ by maximizing the the log-likelihood function[34]

$$\begin{aligned}\mathcal{L}(\theta|D, s, \mathcal{J}^a, dist) \quad = \quad & \sum_{i,j,t} D_{ijt}\ln(\mathcal{P}(D_{jt}=1|\mathcal{J}^a_{ijt}, s_{ijt}, dist_j;\theta)) \\ & +(1-D_{ijt})\ln(\mathcal{P}(D_{jt}=0|\mathcal{J}^a_{ijt}, s_{ijt}, dist_j;\theta)),\end{aligned}$$

[34]For parsimony, there is a slight abuse of notation in equation A5 where we allow θ^T to stand in for θ^S or θ^U for supported and unsupported firms, respectively.

where

$$\mathcal{P}(D_{jt}=1|\mathcal{J}^a_{ijt}, s_{ijt}, dist_j;\theta) = \Phi(\theta_2^{-1}(\eta^{-1}\mathbb{E}[r^o_{ijt}|\mathcal{J}^a_{ijt}] - \theta_0^T - \theta_1^T dist_j)). \tag{A5}$$

The assumption that $\mathbb{E}[r_{ijt}|\mathcal{J}_{ijt}] = \mathbb{E}[r_{ijt}|\mathcal{J}^a_{ijt}]$ implies that measurement error from the estimated model is the same as the firm's true expectational error. Rational expectations further imply the expectation of the firm's true expectational error is zero as is its covariance with expected revenues. In the context of probit model (A5), wrongly assuming perfect foresight will induce bias in the fixed cost parameters.[35]

B.2 Moment Inequality Estimation

This section describes both the odds-based and revealed preference moment inequalities used to identify model parameters.

[35] Technically, this result depends on two conditions. First, it depends the fixed value of η. Second, it depends on functional form of the distribution of unobserved expectations and the expectational error. Yatchew and Griliches, 1985 document that if true expectations and expectational errors are normally distributed, $\mathbb{E}[r^o_{ijt}|\mathcal{J}_{ijt}] \sim \mathbb{N}(0,\sigma_e^2)$ and $\varepsilon_{ijt}|(\mathcal{J}_{ijt}, \nu^T_{ijt}) \sim \mathbb{N}(0,\sigma_\varepsilon^2)$, then β_0^T, β_1^T and σ_T will be upwards biased. Dickstein and Morales, 2018 demonstrate that this result holds more broadly across different distributions for $\mathbb{E}[r^o_{ijt}|\mathcal{J}_{ijt}]$ and ε_{ijt}. We document below that result holds for unsupported firms. For supported firms it holds in absolute magnitude but not necessarily direction.

B.2.1 Odds-based moment inequalities

For any covariate in the firm's information set $Z \subseteq \mathcal{J}_{ijt}$ Dickstein and Morales, 2018 define the conditional *odds-based* moment inequalities as[36]

$$\mathcal{M}_{ob}^{T}(Z_{ijt};\theta^T) = \mathbb{E}\left[\begin{array}{c} m_{ob}^{l,T}(D_{ijt}, r_{ijt}^{o}, dist_j, s_{ijt}); \theta^T \\ m_{ob}^{u,T}(D_{ijt}, r_{ijt}^{o}, dist_j, s_{ijt}); \theta^T \end{array} \Big| Z_{ijt}\right] \geq 0, \tag{A6}$$

where

$$\begin{aligned} m_{ob}^{l,T}(\cdot) &= D_{ijt}\frac{1-\Phi((\theta_2^T)^{-1}(\eta^{-1}r_{ijt}^{o} - \theta_0^T - \theta_1^T dist_j))}{\Phi((\theta_2^T)^{-1}(\eta^{-1}r_{ijt}^{o} - \theta_0^T - \theta_1^T dist_j))} - (1-D_{ijt}) &\quad (A7)\\ m_{ob}^{u,T}(\cdot) &= (1-D_{ijt})\frac{\Phi((\theta_2^T)^{-1}(\eta^{-1}r_{ijt}^{o} - \theta_0^T - \theta_1^T dist_j))}{1-\Phi((\theta_2^T)^{-1}(\eta^{-1}r_{ijt}^{o} - \theta_0^T - \theta_1^T dist_j))} - D_{ijt}. &\quad (A8)\end{aligned}$$

In a full information setting conditions (A7) and (A8) are, in expectation, individually equal to zero at the true parameter vector θ^T. In our case, however, conditions (A7) and (A8) depend on the unknown, true information set $\mathcal{J}_{ijt}$. Dickstein and Morales, 2018 show that one can apply Jensen's inequality so that for any observed Z_{ijt} condition (A8) becomes an inequality if we introduce the observed approximation r_{ijt}^{o} in place of the unobserved expectation $\mathbb{E}[r_{ijt}^{o}|\mathcal{J}_{ijt}]$ due to the convexity of $\frac{\Phi(\cdot)}{1-\Phi(\cdot)}$. Thus, inequality (A8) will hold at $\theta = \theta^*$. Similar logic applies to condition (A7).[37]

[36]For parsimony, conditions (A7)-(A8) slighly abuse notation and only distinguish supported and unsupported firms through the parameter vector θ^T rather than directly building in support status s_{ijt} due to the symmetry of the firm's export decision.

[37]Intuitively, by revealed preference equation (**??**) implies that expected export profits are positive. Although necessary and sufficient, the condition $\mathbb{1}\{\eta^{-1}\mathbb{E}[r_{ijt}^{o}|\mathcal{J}_{ijt}] - \beta_0^T - \beta_1^T dist_j - \nu_{ijt}^T\} - D_{ijt} = 0$ cannot be used for identification since it depends on the unobserved terms $\mathcal{J}_{ijt}$ and ν_{ijt}^T. Taking expectations allows the researcher to address ν_{ijt}^T, but the condition continues to depend on $\mathcal{J}_{ijt}$. Rearranging terms yields $\mathbb{E}\left[(1-D_{ijt})\frac{\Phi(\sigma^{-1}(\eta^{-1}\mathbb{E}[r_{ijt}^{o}\mathcal{J}_{ijt}] - \beta_0^T - \beta_1^T dist_j))}{1-\Phi(\sigma_T^{-1}(\eta^{-1}\mathbb{E}[r_{ijt}^{o}\mathcal{J}_{ijt}] - \beta_0^T - \beta_1^T dist_j))} - D_{ijt}\Big|\mathcal{J}_{ijt}, dist_j\right] = 0$, which again holds with equality at the true parameter vector. However, employing the observed proxy r_{ijt}^{o} in place of

B.2.2 Revealed Preference Moment Inequalities

For any covariate in the firm's information set $Z \subseteq \mathcal{J}_{ijt}$ define the conditional *revealed preference* moment inequalities as

$$\mathcal{M}_{rp}^{T}(Z_{ijt};\theta^{T}) = \mathbb{E}\left[\begin{array}{c} m_{l}^{r}(D_{ijt}, r_{ijt}^{o}, dist_{j}, s_{ijt}); \theta^{T} \\ m_{rp}^{u,d}(D_{ijt}, r_{ijt}^{o}, dist_{j}, s_{ijt}); \theta^{T} \end{array} \Bigg| Z_{ijt}\right] \geq 0, \tag{A9}$$

where

$$\begin{aligned} m_{rp}^{l,T}(\cdot) &= -(1-D_{ijt})(\eta^{-1}r_{ijt}^{o} - \theta_0^T - \theta_1^T dist_j) + D_{ijt}\theta_2^T \frac{\phi((\theta_2^T)^{-1}(\eta^{-1}r_{ijt}^{o} - \theta_0^T - \theta_1^T dist_j))}{\Phi((\theta_2^T)^{-1}(\eta^{-1}r_{ijt}^{o} - \theta_0^T - \theta_1^T dist_j))} \\ m_{rp}^{u,T}(\cdot) &= D_{ijt}(\eta^{-1}r_{ijt}^{o} - \theta_0^T - \theta_1^T dist_j) + (1-D_{ijt})\theta_2^T \frac{\phi((\theta_2^T)^{-1}(\eta^{-1}r_{ijt}^{o} - \theta_0^T - \theta_1^T dist_j))}{1-\Phi((\theta_2^T)^{-1}(\eta^{-1}r_{ijt}^{o} - \theta_0^T - \theta_1^T dist_j))}. \end{aligned}$$

