Policy Relevant Information Spillovers in Export Markets*

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Abstract

Employing firm-level export support data from the Danish Trade Council (TC), this paper uses a 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 increase total manufacturing exports from the Danish machinery industry by 1-2 percent per year.

(*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, export-oriented information spillovers are policy-relevant. We demonstrate that information flows between the Danish Trade Council (TC) improve the information set of supported manufacturers. Informational benefits are in addition to the gains accrued from boosting demand or reducing export costs. Second, policy-relevant

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, but, accordingly, also potentially create conditions for market failure if 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 1 provides a simple, intuitive illustration of potential network benefits of export-oriented industrial policy. 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 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 unique empirical setting to characterize the nature and dissemination of policy-relevant trade information. As documented in Buus et al., 2022, the Danish TC approaches individual firms with offers of export support in a quasi-random fashion. Similar to Steinwender, 2018 and Criscuolo et al., 2019, the nature of the 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 nature 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 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 suggest that TC support programs remedy export informational gaps among supported firms. These initial findings are

[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. Consistent with key findings from Dickstein and Morales, 2018: among unsupported firms we cannot reject the hypothesis that large firms and past exporters know all of the above export market characteristics and destination-specific revenue shifters in popular export destinations.

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 employment histories and georgraphy. 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. In this sense, we contribute to the literature aimed at understanding the value of industrial policy in a network setting (Liu, 2019).

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

[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.

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.

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. In that sense, while information spills over across firms, it is far from complete. In this sense, we are able to differentially characterize both the strength and content of informational spillovers across firm networks.

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 be other unprofitable refrain from costly entries abroad. In this sense, informational spillovers help justify TC support programs even at a cost to Danish taxpayers. In this sense, our finding both confirms 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 further sheds 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 (Aghion et al., 2015; Juhász, 2018; Liu, 2019; Bai et al., 2022; Choi and Levchenko, 2021; Lane, 2022; Juhász et al., 2024b).

More broadly, our policy results contribute to a rich branch of research aimed at understand-

ing 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., 2022). Munch and Schaur, 2018 provide compelling evidence that support services are indeed causal determinants of improved export success, while Buus et al., 2022 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 the overall demand or entry costs.[4] 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 to facilitate 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, product and destination specific. The TC works with individual firms selling individual products produced for target destinations. In this sense, the information 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, product-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., 2022 and Section 4, within a product-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

[4]Buus et al., 2022 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. The appendix documents further evidence of TC support on firm level demand and entry costs.

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 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 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.[5] Next, conditional upon entry, all firms set their prices optimally and obtain the corresponding export profits. Information and uncertainty regarding future profits may differ across firms when choosing among export destinations; we let location l arbitrarily correspond to a particular network location. Information and uncertainty 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. We allow export demand to differ across firms supported (S)

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

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^U_{ijt}, and an additional demand premium they would receive with support,[6] $\tilde{\xi}^S_{ijt}$:

$$\xi_{ijt} = [(\xi^U_{ijt})^{\eta-1} + s_{ijt}(\tilde{\xi}^S_{ijt})^{\eta-1}]^{\frac{1}{\eta-1}}$$

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^T_{ijt}, where the superscript T again indicates that fixed export costs may differ across supported and unsupported firms.[7] Specifically, exporting firm i pays fixed export costs f^T_{ijt} in market j:

$$f_{ijt} = (1 - s_{ijt})(\beta^U_0 + \beta^U_1 dist_j + \nu^U_{ijt}) + s_{ijt}(\beta^S_0 + \beta^S_1 dist_j + \nu^S_{ijt}) \tag{1}$$

$dist_j$ is the distance between country h and country j and the firm-specific fixed cost component ν^T_{ijt} 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^T_{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., 2022, unsupported firms do not benefit from additional TC driven demand, even if they enjoy additional knowledge of demand conditions through peer

[6] 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.

[7] We could also allow variable trade costs to vary across supported and unsupported firms 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., 2022) suggests that TC support primarily operates through demand channels.

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

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

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

$$\alpha^U_{ijt} \equiv \left(\frac{\xi^U_{ijt}\tau_{iht}P_{jt}}{\xi_{iht}\tau_{ijt}P_{ht}}\right)^{\eta-1}\frac{Y_{jt}}{Y_{ht}} \text{ and } \alpha^S_{ijt} \equiv \left(\frac{\tilde{\xi}^S_{ijt}\tau_{iht}P_{jt}}{\xi_{iht}\tau_{ijt}P_{ht}}\right)^{\eta-1}\frac{Y_{jt}}{Y_{ht}}$$

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 infor-

mation 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, $\mathbb{E}[\pi_{ijt}|\mathcal{J}_{ijlt}, dist_j, \nu^T_{ijt}] \geq 0$, or for an unsupported firm

$$D_{ijt} = \mathbb{1}\{\eta^{-1}\mathbb{E}[\alpha^U_{jt} r_{iht}|\mathcal{J}_{ijlt}] - \beta^U_0 - \beta^U_1 dist_j - \nu^U_{ijt} \geq 0\}, \tag{5}$$

where $\mathbb{1}\{\cdot\}$ is an indicator function. The probability that unsupported firm i exports to market j in year t is represented by the probit model

$$\begin{aligned}\mathcal{P}(D_{ijt} = 1|\mathcal{J}_{ijt}, dist_j, s_{ijt} = 0) &= \int_{\nu^U} \left(\mathbb{1}\{\eta^{-1}\mathbb{E}[\alpha^U_{jt} r_{iht}|\mathcal{J}_{ijt}] - \beta^U_0 - \beta^U_1 dist_j - \nu^U \geq 0\} \frac{1}{\sigma_U} \right. \\ &\quad \left. \times \phi\left(\frac{\nu^U}{\sigma_U}\right) d\nu^U \right) \\ &= \Phi(\sigma_U^{-1}(\eta^{-1}\mathbb{E}[\alpha^U_{jt} r_{iht}|\mathcal{J}_{ijt}] - \beta^U_0 - \beta^U_1 dist_j)), \end{aligned} \tag{6}$$

where ϕ and Φ are the standard normal probability density function and cumulative distribution function, respectively. 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 lower fixed costs, $\beta^S_0 + \beta^S_1 dist_j + \nu^S_{ijt}$.

Specification (6) 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 common value from the literature. Second, integrating over ν^T_{ijt} in equation (6) 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-off 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) will then 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, we note that 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 sunk entry costs and reconsidering the benchmark information tests through the lens of the augmented model. Last, the model imposes the assumption that there is systematic difference in export demand arising from differences in firm network location. While it would be straightforward to accommodate demand difference 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.

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 is the most important component of total Danish manufacturing exports. 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 all of the following 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 and whether TC contact was initiated by the firm or a TC employee. Third, we obtain firm-destination level export data from the statistics for International Trade in Goods, also provided by Statistics Denmark. For each firm in our sample we observe the value of exports to each local buyer by destination 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 as well as at least 5 promotion purchases. On the one hand, given the high degree of integration across EU countries, the 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 sample *indirectly* supported firms, the second EU-inclusive allows us to investigate and validate the informational content of export support programs among directly supported firms.[8]

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 6 firms per year receive TC support for either the USA or China, on average, 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 2a 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., 2022 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 2b illustrate that the differences in export sales are, proportionally, even greater than the differences in domestic sales. Indeed, Buus et al., 2022 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., 2022, TC calls *quasi-random*: 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. 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.

[8] At present, all results using the EU-inclusive sample are in progress.

We add to the existing evidence of this feature 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 2c and 2d 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 difference in observed sales outcomes.

