Information Spillovers for Export Markets*

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Abstract

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

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

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1 Introduction

Government subsidized export support is often justified by claiming that greater export participation is socially desirable and that industrial policy can remedy market failures. However, evidence that export-oriented industrial policy generates public benefits is lacking. This paper provides evidence that government support programs create informational spillovers through firm networks, demonstrating the public good nature of export support. We find that informational spillovers from the Danish Trade Council boost exports by 1–2 percent annually in the Danish machinery industry.

Information frictions are well-established impediments to firm and industry exports (Allen, 2014; Atkin et al., 2017; Dickstein and Morales, 2018; Steinwender, 2018). However, private information frictions alone do not justify public intervention. The critical point is that information networks generate large spillovers for firms (Fernandes and Tang, 2014; Mion and Opromolla, 2014; Kamal and Sundaram, 2016; Cai and Szeidl, 2017; Bisztray et al., 2018; Chaurey et al., 2025) and 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), suggesting that trade-relevant information has public good characteristics—it is at least partially non-excludable (Fernandes and Tang, 2014; Wei et al., 2021). This raises a central question: If export support programs create informational public goods, can they improve firm outcomes on export markets? This paper addresses four related questions: How does information spread across firms through export support? What specific knowledge do firms gain? Are the resulting gains large enough to justify public intervention?

This study establishes three novel results regarding informational spillovers in export markets. First, we document that the Danish Trade Council (TC) improves exporters' knowledge of foreign markets, beyond any direct cost reductions or demand effects. Second, export information spills over to unsupported firms that are peers of supported firms. While supported firms and their peers gain knowledge of export markets, firms without supported peers typically do not. This confirms that export support creates a public good that can address market failures where entry is too low. Third, these spillovers are economically significant. Using our structural model, we separate the public gains from TC support from the private benefits to

supported firms. Information spillovers alone increase aggregate exports by 1–2 percent annually among unsupported firms. We establish these findings through a unique empirical setting, partial identification methods, and a structurally-identified quantitative trade model.

Figure 1 illustrates the network benefits of export-oriented industrial policy using firm-level network data. We focus on unsupported firms—those not directly supported by the TC—comparing export propensity between firms indirectly linked to the TC through employee or geographic networks versus those completely unconnected to the TC. We find that indirectly TC-linked firms are substantially more likely to export, with differences most pronounced for small firms and unpopular destinations—contexts where information frictions are acute. While suggestive these patterns could reflect alternative explanations: selection bias, forward-looking policy targeting, or differences in costs and demand.

We address these concerns by exploiting a natural experiment to characterize how policy-relevant trade information diffuses. The Danish TC approaches firms with export support offers quasi-randomly (Buus et al., 2025), providing quasi-random variation in information access. This contributes to research quantifying the role of information frictions in international trade (Steinwender, 2018; Criscuolo et al., 2019).

Critically, TC outreach is firm-specific, allowing us to identify precisely which firms receive new export market information. As in Fernandes and Tang, 2014, Bisztray et al., 2018 and Chaurey et al., 2025, we construct firm-level peer networks to study indirect TC spillovers and estimate their downstream effects.[1] We document that firms connected to the TC only through supported peers benefit from TC export information, despite lacking direct TC contact.

The quasi-experimental data yield particularly novel insights when combined 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 econometric approaches require strong ex-ante assumptions about firms' information sets and how information diffuses. The moment inequality approach offers a key advantage: we recover model parameters without specifying which firms possess particular information or how it spreads across networks.

[1]Like Wei et al., 2021, we use this setting to identify the firm-level source of information and measure its impact on peers through networks.

Our approach complements concurrent experimental studies on export support and firm networks. Ali et al., 2025 experimentally examine how fixed market access costs affect export outcomes in Tunisia, while González et al., 2025 study export logistics in Argentina. Unlike these papers, we focus on demand-side information, consistent with evidence from Denmark (Buus et al., 2025). We also complement Chaurey et al., 2025, who examine technological information spillovers across firms. We instead quantify how market-specific demand information diffuses through firm networks.

Following Dickstein and Morales, 2018, we conduct information tests to characterize the public nature of export support. First, we confirm that TC-supported firms are better informed than unsupported firms—a result consistent with historical documentation. Using moment inequality specification tests (Bugni et al., 2015), we reject the hypothesis that unsupported, unconnected firms know more than minimal export market characteristics: past aggregate exports, distance from Denmark, and their own past domestic sales.[2] In contrast, the same tests show that TC support closes informational gaps for supported firms.