Consider the upper bound moment condition, $m_{rp}^{u,d}$ of (A9), for an exporter, $D_{ijt} = 1$.[38] Expectations, conditional on $(D_{ijt}, \mathcal{J}_{ijt}, dist_j, s_{ijt})$, yields

$$D_{ijt}(\eta^{-1}\mathbb{E}[r_{ijt}|\mathcal{J}_{ijt}] - \beta_0^T - \beta_1^T dist_j) + S_{ijt} \geq 0 \tag{A10}$$

where $\mathbb{E}[r_{ijt}|\mathcal{J}_{ijt}] = \mathbb{E}[r_{ijt}^{o}|\mathcal{J}_{ijt}]$. The term $S_{ijt} = \mathbb{E}[-D_{ijt}\nu_{ijt}^{T}|D_{ijt}, \mathcal{J}_{ijt}, dist_j, s_{ijt}]$ is a selection correction which accounts for the unobserved determinants of exporting, ν_{ijt}^{T}. Replacing unobserved expectations $\mathbb{E}[r_{ijt}^{o}|\mathcal{J}_{ijt}]$ with the observed covariate r_{ijt}^{o} and taking expectations with respect to the observed vector Z_{ijt}, inequality (A10) becomes weaker as long as $\frac{\phi(\cdot)}{\Phi(\cdot)}$ is convex. Under this assumption, if (A10) holds at $\theta = \theta^{*}$, then (A9) and (A10) will also hold at $\theta = \theta^{*}$.[39]

$\mathbb{E}[r_{ijt}^{o}\mathcal{J}_{ijt}]$ and applying Jensen's inequality, we recover equation (A8) due to the convexity of $\frac{\Phi(\cdot)}{1-\Phi(\cdot)}$.

[38] Intuitively, if $D_{ijt} = 1$ then firm i must expect to earn positive profits, $D_{ijt}(\eta^{-1}\mathbb{E}[r_{ijt}|\mathcal{J}_{ijt}] - \beta_0^T - \beta_1^T dist_j - \nu_{ijt}^{T}) \geq 0$.

[39] An analogous argument holds for the lower bound.

B.3 Identification and Estimation

We estimate fixed cost parameters by combining odds-based and revealed preference moment inequalities. In particular, we employ a set of unconditional moment inequalities defined by a positive-valued instrument function $g^T(\cdot)$:

$$\mathbb{E}\left[\left\{\begin{array}{c} m_{ob}^{l,T}(D_{ijt}, r_{ijt}, s_{ijt}, dist_j; \theta^T) \\ m_{ob}^{u,T}(D_{ijt}, r_{ijt}, s_{ijt}, dist_j; \theta^T) \\ m_{rp}^{l,T}(D_{ijt}, r_{ijt}, s_{ijt}, dist_j; \theta^T) \\ m_{rp}^{u,T}(D_{ijt}, r_{ijt}, s_{ijt}, dist_j; \theta^T) \end{array}\right\} \times g^T(Z_{ijt})\right] \geq 0.$$

The instrument functions used to estimate model parameters, $g^T(\cdot)$, are further decomposed by (i) splitting the observations into two groups depending on whether the value of the instrument is above or below the median value of the instrument *for each TC group* and (ii) weighting by distance from the median value. Denote each distinct moment by $g_a^T(\cdot)$:

$$g_a^T(Z_{ijt}) = \begin{cases} \mathbb{1}\{r_{iht-1} > med(r_{iht-1}|s_{ijt})\} \times (|r_{iht-1} - med(r_{iht-1}|s_{ijt})|)^a, \\ \mathbb{1}\{r_{iht-1} \leq med(r_{iht-1}|s_{ijt})\} \times (|r_{iht-1} - med(r_{iht-1}|s_{ijt})|)^a, \\ \mathbb{1}\{R_{jt-1} > med(R_{jt-1}|s_{ijt})\} \times (|R_{jt-1} - med(R_{jt-1}|s_{ijt})|)^a, \\ \mathbb{1}\{R_{jt-1} \leq med(R_{jt-1}|s_{ijt})\} \times (|R_{jt-1} - med(R_{jt-1}|s_{ijt})|)^a, \\ \mathbb{1}\{dist_j > med(dist_j|s_{ijt})\} \times (|dist_j - med(dist_j|s_{ijt})|)^a, \\ \mathbb{1}\{dist_j \leq med(dist_j|s_{ijt})\} \times (|dist_j - med(dist_j|s_{ijt})|)^a, \end{cases}$$

for $a = \{0, 1\}$. With six instruments, four moment inequalities, and two values of a, there are 48 total moments used in the estimate the 95% confidence set for the support specific parameter vector, $\Theta_{95\%}^T$.

C Fixed Costs

This appendix explores differences in fixed cost estimates across estimation methodologies and support status. Because our primary interest is in the identification of network spillovers we focus on the moment inequality estimates in the main text. However, consistent with Dickstein and Morales, 2018 we find that estimated entry costs vary substantially with estimation methodology.

C.1 Fixed Export Costs and Trade Council Support

Table A1 reports estimates of the fixed cost parameters (β_0^U, β_1^U, σ_U, β_0^S, β_1^S, σ_S) for the full information, minimal information and partial information estimation settings. The first three columns of the top panel report results for unsupported firms.

The first two rows present extreme cases, but are common benchmarks in the literature. In each of these cases, researchers assume that they have all of the components of the firm's information set. In the first case, we assume that firms have perfect foresight. This setting captures a case where firms are inherently well-informed about export markets; it would also represent an environment where information spillovers are complete and ubiquitous. In the second row, each firm is assumed to only have the minimal information set. This assumption represents a setting where unsupported firms are poorly informed and there are no information spillovers from supported to unsupported firms.

The third and fourth rows present fixed cost estimates recovered from the partial information setting. While we employ the same minimal information set for estimation, the partial identification approach does not require assuming that firms have the same information or that there are no information spillovers across firms. Our findings are broadly consistent with those reported in Dickstein and Morales, 2018: the full information setting returns the largest fixed cost parameters, while the moment inequality approach delivers much smaller fixed cost parameters; the differences remain large even when compared to the MLE estimate from a minimal information model.

The last three columns of Table A1 report fixed export cost parameters for supported firms, which are starkly different than those for their unsupported counterparts. In particular, the coefficient on distance, β_1, is *negative* in either the full or minimal informational setting estimated by MLE. This, in turn, implies that fixed export costs decline as the distance to the export destination rises among supported firms. While this could potentially indicate a TC export subsidy schedule that disproportionately rises with distance, it is again plausible that it reflects estimation bias.

To better understand the sources of estimation bias in our context we consider the likelihood function for the decision to export.[40] As in the main text, ξ^T_{ijlt} denotes the difference between the researcher's proxy for firm expected potential revenue and the firm's true expected potential export revenue, $\xi^T_{ijlt} = \mathbb{E}[r^{T,o}_{ijlt}|\mathcal{J}^a_{ijlt}] - \mathbb{E}[r^{T,o}_{ijlt}|\mathcal{J}_{ijlt}]$. Ideally $\mathbb{E}[r^{T,o}_{ijlt}|\mathcal{J}^a_{ijlt}]$ perfectly captures firm expectations and, conditional on model structure, we have discrete choice model

$$D_{ijlt} = \mathbb{1}\{\eta^{-1}\mathbb{E}[r^{T,o}_{ijlt}|\mathcal{J}^a_{ijlt}] - \beta^T_0 - \beta^T_1 dist_j - \nu^T_{ijlt} \geq 0\}, \quad \nu^T_{ijlt} \sim \mathbb{N}(0, \sigma^2_T) \tag{A11}$$

where the superscript T denotes whether the firm is supported (S) by the TC or unsupported (U), $T \in \{S, U\}$. Unbiased estimates of $(\beta^T_0, \beta^T_1, \sigma_T)$ are obtained by maximizing the likelihood function $\mathcal{L}_a(\cdot)$:

$$\begin{gathered}\mathcal{L}_a(\theta^T|D, \mathcal{J}^a, dist) = \qquad \text{(A12)}\\ \textstyle\sum_{i,j,t} \Big\{ D_{ijlt} \ln \Big(\int_\nu \mathbb{1}\{\eta^{-1}\mathbb{E}[r^{T,o}_{ijlt}|\mathcal{J}^a_{ijlt}] - \theta^T_0 - \theta^T_1 dist_j - \nu^T \geq 0\} f_{\nu^T}(\nu^T|\mathcal{J}^a_{ijlt}, dist_j; \theta^T_2) \Big) + \\ (1 - D_{ijlt}) \ln \Big(\int_\nu \mathbb{1}\{\eta^{-1}\mathbb{E}[r^{T,o}_{ijlt}|\mathcal{J}^a_{ijlt}] - \theta^T_0 - \theta^T_1 dist_j - \nu^T \leq 0\} f_{\nu^T}(\nu^T|\mathcal{J}^a_{ijlt}, dist_j; \theta^T_2) \Big) \Big\}\end{gathered}$$

where $f_{\nu^T}(\nu^T|\mathcal{J}^a_{ijlt}, dist_j; \theta^T_2)$ is the density function of ν^T_{ijlt} conditional on $(\mathcal{J}^a_{ijlt}, dist_j)$.

If $\xi^T_{ijlt} \neq 0$ the export decision conditional on $\mathbb{E}[r^{T,o}_{ijlt}|\mathcal{J}^a_{ijlt}]$ is instead

$$\begin{aligned} D_{ijlt} &= \mathbb{1}\{\eta^{-1}\mathbb{E}[r^{T,o}_{ijlt}|\mathcal{J}_{ijlt}] - \beta^T_0 - \beta^T_1 dist_j - \nu^T_{ijlt} \geq 0\}, \\ &= \mathbb{1}\{\eta^{-1}(\mathbb{E}[r^{T,o}_{ijlt}|\mathcal{J}^a_{ijlt}] - \xi^T_{ijlt}) - \beta^T_0 - \beta^T_1 dist_j - \nu^T_{ijlt} \geq 0\}, \\ &= \mathbb{1}\{\eta^{-1}\mathbb{E}[r^{T,o}_{ijlt}|\mathcal{J}^a_{ijlt}] - \beta^T_0 - \beta^T_1 dist_j - (\eta^{-1}\xi^T_{ijlt} + \nu^T_{ijlt}) \geq 0\} \end{aligned} \tag{A13}$$

where the composite error $\eta^{-1}\xi^T_{ijlt} + \nu^T_{ijlt}$ accounts for both the structural error ν^T_{ijlt} and mea-

[40] This discussion closely follows Online Appendix D.1 from Dickstein and Morales, 2018.

surement error ξ^T_{ijlt}. The correct log likelihood is then

$$\mathcal{L}(\theta^T|D,\mathcal{J}^a,dist) = \tag{A14}$$
$$\sum_{i,j,t}\Big\{D_{ijlt}\ln\Big(\int_{\chi^T}\mathbb{1}\{\eta^{-1}\mathbb{E}[r^{T,o}_{ijlt}|\mathcal{J}^a_{ijlt}]-\theta^T_0-\theta^T_1 dist_j-\chi^T\geq 0\}f_{\chi^T}(\chi^T|\mathcal{J}^a_{ijlt},dist_j;\theta^T_2)\Big)+$$
$$(1-D_{ijlt})\ln\Big(\int_{\chi^T}\mathbb{1}\{\eta^{-1}\mathbb{E}[r^{T,o}_{ijlt}|\mathcal{J}^a_{ijt}]-\theta^T_0-\theta^T_1 dist_j-\chi^T\leq 0\}f_{\chi^T}(\chi^T|\mathcal{J}^a_{ijlt},dist_j;\theta^T_2)\Big)\Big\}$$

where $\chi^T_{ijlt}=\xi^T_{ijlt}+\nu^T_{ijlt}$ and $f_{\chi^T}(\cdot)$ is the conditional density of χ^T_{ijlt}. The log likelihood maximizing values of θ^T will generally differ across equations (A12) and (A14) since the conditional density functions, $f_{\nu^T}(\nu^T|\mathcal{J}^a_{ijlt},dist_j;\theta^T_2)$ and $f_{\chi^T}(\chi^T|\mathcal{J}^a_{ijlt},dist_j;\theta^T_2)$, differ.

We consider sources of bias which affect the direction and magnitude of the maximum likelihood parameter estimates relative to those obtained from moment inequality estimation. First, χ^T_{ijlt} may not be independent of $(\mathcal{J}^a_{ijlt},dist_j)$ even if ν^T_{ijlt} is independent of $(\mathcal{J}^a_{ijlt},dist_j)$. If we assume a rich information set, when the true information set is relatively sparse, it is likely that $\mathcal{J}^a_{ijlt}$ will include a covariate that is not in the true information set, $\mathcal{J}_{ijlt}$. In our setting, this potential source of bias is more likely to be present among unsupported firms in unconnected networks where we expect that firm information sets have comparatively little information.

Second, the functional form of the distribution $f_{\chi^T}(\chi^T|\mathcal{J}^a_{ijlt},dist_j;\theta^T_2)$ is unlikely to be normally distributed even when ν^T_{ijt} is normally distributed. More broadly, $f_{\chi^T}(\chi^T|\mathcal{J}^a_{ijlt},dist_j;\theta^T_2)$ is unlikely to take the same functional form as $f_{\nu^T}(\nu^T|\mathcal{J}^a_{ijlt},dist_j;\theta^T_2)$. In our setting ν^T_{ijlt} is assumed to be normal for both supported and unsupported firms. However, $\nu^T_{ijlt}+\xi^T_{ijlt}$ will only be normally distributed if ξ^T_{ijlt} is independent and also normally distributed. Not only is this assumption likely to fail, it is particularly likely to fail for supported firms since supported firms are likely to draw demand shocks from a highly skewed distribution. Assuming that the joint error is normally distributed when it is not is likely to introduce significant bias, as suggested by the parameter estimates in Tables 4-A2.

Last, the estimate of θ^T_2 that maximizes the likelihood function (A14) will generally be different from that which maximizes likelihood function (A12) as long as the variance of variance of ν^T_{ijlt} and that of ξ^T_{ijlt} are different. Indeed, even if ξ^T_{ijlt} and ν_{ijlt} are independent the variance of the structural error will converge to $\sigma^2_T+\eta^{-2}var(\xi^T_{ijlt})$ instead of φ^2_T. Less obviously, larger fixed cost shocks are likely to have a differential impact on the direction of fixed cost bias across firm-level support status. Among unsupported firms where export propensities are *low*, θ_0^U and θ_1^U must explain why seemingly profitable exporters do not export even though they are relatively likely to draw small (or negative) fixed cost shocks. Accordingly, the θ_0^U and θ_1^U are likely to be biased upwards. Among supported firms where export propensities are *high*, θ_0^S and θ_1^S must explain why seemingly unprofitable exporters choose to export even though they are likely to draw large, positive fixed cost shocks. In this case, the likelihood rationalizes these outcomes by choosing values of θ_0^S and θ_1^S that are biased downwards. Weaking the informational assumption by moment inequalities arbitrarily allows firms to have strong, existing information about near markets and poorer information regarding distant markets. That is, the estimated model does not need an unintuitive negative distance coefficient to explain the differential rates of supported firms in near and distant markets.