The right-most bars of Figures 2a and 2b repeat this experiment, but instead of distinguishing firms by call status, we compare outcomes across supported and unsupported firms. We 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 employment history.[9]

4.2.1 Employment Networks

Linking Danish firms to employee history we proceed to build employment networks. Specifically, we consider an unsupported firm-destination-year observation indirectly linked to TC firm at least one of their current employees was a previously employed by a different firm during a period where the previous employer received TC support for the same destination.[10] 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

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

[10]Specifically, a firm is indirectly TC support for destination d in year t if a current employee that works in firm i previously worked in firm i' ($i \neq i'$) during year $t' < t$ and i' received support for destination d in year t' while this employee worked at firm i'.

definition of firm peers, we find that 5 percent of firm-year-destination observations are indirectly supported by the TC.

If employee transitions are a mechanism by which information diffuses across firms, we expect that these spillovers will be particularly salient among skilled workers.[11] To investigate this hypothesis will build a second employment-based network whereby we treat two firms as peers if they are linked by the transition of skilled worker at a supported firm to a unsupported firm. As above, we confine the potential knowledge embedded in the worker to the destination for which TC support was received at their previous employer. A skilled worker definition of firms peers suggests that 2.1 percent of unsupported firms may be indirectly supported through skilled worker transitions.[12]

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 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 (i) the same municipality or, even wider, (ii) the same district.

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 or municipalities are supported at least once, this does not necessarily imply that many of the unsupported firms have a supported peer. For example, Denmark has 98 distinct municipalities, 90 of which are represented in our sample. Of these 90 municipalities, 42 municipalities are receive support to at least one firm in one sample year.

[11] We define a skilled worker as one with some tertiary education.

[12] At present, testing based on skilled worker transitions are in progress.

However, this does not imply that most firms are located in a supported municipality in any year. Rather, only 8 percent of firm-destination-year observations among unsupported firms belong to a supported (destination-year) municipality. The fraction of unsupported firm-destination-year observations in a supported zip code is even smaller, totaling only 3 percent.

On the one hand, we have over unsupported 25000 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 in unsupported locations are much larger raising that differential results may yet reflect testing power despite large samples. To address this concern we take a two pronged approach. First, we aperform the same tests using districts as definition of treatment network. In this last case, 45 percent of unsupported firm-year-destinations are located in supported districts, yielding testing samples that are nearly identical in size, but where we may suspect informational spillovers will be weakest. Second, we again leverage the EU-inclusive which increases both the number of all types of firms, though it does so for markets where information frictions are likely less binding.

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. We find no evidence of this in the description of TC outreach. We also find no statistical evidence of this concern either.

Panel (a) of Figure 3 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 3 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, $r^o_{ijt} = (\alpha^U_{jt} + \alpha^S_{jt} s_{ijt}) r_{iht} + e_{ijt}$, captures year and market specific demand conditions for both supported and unsupported firms. However, as evidenced by Table 1, only 6 percent of firms receive TC support over our entire sample; accordingly, 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 $\mathbb{E}[e^S_{ijt}|\mathcal{J}_{ijt}] = 0$, $\mathbb{E}[e^U_{ijt}|\mathcal{J}_{ijt}] = 0$ and $\mathbb{E}[e_{ijt}|\mathcal{J}_{ijt}] = 0$ ensuring that $\mathbb{E}[r_{ijt}|\mathcal{J}_{ijt}] = \mathbb{E}[r^o_{ijt}|\mathcal{J}_{ijt}]$. Although this structure holds across all informational settings, identifying the impact of TC support requires additional assumptions on the relationship between firm-level information $\mathcal{J}_{ijt}$ and 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, $\mathbb{E}[r_{ijt}|\mathcal{J}_{ijt}]$, identifying model parameters and performing counterfactual experiments nonetheless requires modest restrictions on firm information, $\mathcal{J}_{ijt}$ (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 spills over across firms, 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 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 $Z \subseteq \mathcal{J}_{ijt}$, we define the conditional

[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.

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

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

$$\mathcal{M}^T(Z_{ijt};\theta^T) = \mathbb{E}\left[\begin{array}{c} m_{ob}^{l,T}(D_{ijt}, r_{ijt}^o, dist_j, s_{ijt});\theta^T \\ m_{ob}^{u,T}(D_{ijt}, r_{ijt}^o, dist_j, s_{ijt});\theta^T \\ m_{rp}^{l,T}(D_{ijt}, r_{ijt}^o, dist_j, s_{ijt});\theta^T \\ m_{rp}^{u,T}(D_{ijt}, r_{ijt}^o, dist_j, s_{ijt});\theta^T \end{array}\middle| Z_{ijt}\right] \geq 0, \tag{7}$$

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

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

$$m_{ob}^{u,T}(\cdot) = (1-D_{ijt})\frac{\Phi((\theta_2^T)^{-1}(\eta^{-1}r_{ijt}^o - \theta_0^T - \theta_1^T dist_j))}{1-\Phi((\theta_2^T)^{-1}(\eta^{-1}r_{ijt}^o - \theta_0^T - \theta_1^T dist_j))} - D_{ijt} \tag{9}$$

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

$$\begin{aligned} m_{rp}^{u,T}(\cdot) &= D_{ijt}(\eta^{-1}r_{ijt}^o - \theta_0^T - \theta_1^T dist_j) \\ &\quad + (1-D_{ijt})\theta_2^T\frac{\phi((\theta_2^T)^{-1}(\eta^{-1}r_{ijt}^o - \theta_0^T - \theta_1^T dist_j))}{1-\Phi((\theta_2^T)^{-1}(\eta^{-1}r_{ijt}^o - \theta_0^T - \theta_1^T dist_j))}. \end{aligned} \tag{11}$$

Consider equation (9), 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 earn positive profits, $\eta^{-1}\mathbb{E}[r_{ijt}|\mathcal{J}_{ijt}] - \beta_0^U - \beta_1^U dist_j - \nu_{ijt}^U \geq 0$. Expectations, conditional on $(D_{ijt}, \mathcal{J}_{ijt}, dist_j, s_{ijt})$, yields

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

[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 (10) and (11) requires assuming a distribution for ν_{ijt}^T up to a scale parameter, σ_T.

Although condition (12) 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 $\mathcal{J}_{ijt}$. Employing Jensen's inequality Dickstein and Morales, 2018 derive weaker, but feasible moment inequalities that hold at $\theta = \theta^*$

$$\mathbb{E}\left[(1 - D_{ijt})\frac{\Phi(\sigma_U^{-1}(\eta^{-1}\mathbb{E}[r_{ijt}|Z_{ijt}] - \beta_0^U - \beta_1^U dist_j))}{1 - \Phi(\sigma_T^{-1}(\eta^{-1}\mathbb{E}[r_{ijt}|Z_{ijt}] - \beta_0^U - \beta_1^U dist_{ijt}))} - D_{ijt}\Big| Z_{ijt}\right] \geq 0 \tag{13}$$

where the observable values of $\mathbb{E}[r_{ijt}|Z_{ijt}]$ takes the place of the unobserved $\mathbb{E}[r_{ijt}|\mathcal{J}_{ijt}]$ and the moment inequalities are conditioned on the instrument vector Z_{ijt} instead of the unobserved information set $\mathcal{J}_{ijt}$. 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, $g^T(\cdot)$:

$$\mathbb{E}\left[\left\{\begin{array}{l} m_{ob}^{l,T}(D_{ijt}, r_{ijt}, s_{ijt}, dist_j; \theta^T) \\ m_{ob}^{u,T}(d_{ijt}, r_{ijt}, s_{ijt}, dist_j; \theta^T) \\ m_{rp}^{l,T}(D_{ijt}, r_{ijt}, s_{ijt}, dist_j; \theta^T) \\ m_{rp}^{u,T}(D_{ijt}, r_{ijt}, s_{ijt}, dist_j; \theta^T) \end{array}\right\} \times g^T(Z_{ijt})\right] \geq 0. \tag{14}$$

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 (14) 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

Table 2 reports the estimated market demand shifters for each destination country. The first column documents annual average values of market demand for unsupported firms, α_{jt}^U, while the bottom row presents the additional demand premium enjoyed by firms directly supported by the TC, α_j^S. Two empirical patterns are immediately evident. First, on average, supported firms enjoy much larger export market demand than comparable unsupported firms. Indeed, Table 2 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. 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

[16] See Appendix B.3 for details.

large export markets for both supported and unsupported firms and their export demand is 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., 2022 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 indirectly supported differentially from those unsupported by the TC. The estimated demand premia among indirectly supported firms is reported in the third column of Table 2, where the estimated demand premia are exceptionally small or negative in 7 out of 8 markets.[17] Given that both existing evidence and our model-consistent estimates do not find significant evidence of widespread demand spillovers, we conclude this benchmark model assumption is broadly supported by the data.