These findings align with modern trade policy research (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 the trade-information literature (Allen, 2014; Atkin et al., 2017; Dickstein and Morales, 2018; Steinwender, 2018). Critically, they demonstrate that industrial policy can address informational externalities (Juhász et al., 2024a).[3]

Building on this finding, we construct firm-level networks to investigate whether unsupported firms connected to supported firms are better informed about export markets. We develop two types of networks. Employment networks link an unsupported firm to the TC indi-

[2]Important exceptions exist. Among unsupported firms, we cannot reject that large firms and past exporters know export demand conditions, reminiscent of bidding behavior differences between large and small producers in electricity markets (Hortaçsu and Puller, 2008; Hortaçsu et al., 2019).

[3]In related work, Carballo et al., 2023 study how investment support reduces information frictions, but do not examine firm-level spillovers.

rectly if it hires an employee who previously worked for a supported firm during the support period. Employment networks reveal *how* information diffuses across firms within the same industry. Geographic networks link firms in the same region, allowing us to test how information decays over distance.[4] These complementary network approaches contribute to understanding industrial policy's value in networked settings (Liu, 2019).

We find consistent evidence that information spills over from supported firms to unsupported peers in the same network. These informational spillovers are particularly strong for less popular export markets, such as China, India, and Turkey. Geographic networks reveal a similar pattern: spillovers are strongest among unsupported firms in the same zip code as a supported peer. Consistent with Bisztray et al., 2018, the strongest informational spillovers are *localized* in nature.

To characterize what information diffuses, we decompose market demand into two components: buyer quality in a given location and the number of buyers. Closely-linked unsupported firms learn both the number of buyers and typical buyer quality. Weakly-linked firms learn the number of buyers but lack reliable knowledge of buyer quality. Thus, while information does spill over across firms, the spillovers are incomplete and depend on network proximity.

We quantify the aggregate economic value of informational spillovers using counterfactual experiments. Information spillovers alone increase aggregate exports by 1–2 percent annually. These gains operate primarily through improved sorting: profitable exporters expand into foreign markets, while unprofitable firms avoid costly entry. Information thus improves the composition of exporters rather than dramatically increasing entry rates. These results validate TC support programs and contribute to the literature on network effects in 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), industrial policy (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; Juhász et al., 2024b; Lane, 2025).

[4]Information decay in our setting parallels the concept of economic dispersion in Feyrer et al., 2017, where firms farther from an informational shock are less likely to benefit from it.

We investigate whether targeted program design could maximize public benefits from TC support. We compare three assignment strategies: random allocation, targeting firms with the highest private returns, and targeting the most-connected firms. Targeting connected firms generates the greatest public benefits when informational spillovers are present.

Our findings contribute to the literature on firm-level export support programs. Early studies using state-level data find limited effects (Bernard and Jensen, 2004; Görg et al., 2008). In contrast, research using disaggregated firm-level data—like ours—consistently shows that export support improves firm outcomes (Volpe Martincus and Carballo, 2008; Volpe Martincus and Carballo, 2010a; Volpe Martincus and Carballo, 2010b; Volpe Martincus and Carballo, 2010c; Van Biesebroeck et al., 2015; Buus et al., 2025). Munch and Schaur, 2018 provide causal evidence that support services drive export success, while Buus et al., 2025 show that Danish TC support increases export quantities without substantially affecting prices, costs, or product characteristics.

Our work builds on these findings but advances the literature in two ways. First, we quantify the information spillovers to unsupported firms. Second, we characterize how information diffuses across firm networks. These contributions address the call in Goldberg and Pavcnik, 2016 to better understand 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

The Danish Trade Council (TC) administers all Danish export support programs. Support services are tailored to individual firms and delivered through Danish embassies and consulates

abroad. Although firms must purchase these services from the TC, prices are heavily subsidized.

TC export support programs have one key feature: they primarily target informational frictions, though they may also affect demand or entry costs.[5] The most frequently purchased services fall into three categories. Partner search services include matchmaking, meeting facilitation, and network integration to connect Danish firms with foreign partners and mitigate supply chain risks. Foreign marketing services support participation in fairs, exhibitions, conferences, and other promotional events. Market intelligence services provide formal market analysis, regulatory guidance, and market monitoring. Across all three categories, the TC's role is fundamentally informative.

Second, TC support is firm-, industry-, and destination-specific. The TC tailors services to individual firms, targeting specific products and markets. This specialization means information is highly specialized and delivery remains private between the TC and firm. Consequently, identifying supported firms allows us to trace the origin of new, industry- and destination-specific information within firm networks.