C.2 Dynamic Entry Costs

This appendix explores the impact of allowing fixed costs to systematically differ with export history. We adopt a fixed cost specification which distinguishes first time (or sunk) export costs incurred by first time exporters and maintenance (or fixed) export costs incurred by all firms. Specifically, potential export profits for a given unsupported firm is:

$$\pi_{ijlt}^U = \eta^{-1} r_{ijlt}^U - f_{ijt}^U - (1 - D_{ij,t-1}) F_{ijt} \tag{A15}$$

where F_{ijt} represents initial first time (sunk) entry costs,

$$F_{ijt} = \rho_0 + \rho_1 dist_j. \tag{A16}$$

We assume that only unsupported firms are subject to first time entry costs; supported firms only incur fixed (maintenance) costs due to TC support and abstract from the dynamic problem for supported firms hereafter.[41] We maintain the assumption in Dickstein and Morales, 2018

[41] Relaxing this assumption for supported firm returned estimates of sunk entry costs which were indistinguishable from zero among supported firms. Fundamentally, given high export

that firms know first time entry costs when deciding whether to export to a destination and the evolution of firm-level information sets is independent of past export decisions

$$(\mathcal{J}_{ijl,t+1}, f^T_{ij,t+1}, F_{ij,t+1})|(\mathcal{J}_{ijlt}, f^T_{ijt}, F_{ijt}, D_{ijt}) \sim (\mathcal{J}_{ijl,t+1}, f^T_{ij,t+1}, F_{ij,t+1})|(\mathcal{J}_{ijlt}, f^T_{ijt}, F_{ijt}).$$

Using $V(\cdot)$ to denote the firm'svalue function, the decision to export to destination j in year t is expressed as

$$\begin{aligned} D_{ijt} \;=\; & \mathbb{1}\left\{\eta^{-1}\mathbb{E}[\alpha^T_{jt} r_{iht}|\mathcal{J}_{ijlt}, s_{ijt}] - \beta^T_0 - \beta^T_1 dist_j - (1 - d_{ij,t-1})(1 - s_{ijt})(\rho_0 + \rho_1 dist_j) - \nu^T_{ijt}\right. \\ & +\rho\mathbb{E}[V(\mathcal{J}_{ijl,t+1}, f^T_{ij,t+1}, F_{ij,t+1}, D_{ijt})|(\mathcal{J}_{ijl,t+1}, f^T_{ijt}, F_{ijt}, D_{ijt} = 1)] \\ & \left.-\rho\mathbb{E}[V(\mathcal{J}_{ijl,t+1}, f^T_{ij,t+1}, F_{ij,t+1}, D_{ijt})|(\mathcal{J}_{ijl,t+1}, f^T_{ijt}, F_{ijt}, D_{ijt} = 0)] \geq 0\right\} \end{aligned}$$

where ρ is the discount factor.

As in the static setting, we rely on observed revenues to form an expectation of potential revenues in destination markets. To account for the difference in value functions we adopt the Euler approach in Morales et al., 2019. Using odds-based and revealed preference moment inequalities, the Morales et al., 2019 approach allows us to partially identify $\theta = (\beta^U_0, \beta^U_1, \rho_0, \rho_1, \sigma_U)$ without taking a stand on the information set of each exporter or specifying the planning horizon of the firm.

Tables A3-A4 document the estimated sunk and fixed costs for the dynamic model. We find that estimated fixed costs decline modestly relative to the static model. Estimated sunk entry costs are potentially large relative to fixed costs; the upper bound of the sunk entry cost confidence set is an order of magnitude larger than that the fixed cost confidence set for the United States and China in Table A4. That said, the lower bound of the confidence is quite small in both cases, and the midpoint implies sunk costs in line with existing estimates in the literature Das et al., 2007; Dickstein and Morales, 2018. As in Dickstein and Morales, 2018 estimated sunk costs are particularly driven by the coefficient on distance, γ_1, which is large.

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propensities and destination market persistence among supported firms, we cannot credibly estimate differential sunk and fixed cost parameters among supported firms.

Notably, the estimated sunk cost for Norway overlaps zero, suggesting that entry into this neighbouring country is particularly inexpensive. We highlight that in no case to the estimated confidence joint confidence sets ever imply negative entry costs; rather the sum of fixed and sunk costs are always estimated to bounded above zero in all cases, including Norway.

D Adding EU Export Destinations

In this section we incorporate EU export destinations to the model estimation and testing. A primary advantage of including the EU sample of export destinations is that it allows us to increase the number of supported firm-year-destination level observations. However, additional complications arise which prevent us from simply adding more destination countries to the benchmark sample.

The first complication is that threshold size for an export flow recorded by the customs authorities differs within and outside of the EU. Specifically, the minimum threshold among EU destinations is significantly greater than that outside of the EU. This will systematically alter measured demand shifters (see equation (2) and, accordingly, estimated fixed costs.

Second, there is inherently much greater economic and trade integration among EU countries. We expect that cost parameters will potentially differ systematically across EU and non-EU export destinations.

To incorporate EU destinations we first estimate EU demand shifters according to equation (2) under the caveat that an EU demand shifter is subject to a separate reporting threshold. We proceed to estimate EU specific fixed export costs. To understand the differences between the EU fixed cost specification and the benchmark fixed cost specification recall that equation (1) specifies fixed export costs as

$$f_{ijt} = (1 - s_{ijt})(\beta_0^U + \beta_1^U dist_j + \nu_{ijt}^U) + s_{ijt}(\beta_0^S + \beta_1^S dist_j + \nu_{ijt}^S) \tag{A17}$$

where $\nu_{ijlt}^T|(\mathcal{J}_{ijt}, dist_j, s_{ijt}) \sim \mathcal{N}(0, \sigma^2)$ and the estimating equation (5) is represented by the probit model[42]

$$\mathcal{P}(D_{ijt}=1|\mathcal{J}_{ijt},dist_j,s_{ijt};\theta) \;=\; \Phi\left(\frac{1}{\theta_2^T}\left(\frac{1}{\eta}\mathbb{E}[\alpha_{jt}^T r_{iht}|\mathcal{J}_{ijt}^a]-\theta_0^T-\theta_1^T dist_j\right)\right). \quad \text{(A18)}$$

The implied relationships between estimated and model parameters are then $\sigma=\frac{1}{\eta}\frac{1}{\theta_2}$, $\beta_0=-\frac{1}{\eta}\frac{\theta_0}{\theta_2}$, and $\beta_1=-\frac{1}{\eta}\frac{\theta_1}{\theta_2}$. Fixed costs for non-EU countries have the same form as before and re-estimated with the EU-augmented sample. Fixed costs for exporting to EU countries are specified as

$$f_{ijt}^{EU}=(1-s_{ijt})(\beta_0^{EU,U}+\nu_{ijt}^{EU,U})+s_{ijt}(\beta_0^{EU,S}+\nu_{ijt}^{EU,S}) \quad \text{(A19)}$$

where $\nu_{ijlt}^{EU,T}|(\mathcal{J}_{ijt},dist_j,s_{ijt})\sim\mathcal{N}(0,\sigma^2)$. We likewise augment the estimating equation for EU destinations in the following way:

$$\begin{aligned}\mathcal{P}(D_{ijt}=1|\mathcal{J}_{ijt},dist_j,s_{ijt};\theta) \;=\; & \Phi\Bigg(\left(\frac{1}{\theta_2+\theta_3\mathbf{1}\{j\in EU\}}\right) \quad \text{(A20)}\\ & \times\left(\frac{1}{\eta}\mathbb{E}[\alpha_{jt}^T r_{iht}|\mathcal{J}_{ijt}^a]-\theta_0-\theta_1 dist_j\mathbf{1}\{j\notin EU\}\right)\Bigg)\end{aligned}$$

so that the relationship between EU specific parameters is

$$\sigma_{EU}=\frac{1}{\eta}\frac{1}{\theta_2+\theta_3}\;,\;\beta_0^{EU}=-\frac{1}{\eta}\frac{\theta_0}{\theta_2+\theta_3}.$$

A number specification choices merit comment. First, we allow the variance of fixed cost shocks to differ between non-EU and EU. Separate variance parameters needed to capture differences in entry and exit rates over differential EU and non-EU reporting thresholds. Second, fixed costs to EU destinations are assumed to be independent from distance. We estimated a number of models including a distance term within the EU, but the estimated confidence set was always overlapped zero and estimated to be very wide. This result is intuitive: distance is plausibly a less important determinant of trade flows within highly-integrated EU destinations. Third, $\beta_0^{EU,T}$ differs from β_0^T only because they are scaled by different variance terms.

[42] As in section B, the notation $\mathcal{J}_{ijlt}^a$ specifies that the information set specified by the researcher is the same as that used by the firm for its export decision.

An advantage of this specification is that it reduces the number of new parameters to the EU-inclusive, maximizing the power of the information tests. Fundamentally, we recall that the primary purpose of this exercise is to increase the size of the supported sample, allowing for greater power in the information tests among supported firms.