6.2 Fixed Export Costs

Table 3 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 4 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 the estimated fixed costs are estimated to be substantive, increasing in distance, and vary little across firms. Across destinations export entry

[17] The sole exception is China where we find some evidence of potential demand spillovers.

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. The variance of fixed cost shocks suggests they play a modest role in determining export outcomes; a one-standard deviation fixed export cost shock represents 2.7 to 6.5 percent of the average fixed export cost.

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 documents that ML fixed cost estimates suffer from significant bias in informationally opaque export markets.[18]

The last three columns of Tables 3 and 4 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 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

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

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., 2022 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 3 and 4.

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 2, within a size bin there 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.

We conduct two series of tests. We start by separately testing what supported and unsupported firms know about export markets, documenting differences along firm characteristics 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.

6.3.1 Are TC supported firms better informed?

This section considers a series first-stage tests aimed at (i) validating the hypothesis that supported firms are better informed than their unsupported counterparts and (ii) characterizing information differences across heterogeneous producers.

Table 5 documents p-values from a benchmark series of information tests. 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, we repeat the same exercise, but test whether firms know r^o_{ijt}; that is, whether firm information sets are sufficiently rich allow firms to perfectly predict observed profits from exporting. For each sample, we clearly reject, at conventional significance levels, that firms have perfect foresight regardless of TC support. The rejection of the null hypothesis, even for supported firms, highlights that the failure to reject the null hypothesis that supported firms have knowledge of export market demand conditions does not solely reflect smaller sample sizes and/or an underpowered specification test. Rather, for an inappropriate information set, the information test clearly rejects the null hypothesis.

In Panel C, we test whether firms have knowledge of the relevant export market demand shifters 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 $\alpha^U_{j,t-1} + \alpha^S_j$. In columns (1) and (2) 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 in columns (3) and (4), suggesting that supported firms are aware of export market demand conditions.

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.[19] 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.[20] 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, $(\alpha_{jt}^U + \alpha_j^S) r_{iht}$, and pay modest fixed export costs, f_{ijt}^S. Thus, in light of the model, the specification test effectively rationalizes their decision *not to export 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.

[19] 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.

[20] 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.[21]

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, it ignores from how firms come into contact with the TC itself. 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 these firms know destination market export conditions. 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.

The last row of Panel F documents the findings among firms that not called by the TC. We again reject the hypothesis that unsupported firms know export market conditions, and fail to

[21] 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.

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 supported firms that self-select into support and those which are first contacted by the TC.

Overall, the information tests across all panels reinforce the common narrative that TC support improves the firm-level information of export market conditions. It is encouraging that the above first stage information tests return economically reasonable findings, confirming existing narrative and historical evidence. Yet, substantive benefits to supported firms do not in of themselves 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 next 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. Instead, with the recovered model parameters in hand we proceed to test the nature information across firm networks.

We proceed to test whether unsupported firms in supported locations have better information than unsupported firms in unsupported locations codes. The first column in Panel A of Table 6 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, 3 and 4 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 district as a supported firm; in column 3, the same municipality; and 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 2-5 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.

In Panel B we check that these benchmark findings do not reflect firms that have other contact with the TC, confounding 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 consider the same hypothesis for the group of uncalled firms and each firm network. We again find that 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 2-5). 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 would intuitively expect that connections between firms in the same zip code are plausibly stronger than those in wider districts. 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 firm networks. In this sense, failing to reject the null hypothesis may be indicative of a lack of statistical power.

Table 6 provides two pieces of evidence counter this interpretation. First, even when we consider the widest definition of firm network (districts) we continue to fail to reject the null

hypothesis. In this case, nearly half of the unsupported firms are treated as informed. Second, in Panel C we consider a placebo test for the most narrow definition of firm networks, supported zip codes. In this 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.[22] The fourth column of Panel C documents the mean value of 50 placebo tests and indicates that, on average, we would clearly reject the same null hypothesis. Indeed, in no individual placebo sample do we ever return a p-value above 0.044. In this sense, Panel C suggests that if firms in supported zip codes did not have knowledge of export market conditions there is sufficient statistical power to reject that null hypothesis. Yet, in constrast to all placebo samples, we cannot reject the null hypothesis for the true sample of indirectly supported firms.

6.4.1 Export market information across firms and geography

To further characterize the nature of information spillovers Table 7 distinguishes unsupported firms by firm and market characteristics (small vs large firms, popular vs unpopular markets), while each column distinguishes different each null hypothesis by firm network. The first column of Panels A and B in Table **??** 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 5 and is strongly rejected.[23]

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

[22] 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.

[23] 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.

across unpopular markets if they are indirectly connected to the TC through a firm sharing the municipality (column 3) or district (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 or district level networks. Overall, these findings are broadly consistent with stronger informational spillovers, particularly for larger export markets and in more narrowly defined firm networks.

The last column of Table 7 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 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 what exactly type of export-relevant information diffuses 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 of 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 8 reports findings across network types.[24] 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 substantially 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 information spillovers across regional networks, we find greater 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 aggre-

[24] Appendix tables A5-A7 reports results across support status. Since these results simply confirm all the findings in Table 5, we omit further discussion hereafter.

gation, 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 which 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 unsupported network do not. Panels A-D repeat the counterfactual for each network structure and document results in Table **??**.

We find that the transfer of information to unsupported firms in supported zip codes (Panel A) increases export participation by as such 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. Indeed, among small exporters, improved information causes average firm exports to fall.

Small changes in the propensity to export and mean export profits might suggest that information spillovers are of little economic consequence. This conclusion would be misleading for at least two reasons. First, only 3 percent of observations are in supported zip codes. Second, aggregate outcomes will reflect changes in both the propensity to export and a rise in average exports. Indeed, 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. 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. Comparing Panel C, where unsupported firms in supported districts enjoy information spillovers, to Panel A we observe a tripling of the predicted growth in export propensities, mean export growth that is an order of magnitude larger, and information spillover driven aggregate export growth of 5-10 percent per annum.

Panel D considers the same decomposition for employee networks. We no longer 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 grow into export markets. 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 important to recognize that information spillovers alone account in export profits of 1.6-2.5 million DKK (2.25-3.5 million USD) even this very narrow case. The total subsidy cost of supplying directly supported with TC support amounted to 0.32 million DKK, a fifth of the minimum public benefits.

Last, Panel E considers a setting with informational decay in both quality and quantity. Specifically, we assume, consistent with our information tests, that unsupported firms in supported receive a full informational spillovers, while those in wider muncipalities 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 fall between the Panels A and B. On average, we observe a total change in export propensity which relatively modest; indeed, the overall change overlaps with the zip code policy experiment closely. In contrast, mean export growth is relatively strong, as in Panel B, where municipalities full information spillovers. Even with

partial information, firms are able to better sort into export markets. Accordingly, aggregate gains from information spillovers are relatively large even wider less connected only receive partial information.