Table A5 reports the moment inequality fixed cost parameter estimates, while Table A6 documents the implied differences in estimated fixed export costs relative to the benchmark sample. Relative to benchmark estimates there is a modest increase in the upper and lower bounds of the confidence sets for the parameters σ_U, σ_S, β_O^U, and β_0^S, though in all but β_0^U the EU-inclusive confidence sets largely overlap the benchmark confidence sets. There is a commiserate decline in the upper and lower bounds of the confidence sets of β_1^U and β_1^S, though there is again substantial overlap in the latter case. These differences in the parameter estimates are not surprising. Parameter θ_2 enters both equations (A18) and (A20), a larger estimate of which helps explain within-EU variation in exporting over a different reporting threshold. Drawing structural fixed cost shocks from a distribution with a larger variance in turn affects the relative role β_0^T and β_1^T for explaining entry behaviour across export destinations.

Comparing σ_T and $\sigma_{EU,T}$ we observe that the distribution of fixed costs shocks among EU destinations is larger than that among non-EU destinations, reflecting the difference in reporting thresholds. Likewise, the upper bound of the EU-specific fixed cost intercept, $\beta_O^{EU,T}$ is larger than than of non-EU destinations, β_O^T. While this may appear counterintuitive, we recall that the distance costs for EU destinations are fixed to zero. Overall, Table A6 returns estimates of fixed cost confidence sets that overlap our benchmark confidence sets in all but one case. The sole exception is among the fixed export costs for Norway among unsupported firms where they are modestly larger than the benchmark. In that case, the lower bound is estimated to rise by roughly 224,000 DKK (33,000 USD) while the upper bound increases by 290,000 DKK (43,500 USD). These magnitude are small relative to the average export sales to Norway where the typical exporter accrues revenues of 2,020,000 DKK (303,000 USD) annually.

Using the EU-augmented model, we proceed to perform benchmark information tests on both unsupported and supported samples. Table A7 reports analogous results to those in main text for both samples. For both unsupported firms and supported firms we cannot reject the separate hypotheses that they individually do not know the minimal information set. Again, for both unsupported firms and supported firms we clearly reject the separate hypotheses that they individually have perfect foresight of export market conditions. Last, while we reject the hypothesis that unsupported firms know the minimal information set and the country shifter, we cannot reject the same hypothesis among supported firms. This evidence lends further support to common narrative that supportive firms know demand conditions in export destination markets.

E Information (Specification) Tests

We employ the "Test RC" model specification test from Bugni et al., 2015 to evaluate whether firms have knowledge of demand conditions when deciding to enter export markets. We follow the implementation in Dickstein and Morales, 2018 closely; all modifications are minor in nature and this appendix is provided to give the interested reader a sense of the implementation of the specification based information tests in this setting.[43] Below we focus on tests for unsupported firms; the testing procedure for supported firms are analogous.

E.1 Computation Details

Denote the moment inequalities used for identification $\bar{\mathcal{M}}^U(X_{ijt}, Z_{ijt}, \theta^U; \hat{\alpha}^U)$ where $\hat{\alpha}^U \equiv \{\hat{\alpha}^U_{jt}; \forall j, t\}$ and $X_{ijlt} = (D_{ijt}, dist_j, r^o_{ijlt})$. The identified set Θ_0 includes all values of θ^U consistent with $\bar{\mathcal{M}}^U(X_{ijt}, Z_{ijt}, \theta^U; \hat{\alpha}^U) \geq 0$. The model defined by moment inequalities $\bar{\mathcal{M}}^U(X_{ijt}, Z_{ijt}, \theta^U; \hat{\alpha}^U) \geq$

[43] Further details for the model specification tests we employ can be found in Bugni et al., 2015 and Appendix A.8 of Dickstein and Morales, 2018. This class of tests builds on earlier specification tests proposed in Andrews and Soares, 2010, which argues that earlier specification tests are relatively conservative. Bugni et al., 2015 propose two tests, Test RC and Test RS, with greater power than those described in Andrews and Soares, 2010. As in Dickstein and Morales, 2018 we choose to use test RC to minimize the computational burden associated with conducting many specification tests.

0 is correctly specified when Θ_0 is non-empty:

$$H_0 : \Theta_0 \neq \emptyset \quad \text{vs} \quad H_1 : \Theta_0 = \emptyset.$$

The null hypothesis in our specification test is that the model is correct: demand conditions are part of the information set used by firms when making export decisions. In other words, Θ_0 is a non-empty set.

To operationalize this test we first define a grid Θ_g^U containing the confidence set as a three-dimensional orthotope, one dimension for each parameter in θ^U, and define the limits of Θ_g^U following the non-linear optimization procedure in Dickstein and Morales, 2018. We then chose point $\theta_p^U \in \Theta_g^U$ to test the null hypothesis, $H_0 : \theta^{U*} = \theta_p^U$ vs $H_1 : \theta^{U*} \neq \theta_p^U$, and evaluate the Modified Method of Moments (MMM) test statistic at point θ_p^U:

$$Q(X_{ijt}, Z_{ijt}, \theta_p^U; \hat{\alpha}^U) = \sum_{k=1}^{K} \left(\min \left\{ \frac{\bar{\mathcal{M}}_k^U(X_{ijt}, Z_{ijt}, \theta_p^U; \hat{\alpha}^U)}{\hat{\sigma}_k(X_{ijt} Z_{ijt}, \theta_p^U; \hat{\alpha}^U)}, 0 \right\} \right)^2,$$

where θ^{U*} is the true parameter vector, k indexes individual (both odds-based and revealed preference) moment inequalities $\bar{\mathcal{M}}_k^U(X_{ijt}, Z_{ijt}, \theta_p^U; \hat{\alpha}^U) = n^{-1} \sum_i \sum_j \sum_t \mathcal{M}_k^U(X_{ijt}, Z_{ijt}, \theta_p^U; \hat{\alpha}^U)$, n is the number of distinct ijt triplets in our sample, and

$$\hat{\sigma}_k(X_{ijt}, Z_{ijt}, \theta_p^U; \hat{\alpha}^U) = \sqrt{n^{-1} \sum_i \sum_j \sum_t (\mathcal{M}_k^U(X_{ijt}, Z_{ijt}, \theta_p^U; \hat{\alpha}^U) - \bar{\mathcal{M}}_k^U(X_{ijt}, Z_{ijt}, \theta_p^U; \hat{\alpha}^U))^2}.$$

We next need to simulate the asymptotic distribution of the test statistic $Q(X_{ijt}, Z_{ijt}, \theta_p^U; \hat{\alpha}^U)$. To do so, we first compute the correlation matrix of moments, $\Omega(\theta_p)$, for each θ_p,

$$\hat{\Omega}(\theta_p) = Diag^{-1/2}(\hat{\Sigma}(\theta_p))\hat{\Sigma}(\theta_p)Diag^{-1/2}(\hat{\Sigma}(\theta_p)),$$

conditional on the first stage estimates of demand conditions, $\hat{\alpha}^U$. The matrix $Diag(\hat{\Sigma}(\theta_p))$ is a $K \times K$ diagonal matrix where the diagonal elements are those of $\hat{\Sigma}(\theta_p)$ such that

$$Diag^{-1/2}(\hat{\Sigma}(\theta_p))Diag^{-1/2}(\hat{\Sigma}(\theta_p)) = Diag^{-1}(\hat{\Sigma}(\theta_p))$$

and

$$\hat{\Sigma}(\theta_p) = n^{-1}\sum_i\sum_j\sum_t(\mathbf{M}^U(X_{ijt}, Z_{ijt}, \theta_p; \hat{\alpha}^U) - \bar{\mathbf{M}}^U(X_{ijt}, Z_{ijt}, \theta_p; \hat{\alpha}^U))$$
$$\times(\mathbf{M}^U(X_{ijt}, Z_{ijt}, \theta_p; \hat{\alpha}^U) - \bar{\mathbf{M}}^U(X_{ijt}, Z_{ijt}, \theta_p; \hat{\alpha}^U))'$$

where $\mathbf{M}^U(\cdot)$ denotes the vector $\mathbf{M}^U(X_{ijt}, Z_{ijt}, \theta_p; \hat{\alpha}^U) = (\mathcal{M}_1^U(X_{ijt}, Z_{ijt}, \theta_p; \hat{\alpha}^U), ..., \mathcal{M}_K^U(X_{ijt}, Z_{ijt}, \theta_p; \hat{\alpha}^U))$, $k = 1, ..., K$. We then simulate the asymptotic distribution of $Q(X_{ijt}, Z_{ijt}, \theta_p^U; \hat{\alpha}^U)$ by randomly drawing the vector ζ_r of size K from the multivariate normal distribution $\mathbb{N}(0_K, I_K)$ where 0_K is a zero vector of size K and I_K is a $K \times K$ identity matrix. For each draw $r = 1, ..., R$ we compute the criterion function $Q_r^A(X_{ijt}Z_{ijt}, \theta_p^U; \hat{\alpha}^U)$

$$Q_r^A(X_{ijt}, Z_{ijt}, \theta_p^U; \hat{\alpha}^U) = \sum_k \left\{(\min\{[\hat{\Omega}^{1/2}(\theta_p^U)\zeta_r]_k, 0\})^2 \times \mathbb{1}\{\sqrt{n}\frac{\bar{\mathcal{M}}_k^U(X_{ijt}, Z_{ijt}, \theta^U; \hat{\alpha}^U)}{\hat{\sigma}_k(X_{ijt}, Z_{ijt}, \theta^U; \hat{\alpha}^U)} \leq \sqrt{\ln n}\}\right\}$$

where $[\hat{\Omega}_n^{1/2}(\theta_p^U)\zeta_r]_k$ is the k^{th} element of the vector $\hat{\Omega}_n^{1/2}(\theta_p^U)\zeta_r$. With simulated criterion values $Q_1^A(X_{ijt}, Z_{ijt}, \theta_p^U; \hat{\alpha}^U), ..., Q_R^A(X_{ijt}, Z_{ijt}, \theta_p^U; \hat{\alpha}^U)$ in hand, we compute the critical value $\hat{c}^A(Z_{ijt}, \theta_p^U, 1-\delta; \hat{\alpha}^U)$ from the $(1-\delta)$-quantile of the $Q_r^A(X_{ijt}, Z_{ijt}, \theta_p^U; \hat{\alpha}^U)$ distribution. Collecting all of critical values $\hat{c}^A(X_{ijt}, Z_{ijt}, \theta_p^U, 1-\delta; \hat{\alpha}^U)$ across grid points $\theta_p^U \in \Theta_g^U$ we compute the minimum critical value $\hat{c}^{RC}(X_{ijt}, Z_{ijt}, 1-\delta; \hat{\alpha}^U) = \inf_{\theta_p^U \in \Theta_g^U} \hat{c}^A(X_{ijt}, Z_{ijt}, \theta_p^U, 1-\delta; \hat{\alpha}^U)$.

We next compute a test statistic, $T(\hat{\alpha})$, to compare to $\hat{c}^{RC}(X_{ijt}, Z_{ijt}, 1-\delta; \hat{\alpha}^U)$. The criterion function based test statistic is computed as the infimum across all $\theta_p^U \in \Theta_g^U$,

$$T(\hat{\alpha}) = \inf_{\theta_p^U \in \Theta_p^U} Q(X_{ijt}, Z_{ijt}, \theta_p^U; \hat{\alpha}^U),$$

based on the confidence set for the true parameter vector θ^U. We reject the null hypothesis, H_0, if $T(\hat{\alpha}) > \hat{c}^{RC}(X_{ijt}, Z_{ijt}, 1-\delta; \hat{\alpha}^U)$.

Adjustment for testing multiple hypotheses follows Holm, 1979. Ranking hypotheses $s = 1, ..., S$ in increasing order of their individual p-values, p_s, adjusted p-values, $\tilde{p}_s$ are computed as $\tilde{p}_s = \max_{j \leq s}\{\min\{(S-j+1)p_j, 1\}\}$.

E.2 Identifying Information Spillovers

Recall that the moment inequalities used to identify whether unsupported firms know export demand conditions are denoted $\bar{\mathcal{M}}^U(X_{ijt}, Z_{ijt}, \theta^U; \hat{\alpha}^U)$ where $\hat{\alpha}^U \equiv \{\hat{\alpha}^U_{jt}; \forall j, t\}$. The identified set Θ_0 includes all values of θ^U consistent with $\bar{\mathcal{M}}^U(X_{ijt}, Z_{ijt}, \theta^U; \hat{\alpha}^U) \geq 0$. The model defined by moment inequalities $\bar{\mathcal{M}}^U(X_{ijt}, Z_{ijt}, \theta^U; \hat{\alpha}^U) \geq 0$ is correctly specified when Θ_0 is non-empty:

$$H_0 : \Theta_0 \neq \emptyset \quad \text{vs} \quad H_1 : \Theta_0 = \emptyset.$$

The null hypothesis that demand conditions are part of the information set used by firms when making export decisions is generally rejected in our tests where all unsupported firms are treated as informed. In other words, we reject the null hypothesis that Θ_0 is a non-empty set.

Under the assumption that the model is corrected specified, these tests provide evidence that unsupported are not broadly informed of export market conditions. To conclude that there are information spillovers across firm networks, we require the same null hypothesis is not rejected when only the connected firms are informed of export demand conditions.

Let $\tilde{\mathcal{M}}^U(X_{ijt}, Z_{ijt}, \theta^U; \hat{\alpha}^U)$ denote the moment inequalities under the assumption that connected firms are informed while unconnected firms at least know the minimum information set; element Z_{ijt}, demand conditions, are in the information set among informed firms, but not among uninformed firms. For point $\theta^U_p \in \Theta^U_g$ we test the null hypothesis, $H_0 : \theta^{U*} = \theta^U_p$ vs $H_1 : \theta^{U*} \neq \theta^U_p$, by evaluating the MMM test statistic at point θ^U_p:

$$\tilde{Q}(X_{ijt}, Z_{ijt}, \theta^U_p; \hat{\alpha}^U) = \sum_{k=1}^{K} \left(\min \left\{ \frac{\tilde{\mathcal{M}}^U_k(X_{ijt}, Z_{ijt}, \theta^U_p; \hat{\alpha}^U)}{\hat{\tilde{\sigma}}_k(X_{ijt}, Z_{ijt}, \theta^U_p; \hat{\alpha}^U)}, 0 \right\} \right)^2,$$

where θ^{U*} is the true parameter vector, k indexes individual moment inequalities $\tilde{\mathcal{M}}^U(X_{ijt}, Z_{ijt}, \theta^U; \hat{\alpha}^U) = \frac{1}{n}\sum_i \sum_j \sum_t \mathcal{M}^U(X_{ijt}, Z_{ijt}, \theta^U_p; \hat{\alpha}^U)$, and

$$\hat{\tilde{\sigma}}_k(X_{ijt}, Z_{ijt}, \theta^U_p; \hat{\alpha}^U) = \sqrt{n^{-1} \sum_i \sum_j \sum_t (\mathcal{M}^U_k(X_{ijt}, Z_{ijt}, \theta^U_p; \hat{\alpha}^U) - \tilde{\mathcal{M}}^U_k(X_{ijt}, Z_{ijt}, \theta^U_p; \hat{\alpha}^U))^2}.$$

Among informed firms the moment inequalities correspond to the moment inequalities when firms are informed of export market conditions when deciding to export, $\mathcal{M}^U(X_{ijt}, Z_{ijt}, \theta^U_p; \hat{\alpha}^U)$;

among uninformed firms the moment inequalities correspond to the moment inequalities used to estimate the model under the minimal information assumption, $\mathcal{M}^U(X_{ijt}, Z_{ijt}, \theta_p^U; \hat{\alpha}^U) = \mathcal{M}^U(X_{ijt}, \theta_p^U)$. We proceed to construct test statistics and p-values analogously to the above subsection.

E.3 Threats to Identification

There are at least three potential threats to spillover identification. We address each of these below.