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 spillovers to unsupported firms in through firm networks.

Considering regional firm networks, we find evidence of salient information spillovers are for large firms in unpopular export destinations, small firms in popular export destinations, exporting firms, and in China, India and Turkey. Among firms linked to TC support through the employment history of their workers, evidence of informational spillovers is even stronger.

Yet, indirect benefits are not complete. Decomposing the information spillovers, we find that information pertaining to the number of buyers in foreign markets spills over through peer networks, but 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 economic revenue generated by information spillovers to *unsupported* firms is greater than the total value of subsidies enjoyed by TC *supported* exporters.

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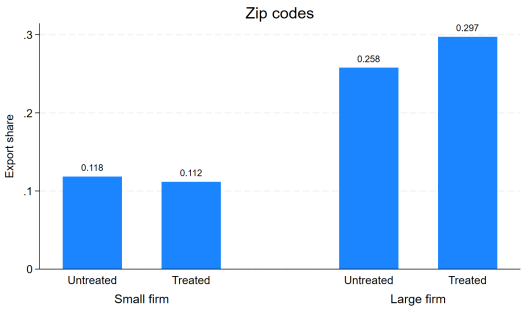
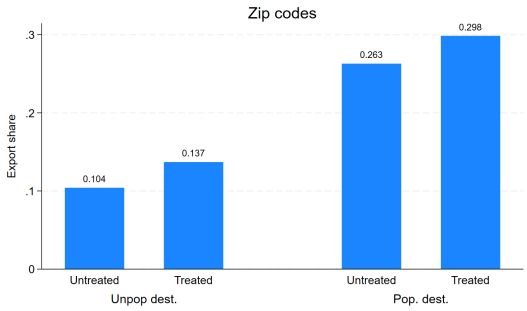
8 Figures

Figure 1: Export Share Across TC Firm Networks

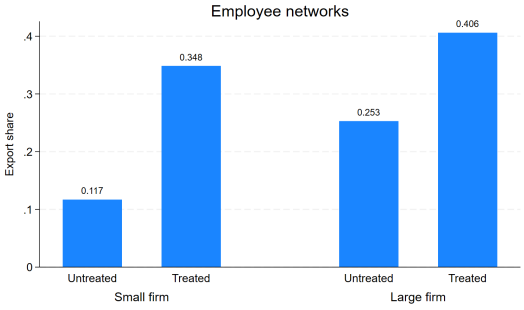
(a) Firm Size & Zipcode



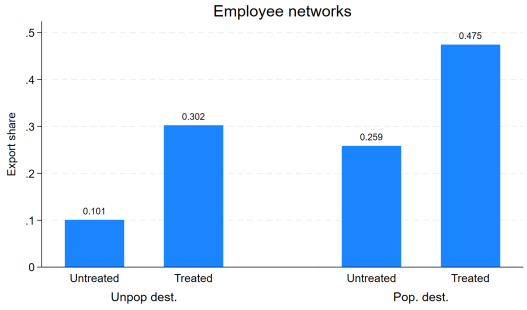
(b) Dest. Popularity & Zipcode



(c) Firm Size & Emp. Network



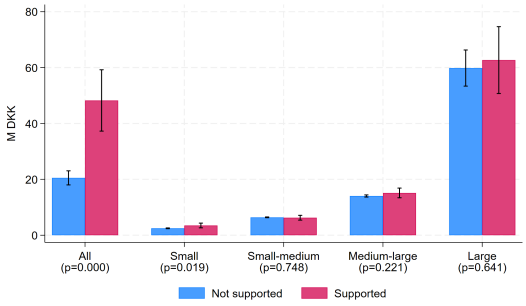
(d) Dest. Popularity & Emp. Network



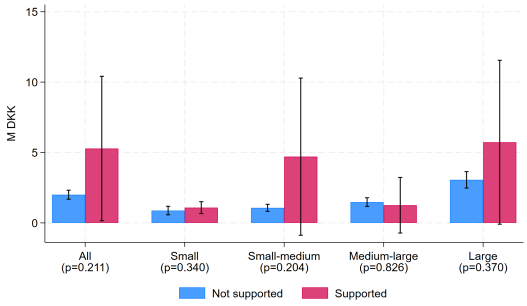
Notes: The above figures report the fraction of exporting firms unsupported by the Danish Trade Council. We separating document export share across firm size and export destination popularity for firms that have a supported neighbour in the same zipcode (panels (i) and (ii)) and firms which have hired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

Figure 2: TC Calls Across Firms and Randomization

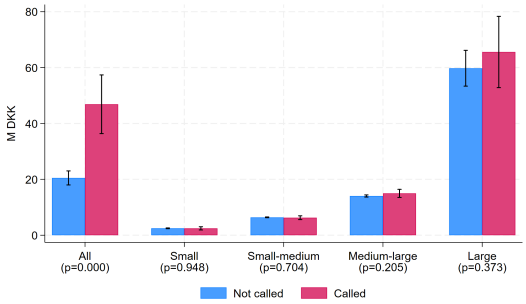
(a) Dom. Sales by Support Status



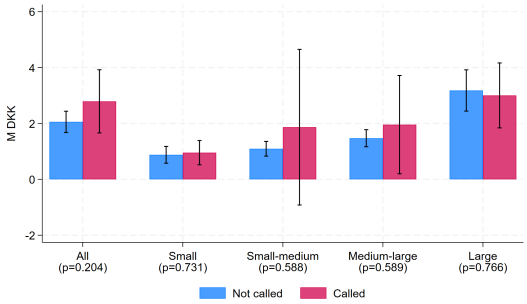
(b) Exp. Sales by Support Status



(c) Dom. Sales by Call Status



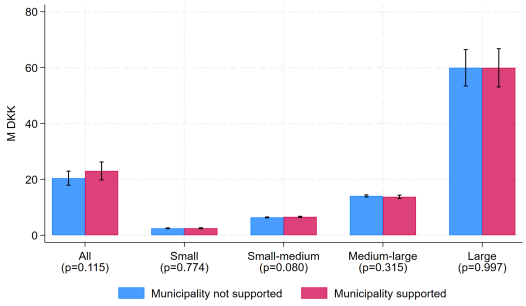
(d) Exp. Sales by Call Status



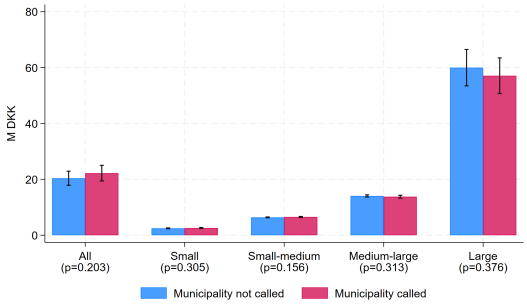
Notes: The above figures report the results from a randomization experiment where we first divide firms into four distinct groups based on lagged firm size, measured by domestic sales. We then report average domestic and export sales, along with corresponding confidence intervals, across firms supported 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 3: 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	0.50	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	0.50	0.83	0.50	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	0.33	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.

Table 2: Country shifters (annual averages)

Country	Unsupported Demand α_{jt}^{U}	Directly Supported Premium α_{j}^{S}	Indirectly Supported Premium
Australia	0.021	0.081	0.004
China	0.062	0.094	0.068
India	0.019	0.035	-0.008
Japan	0.016	0.043	-0.012
Norway	0.036	0.023	-0.014
Russia	0.056	0.000	-0.041
Turkey	0.013	0.000	-0.012
US	0.072	0.239	-0.005

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

Table 3: 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.

Table 4: 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.