E.3.1 Information Spillovers vs. Confoundedness

We cannot reject the null hypothesis that connected firms know export market conditions while unconnected firms know the minimum information set. However, if connected firms all share a particular characteristic that allows them to be well-informed, we may confound network spillovers with that alternative characteristic. For example, suppose all large firms are well informed about export market conditions regardless of network structure and all large firms are also indirectly connected to the TC. It is not obvious that TC information spillovers are driving the difference in p-values rather than systematic differences in the information held by different types of firms.

We provide four pieces of evidence that suggest that confoundedness does not drive our findings. First, we directly condition on select co-variates in Tables 6, 7 and 8. We do find intuitive differences in the informedness of firms across the firm size distribution, export destinations and TC outreach. This does not directly imply the confoundedness is a concern; but it also does not rule it out either. Nonetheless, we highlight here that we do not find that information spillovers only reflect firm size or are confined to a single export destination, suggesting that that firm, destination or outreach specific characteristics are not driving our results alone.

Second, the third and fourth columns of Table 6 demonstrate that, with very few exceptions, that we cannot rejec the hypothesis that supported firms are well-informed of export market conditions in destination markets regardless of which co-variates we condition on.

Third, the placebo tests yield samples of falsely connected firms which are of the same size as the observed set of indirectly connected firms.[44] Table A8 reports directly checks for the balancing of firm characteristics across indirectly supported firms and those from the placebo samples. The odd-numbered columns of Table Table A8 report the smallest p-value from t-tests of the difference between the observed sample of indirectly supported firms across all placebo samples in the year prior to treatment (year $t-1$ when a peer receives TC support in year t). The even numbered columns repeat this exercise for the entire sample of unsupported firms and the difference between the observed sample of indirectly supported firms and the complementary sample of unsupported firms.

Across a host of firm characteristics we do not find evidence of systematic differences across indirectly supported firms and the placebo samples, even though the information tests on the placebo samples yielded the opposite conclusion to those on the sample of firms actually connected to the TC.

Fourth, this conclusion is maintained in the even-numbered columns of Table A8 directly checks for the balancing of firm characteristics across indirectly supported firms and the entire sample of unsupported firms in each of the network specifications. Again, we do not find evidence of systematic differences across indirectly supported firms and unsupported firms. In sum, all evidence suggests that our findings are unlikely to be driven by the confoundedness alone.

E.4 Statistical Power

A second threat to the identification network information spillovers arises due to network sparcity. In a sparse network relatively few firms are indirectly connected to the TC. Accordingly, we are naturally concerned that if tests of the hypothesis that indirectly connected firms are informed of export market conditions are underpowered, they may systematically fail to reject the null hypothesis even when it is false.

To directly address this concern, we develop a series fo placebo experiments using the following steps:

[44] The subsequent subsection details the process for generating placebo samples.

1. Randomly draw a (geographic or employment-based) network node.
2. Artificially (and incorrectly) label the randomly drawn nodes as the origin of TC support. All indirectly connected firms to the randomly drawn nodes are likewise labeled as indirectly supported firms.
3. Repeat this process until the placebo sample of indirectly supported firms reaches the sample size of the number of indirectly treated firms in the actual data.
4. Repeat all information tests on the individual placebo sample identically to the tests conducted on the actual sample.
5. Draw N placebo samples where $N = 50$ in our case.

Panel C of Table 7 reports the mean value of 50 separate placebo tests. In contrast to the benchmark sample, we typically reject the null hypothesis that the placebo sample of indirectly supported firms are well-informed of export market conditions. In fact, we reject the null hypothesis in every placebo sample. While the sparcity of the network specification imply that the most placebo samples will include few firms which have any connection to the TC, it does not imply that the placebo samples are vastly different in underlying characteristics relative to the benchmark sample, as evidenced by Table A8.

E.5 Endogenous Network Targeting

A related concern pertains to the possibility that the TC targets firms which are best connected to their peers in order to facilitate informational spillovers. While there is no narrative evidence to this potential objective, we nonetheless consider the possibility that network targeting by the TC is driving our findings. Figure 4 documents that average firm size across municipalities supported or called by the TC is nearly identical to those uncalled by the TC. Along the firm size dimension, arguably the most visible firm characteristic, there is no evidence of municipality targeting with TC support. Similar results are available upon request for other network specifications and firm/destination characteristics.

F Additional Results

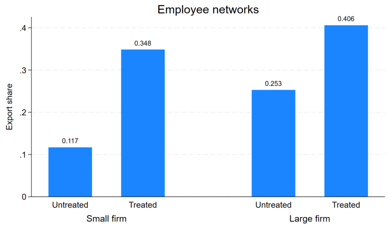
This section briefly discusses additional information test results that were omitted from the main text for brevity. Table A9 reports test whether supported firms know the number of buyers, buyer quality or their interaction premium. In each case, we cannot reject the null hypothesis that supported firms are well informed of each individual demand component. Results for un-supported firms (identical to those reported in Table 9 of the main text) are also reported for comparison purposes.

Table A10 reports the same information tests as those documented in Table 8 of the main text, but adjusts p-values for multiple testing. Column (1) again indicates that, in most cases, we reject the null hypothesis that unsupported firms are informed of export market conditions with few exceptions, each of which are in line with the results discussed in the main text. Columns (2)-(4) indicate that in many cases we cannot reject the same null hypothesis for firm-types or destination-markets among firms which are indirectly linked to the TC through firm networks. In sum, the findings in Table A10 reinforce the evidence of information spillovers from the main text even after adjusting p-values for multiple testing.

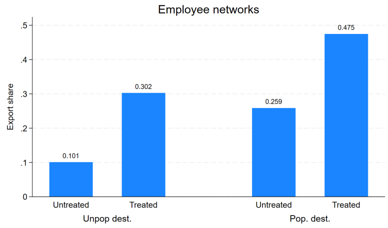
G Additional Figures

Figure A1: Export Share Across TC Firm Networks

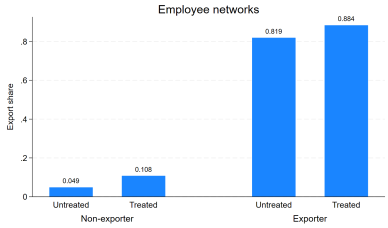
(a) Firm Size & Emp. Net.



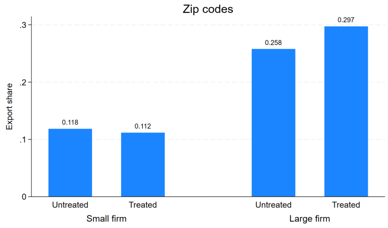
(b) Dest. Pop. & Emp. Net.



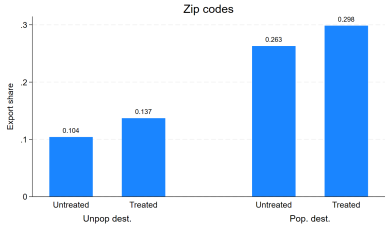
(c) Exp. Status & Emp. Net.



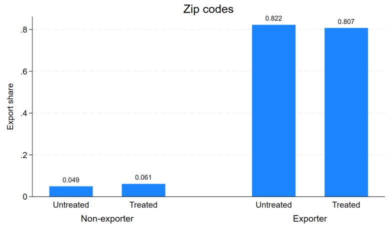
(d) Firm Size & Zipcode



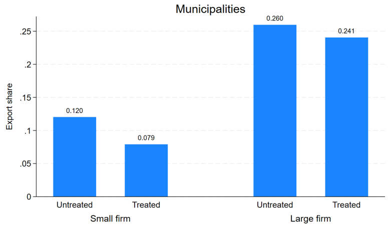
(e) Dest. Popularity & Zipcode



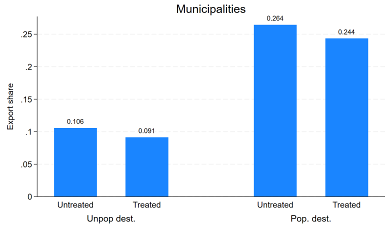
(f) Export Status & Zipcode



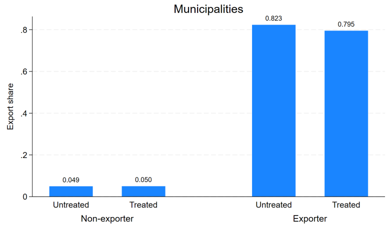
(g) Firm Size & Municipality



(h) Dest. Popularity & Mun.