Table 5: Testing the content of information sets; support status

		Unsupported		Supported	
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 6: Testing the content of information sets; supported regions; independent p-values

Uninformed		None	Unsup. Dist.	Unsup. Muni.	Unsup. Zips	Unsup. Wkrs
Informed		All Unsup.	Sup. Dist.	Sup. Muni.	Sup. Zips	Sup. Wkrs
Firms	Markets					
Panel A: Minimal information & country shifter						
All	All	0.029	0.253	0.230	0.415	0.345
Panel B: Minimal information & country shifter across call status						
Called	All	0.481	0.502	0.541	0.412	0.545
Not called	All	0.039	0.247	0.224	0.416	0.373
Panel C: Minimal information & country shifter for Placebo firms						
All	All	—	—	—	0.039	—
No. of Uninformed Obs.		0	11627	19421	20432	20053
No. of Informed Obs.		21064	9437	1643	632	1011

Notes: The p-values reported in Panel B 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 7: Testing the content of information sets; supported regions; independent p-values

Uninformed		None	Unsup. Dist.	Unsup. Muni.	Unsup. Zips	Unsup. Wkrs
Informed		All Unsup.	Sup. Dist.	Sup. Muni.	Sup. Zips	Sup. Wkrs
Firms	Markets					
Panel A: Minimal information & country shifter across firm and destination groups						
Large	Popular	0.318	0.269	0.425	0.423	0.492
Large	Unpopular	0.002	0.037	0.027	0.438	0.422
Small	Popular	0	0.018	0.147	0.003	0.008
Small	Unpopular	0	0	0	0.001	0.503
Large exp.	All	0.009	0.224	0.377	0	0.412
Large non-exp.	All	0	0	0	0.008	0
Small exp.	All	0	0	0	0	0.001
Small non-exp.	All	0	0	0	0	0.458
Panel B: Minimal information & country shifter across destinations						
All	Australia	0.048	0.034	0.266	0.263	0.518
All	China	0.004	0.138	0.420	0.424	0.444
All	India	0.012	0.152	0.235	0.136	0.364
All	Japan	0.342	0.123	0.435	0.290	0.164
All	Norway	0.368	0.408	0.288	0.354	0.302
All	Russia	0	0	0	0.004	0.381
All	Turkey	0	0.007	0.001	0.341	0.526
All	U.S.	0.272	0.333	0.418	0.453	0.483

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 8: Testing the content of infor. sets; ind. p-values

Uninformed Firms	Informed Markets	None All Unsup.	Unsup. Dist. Sup. Dist.	Unsup. Muni. Sup. Muni.	Unsup. Zips Sup. Zips	Unsup. Wkrs Sup. Wkrs
Panel A: Minimal information & no. of buyers						
All	All	0	0.311	0.366	0.381	0.345
Panel B: Minimal information & buyer quality						
All	All	0.040	0.013	0.016	0.346	0.492
No. of Uninformed Obs.		0	11627	19421	20432	20053
No. of Informed Obs.		21064	9437	1643	632	1011

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 9: Effect of improving info. to unsupported firms in ... (%)

Firms	Markets	Number of exporters	Mean export profits	Aggregate exports
Panel A: 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 B: 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 C: Districts				
All	All	[0.6; 1.9]	[1.7; 3.2]	[5.1; 9.8]
Large	All	[0; 2]	[1.8; 3.5]	[3; 7.8]
Small	All	[0.5; 1.1]	[-0.8; -0.4]	[1.8; 3.4]
All	Large	[1.7; 1.9]	[-0.9; -0.8]	[2.3; 3.5]
All	Small	[-0.1; 0]	[0.1; 0.3]	[0.2; 0.4]
Panel D: 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 E: 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.

Online Appendix

Policy Relevant Information Frictions in Export Markets

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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. Let market-specific demand shocks take the form: $\xi_{ijt} = \left(\sum_{b\in\Omega^T_{ijt}} (\mu^T_b)^{\eta-1}\right)^{\frac{1}{\eta-1}}$ 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 ξ^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 ξ^S_{ijt} as

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

where $n^T_{ijt} = n(\Omega^T_{ijt})$ and $\Delta x = x^S - x^U$ for any variable x. The first component of equation (A1) is simply the demand shifter that would apply to firm i in the absence of TC support. The second component, the TC premium, consists of three separable subcomponent: a component that increases demand through a greater number of buyers, $\bar{\mu}^S_{jt}\Delta(n_{ijt}^{\frac{1}{\eta-1}})$, a component that increases demand through larger order 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, $\Delta\bar{\mu}_{jt}\Delta(n_{ijt}^{\frac{1}{\eta-1}})$. Inserting equation (A1) into equation (2) yields the interpretation of the coefficients in equation (A3).

A.1 From demand to revenues

To map equation (2) to equation (A5), we reformulate equation (3) as

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

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

$$\begin{aligned}
\frac{r_{ijt}}{n_{ijt}} &= \left(\frac{\xi_{iht}\tau_{ijt}P_{ht}}{\bar{\mu}^U\tau_{iht}P_{jt}}\right)^{1-\eta}\frac{Y_{jt}}{Y_{ht}}\left[(1-s_{ijt})r_{iht}+\left(\frac{\bar{\mu}^S}{\bar{\mu}^U}\right)^{\eta-1}s_{ijt}r_{iht}\right] \\
&= \left(\frac{\xi_{iht}\tau_{ijt}P_{ht}}{\bar{\mu}^U\tau_{iht}P_{jt}}\right)^{1-\eta}\frac{Y_{jt}}{Y_{ht}}r_{iht}\left[1+\left[\left(\frac{\bar{\mu}^S}{\bar{\mu}^U}\right)^{\eta-1}-1\right]s_{ijt}\right] \\
&= \left(\frac{\xi_{ht}\tau_{jt}P_{ht}}{\bar{\mu}^U\tau_{ht}P_{jt}}\right)^{1-\eta}\frac{Y_{jt}}{Y_{ht}}r_{iht}\left[1+\left[\left(\frac{\bar{\mu}^S}{\bar{\mu}^U}\right)^{\eta-1}-1\right]s_{ijt}\right]+e^n_{ijt} \\
&= (\gamma^U_{jt}+\gamma^S_j s_{ijt})r_{iht}+e^n_{ijt} \qquad \text{(A2)}
\end{aligned}$$

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

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, $\alpha^{S,\mu}_{ij}$ and number of buyers premium, $\alpha^{S,n}_{ij}$

$$\alpha^S_{ijt} = \alpha^{S,\mu}_{ijt} + \alpha^{S,n}_{ijt} + \alpha^{S,j}_{ijt} \qquad \text{(A3)}$$

where $\alpha^{S,\mu}_{ijt} \equiv \alpha^U_{ijt}\left[\left(\frac{\bar{\mu}^S_{ijt}}{\bar{\mu}^U_{ijt}}\right)^{\eta-1}-1\right]$, $\alpha^{S,n}_{ijt} \equiv \alpha^U_{ijt}\left[\frac{n(\Omega^S_{ijt})}{n(\Omega^U_{ijt})}-1\right]$, $\alpha^{S,j}_{ijt} \equiv \alpha^U_{ijt}\left[\left(\frac{\bar{\mu}^S_{ijt}}{\bar{\mu}^U_{ijt}}\right)^{\eta-1}-1\right]\left[\frac{n(\Omega^S_{ijt})}{n(\Omega^U_{ijt})}-1\right]$. We distinguish a common market-year components from those that vary across firms so that we can express revenue function (3) as

$$r_{ijt} = [\alpha^U_{jt} + (\alpha^{S,\mu}_{jt} + \alpha^{S,n}_{jt} + \alpha^{S,j}_{jt})s_{ijt}]r_{iht} + e_{ijt} \qquad \text{(A4)}$$

where $\mathbb{E}[\alpha^{S,\mu}_{ijt}] = \alpha^{S,\mu}_{jt}$, $\mathbb{E}[\alpha^{S,n}_{ijt}] = \alpha^{S,n}_{jt}$ and $\mathbb{E}[\alpha^{S,j}_{ijt}] = \alpha^{S,j}_{jt}$. As such, potential exporters may have information about any subcomponent of α^S_{jt}, 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 equation (3) the number of buyers each exporter has in market j and year t yields:

$$\frac{r_{ijt}}{n_{ijt}} = (\gamma_{jt}^{U} + \gamma_{j}^{S} s_{ijt}) r_{iht} + e_{ijt} \tag{A5}$$

where $\frac{\gamma_j^S}{\gamma_{jt}^U} = \left(\frac{\bar{\mu}_j^S}{\bar{\mu}_{jt}^U}\right)^{\eta-1} - 1$ and we have again imposed the assumption that TC support premia do not vary over time. We can then compute the quality demand premium subcomponent as $\alpha_{jt}^{S,\mu} = \alpha_{jt}^{U}\left(\frac{\gamma_j^S}{\gamma_{jt}^U}\right)$ which in turn allows to the number of buyers premium $\left[\frac{n_{jt}^S}{n_{jt}^U} - 1\right] = \frac{\alpha_j^S - \alpha_j^{S,\mu}}{\alpha_{jt}^U(1+\gamma_{jt}^S/\gamma_{jt}^U)}$. Using the estimated value of $\left[\frac{n_{jt}^S}{n_{jt}^U} - 1\right]$ we can then recover the remaining components, $\alpha_{jt}^{S,n}$ and $\alpha_{jt}^{S,j}$, as $\alpha_{jt}^{S,n} = \alpha_{jt}^{U}\left[\frac{n_{jt}^S}{n_{jt}^U} - 1\right]$ and $\alpha_{jt}^{S,j} = \alpha_{jt}^{U}\left[\left(\frac{\bar{\mu}_{jt}^S}{\bar{\mu}_{jt}^U}\right)^{\eta-1} - 1\right]\left[\frac{n_{jt}^S}{n_{jt}^U} - 1\right]$. With demand subcomponents in hand, we test whether unsupported and TC supported firms are likely to know to number or quality of potential buyers in export markets.

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}^0 and γ_j^1 from the OLS regression of equation (A5), conditional on $r_{ijt} > 0$). Second, using the estimates of γ_{jt}^0 and γ_{jt}^1 along with our previous estimates of α_{jt}^U and α_{jt}^N, we compute $\alpha_{jt}^{S,\mu} = \alpha_{jt}^U \frac{\gamma_j^S}{\gamma_{jt}^U}$, $\alpha_{jt}^{S,n} = \frac{\alpha_j^S - \alpha_{jt}^{S,\mu}}{1+\gamma_j^S/\gamma_{jt}^U}$ and $\alpha_{jt}^{S,n\mu} = \frac{\gamma_j^S}{\gamma_{jt}^U}\frac{\alpha_j^S - \alpha_{jt}^{S,\mu}}{1+\gamma_j^S/\gamma_{jt}^U}$.

B Estimation Details

B.1 Perfect knowledge of exporter information sets

Consider a setting where the information set specified by the researcher, $\mathcal{J}_{ijt}^a$ is the same as that used by the firm for its export decision, $\mathbb{E}[r_{ijt}|\mathcal{J}_{ijt}] = \mathbb{E}[r_{ijt}|\mathcal{J}_{ijt}^a]$, 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[25]

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

[25]For parsimony, there is a slight abuse of notation in equation A6 where we allow θ^T to stand in for θ^S or θ^U for supported and unsupported firms, respectively.

where

$$\mathcal{P}(D_{jt} = 1|\mathcal{J}^a_{ijt}, s_{ijt}, dist_j; \theta) = \Phi(\theta_2^{-1}(\eta^{-1}\mathbb{E}[r^o_{ijt}|\mathcal{J}^a_{ijt}] - \theta_0^T - \theta_1^T dist_j)). \tag{A6}$$

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 (A6), wrongly assuming perfect foresight will induce bias in the fixed cost parameters.[26]

B.2 Moment Inequality Estimation

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

[26]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[27]

$$\mathcal{M}_{ob}^{T}(Z_{ijt};\theta^{T}) = \mathbb{E}\left[\begin{array}{c} m_{ob}^{l,T}(D_{ijt}, r_{ijt}^{o}, dist_{j}, s_{ijt});\theta^{T} \\ m_{ob}^{u,T}(D_{ijt}, r_{ijt}^{o}, dist_{j}, s_{ijt});\theta^{T} \end{array} \middle| Z_{ijt}\right] \geq 0, \tag{A7}$$

where

$$m_{ob}^{l,T}(\cdot) = D_{ijt}\frac{1-\Phi((\theta_2^T)^{-1}(\eta^{-1}r_{ijt}^{o}-\theta_0^T-\theta_1^T dist_j))}{\Phi((\theta_2^T)^{-1}(\eta^{-1}r_{ijt}^{o}-\theta_0^T-\theta_1^T dist_j))} - (1-D_{ijt}) \tag{A8}$$

$$m_{ob}^{u,T}(\cdot) = (1-D_{ijt})\frac{\Phi((\theta_2^T)^{-1}(\eta^{-1}r_{ijt}^{o}-\theta_0^T-\theta_1^T dist_j))}{1-\Phi((\theta_2^T)^{-1}(\eta^{-1}r_{ijt}^{o}-\theta_0^T-\theta_1^T dist_j))} - D_{ijt}. \tag{A9}$$

In a full information setting conditions (A8) and (A9) are, in expectation, individually equal to zero at the true parameter vector θ^T. In our case, however, conditions (A8) and (A9) 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 (A9) 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 (A9) will hold at $\theta = \theta^{*}$. Similar logic applies to condition (A8).[28]

[27] For parsimony, conditions (A8)-(A9) 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.

[28] Intuitively, by revealed preference equation (5) 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 $\mathbb{E}\left[(1-D_{ijt})\frac{\Phi(\sigma^{-1}(\eta^{-1}\mathbb{E}[r_{ijt}^{o}\mathcal{J}_{ijt}]-\beta_0^T-\beta_1^T dist_j))}{1-\Phi(\sigma_T^{-1}(\eta^{-1}\mathbb{E}[r_{ijt}^{o}\mathcal{J}_{ijt}]-\beta_0^T-\beta_1^T dist_j))} - D_{ijt}\middle| \mathcal{J}_{ijt}, dist_j\right] = 0$, 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

$$\mathcal{M}_{rp}^{T}(Z_{ijt};\theta^{T}) = \mathbb{E}\left[\begin{array}{c} m_{l}^{r}(D_{ijt}, r_{ijt}^{o}, dist_{j}, s_{ijt});\theta^{T} \\ m_{rp}^{u,d}(D_{ijt}, r_{ijt}^{o}, dist_{j}, s_{ijt});\theta^{T} \end{array} \Big| Z_{ijt}\right] \geq 0, \tag{A10}$$

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 (A10), for an exporter, $D_{ijt} = 1$.[29] Expectations, conditional on $(D_{ijt}, \mathcal{J}_{ijt}, dist_{j}, s_{ijt})$, yields

$$D_{ijt}(\eta^{-1}\mathbb{E}[r_{ijt}|\mathcal{J}_{ijt}] - \beta_{0}^{T} - \beta_{1}^{T}dist_{j}) + S_{ijt} \geq 0 \tag{A11}$$

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 (A11) becomes weaker as long as $\frac{\phi(\cdot)}{\Phi(\cdot)}$ is convex. Under this assumption, if (A11) holds at $\theta = \theta^{*}$, then (A10) and (A11) will also hold at $\theta = \theta^{*}$.[30]

$\mathbb{E}[r_{ijt}^{o}\mathcal{J}_{ijt}]$ and applying Jensen's inequality, we recover equation (A9) due to the convexity of $\frac{\Phi(\cdot)}{1-\Phi(\cdot)}$.