(i) Export Status & Mun.



Notes: The above figures report the fraction of exporting firms unsupported by the Danish Trade Council. We separating document export share across firm size, export destination popularity, and export history for firms which have hired an employee who was previously employed by a TC supported firm (panels (a)-(c)), firms that have a supported neighbour in the same zipcode (panels (d)-(f)), and firms that have a supported neighbour in the same municipality (panels (g)-(i)).

H Additional Tables

Table A1: Fixed Cost Parameter estimates, 1,000 DKK

	Unsupported			Supported		
Estimator	σ_U	β_0^U	β_1^U	σ_S	β_0^S	β_1^S
Perfect foresight (MLE)	1,339	1,033	566	8,078	1,977	-6,998
Minimal info. (MLE)	911	738	423	3,499	961	-2,767
Moment inequality	[314; 471]	[326; 480]	[146; 243]	[122; 357]	[109; 322]	[48; 278]
Moment inequality, IV	[320; 471]	[330; 471]	[155; 249]	[106; 417]	[105; 346]	[42; 238]

Notes: Distance is measured in 10,000 kilometers. The demand elasticity η is set to 5.

Table A2: Average fixed export costs, 1,000 DKK

	Unsupported			Supported		
Estimator	USA	China	Norway	United States	China	Norway
Perfect foresight (MLE)	7,262	7,336	5,322	-16,047	-16,966	7,926
Minimal info. (MLE)	5,256	5,311	3,808	-5,447	-5,811	4,029
Moment inequality	[450; 648]	[454; 655]	[336; 493]	[193; 433]	[194; 440]	[117; 327]
Moment inequality, IV	[459; 648]	[463; 655]	[340; 484]	[187; 438]	[188; 442]	[113; 353]

Notes: The above table documents average fixed costs by export destination and estimation approach. The demand elasticity η is set to 5.

Table A3: Dynamic model, parameter estimates, 1,000 DKK; unsupported firms

	σ_U	β_0^U	β_1^U	γ_0^U	γ_1^U
Static model	[308; 410]	[326; 431]	[141; 204]		
Dynamic model	[81; 550]	[20; 350]	[29; 377]	[-250; 250]	[441; 6,000]

Notes: Distance is measured in 10,000 kilometers. The demand elasticity η is set to 5.

Table A4: Dynamic model, average fixed & sunk export costs, 1,000 DKK; unsupported firms

Estimator	United States	China	Norway
Panel A: Static model			
Fixed costs	[442; 570]	[446; 575]	[336; 441]
Panel B: Dynamic model			
Fixed costs	[199; 387]	[203; 388]	[35; 353]
Sunk costs	[290; 4,196]	[302; 4,354]	[-15; 502]
Fixed+sunk costs	[522; 4,583]	[538; 4,742]	[94; 571]

Notes: The demand elasticity η is set to 5.

Table A5: Moment Inequality Fixed Cost Estimates, inclusive of EU sample

	σ_T	β_0^T	β_1^T	$\sigma_{EU,T}$	$\beta_0^{EU,T}$
Panel A: Unsupported Firms					
Excluding EU	[314; 471]	[326; 480]	[146; 243]		
Including EU	[431; 641]	[551; 790]	[82; 129]	[559; 830]	[714; 1,023]
Panel B: Supported Firms					
Excluding EU	[122; 357]	[109; 322]	[48; 278]		
Including EU	[168; 468]	[221; 636]	[32; 177]	[217; 629]	[286; 824]

Notes: Distance is measured in 10,000 kilometers. The demand elasticity η is set to 5. All fixed costs are evaluated in 1,000 DKK.

Table A6: Average fixed export costs, inclusive of EU sample

	Unsupported			Supported		
	USA	China	Norway	USA	China	Norway
Excluding EU	[450; 648]	[454; 655]	[336; 493]	[193; 433]	[194; 440]	[117; 327]
Including EU	[641; 836]	[645; 838]	[560; 783]	[327; 630]	[327; 635]	[234; 626]

Notes: The above table documents average fixed costs by export destination for the fixed cost parameters reported in Table A5. The demand elasticity η is set to 5. All fixed costs are evaluated in 1,000 DKK.

Table A7: Testing the content of information sets; support status; including EU destinations

Firms	Markets	Unsupported Firms	Supported Firms
Panel A: Minimal information			
All	All	0.485	0.612
Panel B: Perfect foresight			
All	All	0.030	0.031
Panel C: Minimal information & country shifter			
All	All	0.038	0.491
No. of Obs.		42218	342

Notes: This table reports the p-values from a test of whether export demand conditions are part of the firm's information set using the Bugni et al., 2015 specification test as in Dickstein and Morales, 2018.

Table A8: Firm - Destination characteristics across indirect TC connectedness

	Municipalities		Zip Codes		Worker Transitions	
	Placebo	All Unsup.	Placebo	All Unsup.	Placebo	All Unsup.
	(1)	(2)	(3)	(4)	(5)	(6)
Dom. Revenues						
	()	()	()	()	()	()
Profits						
	()	()	()	()	()	()
Employment						
	()	()	()	()	()	()
Capital Stock						
	()	()	()	()	()	()
Exports						
	()	()	()	()	()	()
MNC Ownership						
	()	()	()	()	()	()
Australia						
	()	()	()	()	()	()
China						
	()	()	()	()	()	()
India						
	()	()	()	()	()	()
Japan						
	()	()	()	()	()	()
Norway						
	()	()	()	()	()	()
Russia						
	()	()	()	()	()	()
Turkey						
	()	()	()	()	()	()
U.S.						
	()	()	()	()	()	()

Notes: Odd-numbered columns report the maximum difference between the observed sample of indirectly supported firms and each placebo sample. The even numbered columns report the difference between the observed sample of indirectly supported firms and the complementary sample of unsupported firms in the year prior to treatment (year $t-1$ when a peer receives TC support in year t). Standard errors are in parentheses. "Profits" are accounting profits as recorded by Statistics Denmark. "MNC Ownership" is the fraction of foreign-owned firms. "Australia" is the fraction of firms that export to Australia. Export propensity variables for China, India, Japan, Norway, Russia, Turkey and the U.S. are defined analogously.

Table A9: Testing the content of information sets; ind. p-values

		No. of Buyers		Buyer Quality		Interaction	
		Unsup.	Sup.	Unsup.	Sup.	Unsup.	Sup
Firms	Markets						
Panel A: Minimal information & Disaggregated Demand Component							
All	All	0	0.708	0.040	0.681	—	0.686

Notes: The null hypothesis in each case is that all firms (unsupported or supported) are informed of the relevant demand component for their respective type. Supported firms are firms which have received direct support from the TC. Unsupported firms are firms that have not received direct support from the TC regardless of network location. The hypotheses tests are conducted separately for supported and unsupported firms.

Table A10: Testing the content of info. sets across firm networks, by firm/market type

Uninformed		None	Unsup. Muni.	Unsup. Zips	Unsup. Wkrs
Informed		All Unsup.	Sup. Muni.	Sup. Zips	Sup. Wkrs
Firms	Markets				
Panel A: Minimal information & country shifter across firm and destination groups					
Large	Popular	0.318	0.753	0.845	1
Large	Unpopular	0.005	0.108	0.845	1
Small	Popular	0	0.440	0.010	0.045
Small	Unpopular	0	0	0.005	1
Large exp.	All	0.018	0.753	0	1
Large non-exp.	All	0	0	0.023	0
Small exp.	All	0	0	0	0.007
Small non-exp.	All	0	0	0	1
Panel B: Minimal information & country shifter across destinations					
All	Australia	0.190	1	0.238	1
All	China	0.021	1	1	1
All	India	0.058	1	0.816	1
All	Japan	0.815	1	1	1
All	Norway	0.815	1	1	1
All	Russia	0	0	0.028	1
All	Turkey	0	0.007	1	1
All	U.S.	0.815	1	1	1

Notes: p-values adjusted for multiple testing are reported above. A firm is large (small) if domestic revenue was above (below) the median in the previous year. A destination is popular (unpopular) if the number of exporters was above (below) the median in the previous year.