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

[30] 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 $g^T(\cdot)$:

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

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 $g_a^T(\cdot)$:

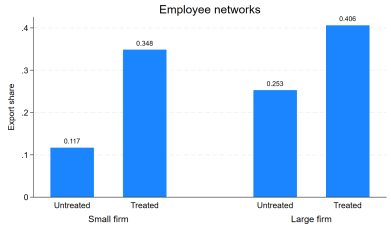
$$g_a^T(Z_{ijt}) = \left\{\begin{array}{l} \mathbb{1}\{r_{iht-1} > med(r_{iht-1}|s_{ijt})\} \times (|r_{iht-1} - med(r_{iht-1}|s_{ijt})|)^a, \\ \mathbb{1}\{r_{iht-1} \leq med(r_{iht-1}|s_{ijt})\} \times (|r_{iht-1} - med(r_{iht-1}|s_{ijt})|)^a, \\ \mathbb{1}\{R_{jt-1} > med(R_{jt-1}|s_{ijt})\} \times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

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, $\Theta_{95\%}^T$.

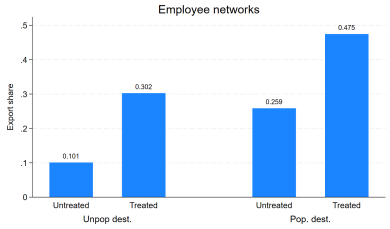
C Additional Figures

Figure A1: Export Share Across TC Firm Networks

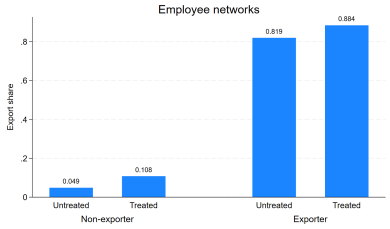
(a) Firm Size & Emp. Net.



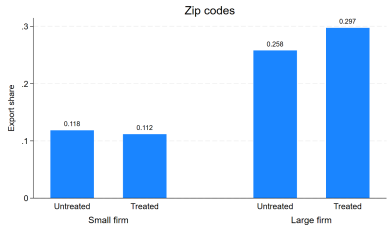
(b) Dest. Pop. & Emp. Net.



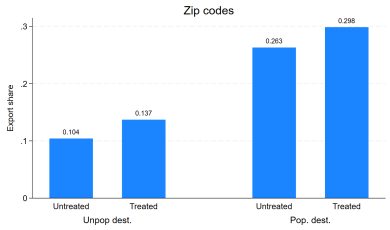
(c) Exp. Status & Emp. Net.



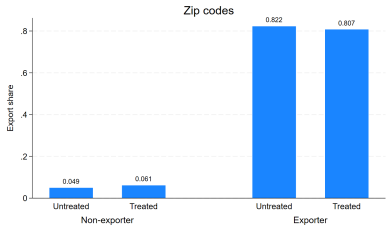
(d) Firm Size & Zipcode



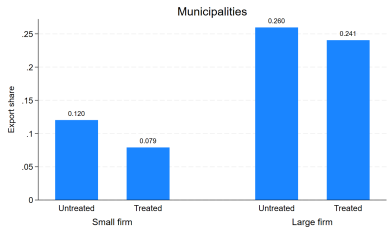
(e) Dest. Popularity & Zipcode



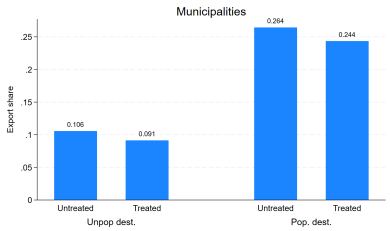
(f) Export Status & Zipcode



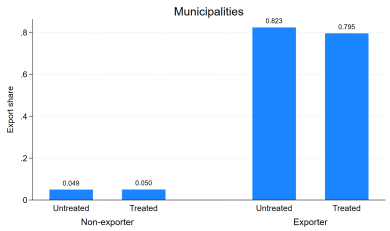
(g) Firm Size & Municipality



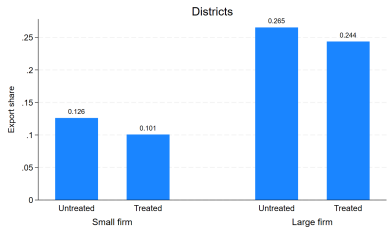
(h) Dest. Popularity & Mun.



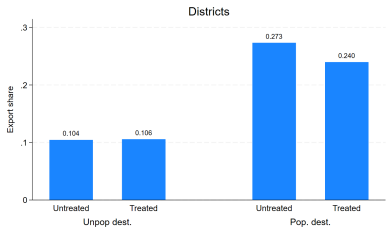
(i) Export Status & Mun.



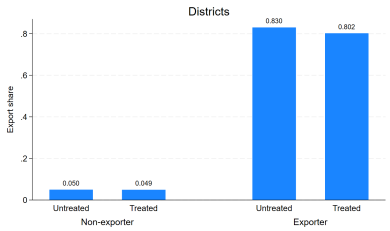
(j) Firm Size & District



(k) Dest. Popularity & District



(l) Export Status & District



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)), firms that have a supported neighbour in the same municipality (panels (g)-(i)), and firms that have a supported neighbour in the same municipality (panels (j)-(l)).

D Additional Tables

Table A1: Fixed Cost Parameter estimates, 1,000 DKK; Unsupported firms

Estimator	σ_U	β_0^U	β_1^U
Perfect foresight (MLE)	1,339	1,033	566
Minimal info. (MLE)	911	738	423
Moment inequality	[314; 471]	[326; 480]	[146; 243]
Moment inequality, IV	[320; 471]	[330; 471]	[155; 249]

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 firms

Estimator	USA	China	Norway
Perfect foresight (MLE)	7,262	7,336	5,322
Minimal info. (MLE)	5,256	5,311	3,808
Moment inequality	[450; 648]	[454; 655]	[336; 493]
Moment inequality, IV	[459; 648]	[463; 655]	[340; 484]

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	β_0	β_1	γ_0	γ_1
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: Testing the content of information sets; support status; no. of buyers

		Number of buyers			
		Unsupported		Supported	
Firms	Markets	Ind. p-value	Adj. p-value	Ind. p-value	Adj. p-value
Panel C: Minimal information & country shifter					
All	All	0	0	0.708	0.708
Panel D: Minimal information & country shifter across firm and destination groups					
Large	Popular	0.338	0.355	0.16	1
Large	Unpopular	0.178	0.355	0.598	1
Small	Popular	0	0	0.574	1
Small	Unpopular	0	0	0.63	1
Large exporter	All	0.007	0.021	0.496	1
Large non-exporter	All	0	0	0.002	0.012
Small exporter	All	0	0	0.383	1
Small non-exporter	All	0	0	0.602	1
Panel E: Minimal information & country shifter across destinations					
All	Australia	0.054	0.216	0.369	1
All	China	0.003	0.015	0.62	1
All	India	0.025	0.123	0.189	1
All	Japan	0.338	0.821	0.202	1
All	Norway	0.377	0.821	0.506	1
All	Russia	0	0	0.586	1
All	Turkey	0	0	0.643	1
All	U.S.	0.274	0.821	0.664	1
Panel F: Minimal information & country shifter across call status					
Called	All	0.438	0.438	0.652	1
Not called	All	0.001	0.001	0.645	1

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 A6: Testing the content of information sets; support status; buyer quality

		Buyer Quality			
		Unsupported		Supported	
Firms	Markets	Ind. p-value	Adj. p-value	Ind. p-value	Adj. p-value
Panel C: Minimal information & country shifter					
All	All	0.04	0.04	0.681	0.681
Panel D: Minimal information & country shifter across firm and destination groups					
Large	Popular	0.342	0.342	0.082	0.571
Large	Unpopular	0.02	0.039	0.605	1
Small	Popular	0	0	0.59	1
Small	Unpopular	0	0	0.634	1
Large exp.	All	0.009	0.026	0.517	1
Large non-exp.	All	0	0	0	0
Small exp.	All	0	0	0.472	1
Small non-exp.	All	0	0	0.572	1
Panel E: Minimal information & country shifter across destinations					
All	Australia	0.048	0.19	0.37	1
All	China	0.004	0.021	0.632	1
All	India	0.015	0.075	0.262	1
All	Japan	0.342	0.813	0.194	1
All	Norway	0.368	0.813	0.506	1
All	Russia	0	0	0.586	1
All	Turkey	0	0	0.643	1
All	U.S.	0.271	0.813	0.658	1
Panel F: Minimal information & country shifter across call status					
Called	All	0.48	0.48	0.625	1
Not called	All	0.031	0.061	0.643	1

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 A7: Testing the content of information sets; support interaction term (only supported firms)

Firms	Markets	Ind. p-value	Adj. p-value
Panel C: Minimal information & country shifter			
All	All	0.686	0.686
Panel D: Min. info. & country shifter, firm and destination groups			
Large	Popular	0.112	0.784
Large	Unpopular	0.592	1
Small	Popular	0.612	1
Small	Unpopular	0.633	1
Large exp.	All	0.512	1
Large non-exp.	All	0.003	0.02
Small exp.	All	0.524	1
Small non-exp.	All	0.581	1
Panel E: Min. info. & country shifter across destinations			
All	Australia	0.361	1
All	China	0.62	1
All	India	0.262	1
All	Japan	0.198	1
All	Norway	0.532	1
All	Russia	0.586	1
All	Turkey	0.64	1
All	U.S.	0.658	1
Panel F: Min. info. & country shifter across call status			
Called	All	0.647	1
Not called	All	0.684	1

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 A8: Testing the content of information sets; supported worker-firms; adjusted p-values

Uninformed Informed Firms	Markets	None All Unsupported	Unsupported Worker-Firms Supported Worker-Firms
Panel B: Minimal information & country shifter across firm and destination groups			
Large	Popular	0.318	1
Large	Unpopular	0.005	1
Small	Popular	0	0.045
Small	Unpopular	0	1
Large exporter	All	0.018	1
Large non-exporter	All	0	0
Small exporter	All	0	0.007
Small non-exporter	All	0	1
Panel C: Minimal information & country shifter across destinations			
All	Australia	0.190	1
All	China	0.021	1
All	India	0.058	1
All	Japan	0.815	1
All	Norway	0.815	1
All	Russia	0	1
All	Turkey	0	1
All	U.S.	0.815	1
Panel D: Minimal information & country shifter across call status			
Called	All	0.481	0.745
Not called	All	0.780	0.745
No. of Uninformed Obs.		0	20053
No. of Informed Obs.		21064	1011

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 A9: Testing the content of infor. sets; supported regions; adj. p-values; no. of buyers

Uninformed Informed Firms	Markets	All Unsup. None	Unsup. Zips Sup. Zips	Unsup. Muni. Sup. Muni.	Unsup. Dist. Sup. Dist.
Panel B: Minimal information & country shifter across firm and destination groups					
Large	All	0.317	0.953	1	0.818
Small	All	0	0.282	1	0.434
All	Popular	0	0.953	1	0.818
All	Unpopular	0	0.953	0	0
Exporter	All	0	0	1	0.818
Non-exporter	All	0	0	0	0
Panel C: Minimal information & country shifter across destinations					
All	Australia	0.216	0.154	1	0.761
All	China	0.015	1	1	0.735
All	India	0.123	0.765	1	0.735
All	Japan	0.821	1	1	0.723
All	Norway	0.821	1	1	0.761
All	Russia	0	0.010	0	0
All	Turkey	0	1	0.013	0.039
All	U.S.	0.821	1	1	0.761
Panel D: Minimal information & country shifter across call status					
Called	All	0.438	0.755	1	0.617
Not called	All	0.001	0.755	1	0.617
No. of Uninformed Obs.		21064	20432	19421	11627
No. of Informed Obs.		0	632	1643	9437

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. Adjusted p-values account for multiple testing.

Table A10: Testing the content of infor. sets; supported regions; adj. p-values; buyer quality

Uninformed Informed Firms	Markets	All Unsup. None	Unsup. Zips Sup. Zips	Unsup. Muni. Sup. Muni.	Unsup. Dist. Sup. Dist.
Panel B: Minimal information & country shifter across firm and destination groups					
Large	All	0.239	0.933	0.134	0.231
Small	All	0.002	0.933	0	0
All	Popular	0	0.933	1	0.529
All	Unpopular	0	0.080	0.008	0
Exporter	All	0	0	1	0.529
Non-exporter	All	0	0	0	0
Panel C: Minimal information & country shifter across destinations					
All	Australia	0.190	0.221	1	0.876
All	China	0.021	1	1	0.876
All	India	0.075	0.855	0.986	0.585
All	Japan	0.813	1	1	0.625
All	Norway	0.813	1	1	0.876
All	Russia	0	0.036	0	0
All	Turkey	0	1	0.013	0.032
All	U.S.	0.813	1	1	0.876
Panel D: Minimal information & country shifter across call status					
Called	All	0.480	0.686	0.971	0.462
Not called	All	0.061	0.686	1	0.024
No. of Uninformed Obs.		21064	20432	19421	11627
No. of Informed Obs.		0	632	1643	9437

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. Adjusted p-values account for multiple testing.

Table A11: Testing the content of information sets; supported worker-firms; adjusted p-values; no. of buyers

Uninformed		None	Unsupported Worker-Firms
Informed		All Unsupported	Supported Worker-Firms
Firms	Markets		
Panel B: Minimal information & country shifter across firm and destination groups			
Large	All	0.613	1
Small	All	0.613	0.058
All	Popular	0	1
All	Unpopular	0	1
Exporter	All	0	1
Non-Exporter	All	0	0
Panel C: Minimal information & country shifter across destinations			
All	Australia	0.216	1
All	China	0.015	1
All	India	0.123	1
All	Japan	0.821	1
All	Norway	0.821	1
All	Russia	0	1
All	Turkey	0	1
All	U.S.	0.821	1
Panel D: Minimal information & country shifter across call status			
Called	All	0.438	0.745
Not called	All	0.001	0.745
No. of Uninformed Obs.		0	20053
No. of Informed Obs.		21064	1011

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 A12: Testing the content of information sets; supported worker-firms; adjusted p-values; buyer quality

Uninformed		None	Unsupported Worker-Firms
Informed		All Unsupported	Supported Worker-Firms
Firms	Markets		
Panel B: Minimal information & country shifter across firm and destination groups			
Large	All	0.626	0.023
Small	All	0	0.915
All	Popular	0.626	0.004
All	Unpopular	0.090	0.915
Exporter	All	0.046	0
Non-Exporter	All	0	0
Panel C: Minimal information & country shifter across destinations			
All	Australia	0.190	0
All	China	0.021	0
All	India	0.075	0.942
All	Japan	0.813	0.003
All	Norway	0.813	0.942
All	Russia	0	0.040
All	Turkey	0	0.942
All	U.S.	0.813	0
Panel D: Minimal information & country shifter across call status			
Called	All	0.480	0.888
Not called	All	0.061	0.888
No. of Uninformed Obs.		0	20053
No. of Informed Obs.		21064	1011

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.