Third, the TC proactively approaches individual firms with service offers. Each embassy and consulate independently conducts outreach for their target destination, with no centralized strategy or coordination. Instead, each embassy or consulate approaches firms solely based on information about industry-specific conditions in the target destination market. As documented by Buus et al., 2025 and Section 4, within any industry-destination pair, firm selection is quasi-random.

Our data distinguishes between three firm types: firms approached by the TC, firms that

[5]This interpretation is supported by existing evidence and firm surveys. Buus et al., 2025 show that TC support does not significantly affect firm-level costs, markups, prices, or product quality. It does find a significant impact of TC support on export demand. Section 6 presents benchmark evidence on TC support's effects on firm demand and entry costs. The TC also surveys a subset of firms that participate in TC support programs. Nearly 40 percent of firms report that the TC programs significantly improved the firm's knowledge about target export markets, while over half report greater export sales. In contrast, only 4 percent report any cost savings from TC support programs.

purchased TC services, and firms that did both. This variation allows us to identify two groups of supported firms: those who sought out TC services independently and those who learned about them through quasi-random TC outreach.

Variation in support and outreach status across firms illuminates information barriers. For instance, a non-trivial number of firms decline TC offers despite being contacted. We test whether these decliners possess information similar to supported firms or to unsupported firms.

Variation in support and TC outreach across firm networks reveals information diffusion patterns. We distinguish two groups of unsupported firms: those in entirely unsupported networks and those connected to supported firms. Using quasi-exogenous variation in peers' information sets, we test whether better-informed peers generate information spillovers across networks.

3 Empirical Model

Firms located in network location l of home market h decide whether to export to each destination market $j = 1, ..., J$ at time $t = 1, ..., \mathcal{T}$. Following Dickstein and Morales, 2018, we develop a model where firms first choose export destinations while incurring a fixed export cost in each market.[6] Conditional on entry, firms then set prices optimally to maximize profits. Firms may have heterogeneous information and beliefs about future profits when choosing export destinations, but information does not differ across firms after entry.

3.1 Demand, Costs, Information

In each country, firms face an isoelastic demand curve $x_{ijlt} = \xi_{ijlt}^{\eta-1} p_{ijt}^{-\eta} P_{jt}^{\eta-1} Y_{jt}$, where ξ_{ijlt} is an idiosyncratic demand shifter and η is the demand elasticity. Export demand differs between firms supported (S) by the TC and unsupported firms (U), which we denote by $T \in S, U$. Let s_{ijt} be an indicator variable equal to one for supported firms and zero otherwise.

We specify the firm-level demand shifter ξ_{ijt} as a CES composite of two components: the

[6] We later relax this assumption to characterize differences in entry costs across new and incumbent exporters.

demand shifter the firm would receive without support, ξ^U_{ijt}, and an additional demand premium from support,[7] ξ^S_{ijt}:

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

We abstract from network demand spillovers for notational simplicity, though the model allows for informational spillovers. Section 6 shows that our data provide little evidence of demand spillovers, while Appendix A presents an extended model that includes both demand and informational spillovers.

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 indicates that fixed costs may differ between supported and unsupported firms.[8] Exporting firm i pays fixed export costs f_{ijt} in market j according to:

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

where $dist_j$ is the distance between country h and country j, and $\nu^T ijt$ represents all fixed cost determinants unobserved by the researcher.

A firm's potential sales revenue in market j at time t is $r_{ijt} = p_{ijt}x_{ijt}$, and $\mathcal{J}ijlt$ represents firm i's information about market j. We adopt standard assumptions from Dickstein and Morales, 2018: firm i's information set $\mathcal{J}ijlt$ includes *some* determinants of r_{ijt} and *all* determinants of fixed costs f_{ijt} when the firm decides whether to export to country j. Following Buus et al., 2025, unsupported firms do not benefit from additional TC-driven demand, even if they gain information about demand conditions through peer networks (reflected in $\mathcal{J}_{ijlt}$). The network subscript l emphasizes that information may vary systematically across firm networks.

[7] As shown in Appendix B.2, this specification is consistent with TC programs that affect the number of buyers firm i reaches in destination j, the quality of those buyers, or both.

[8] We could allow variable trade costs to vary by support status through τ_{ijt}. We abstract from this possibility because (i) variable trade cost shocks are isomorphic to demand shocks in the revenue function, and (ii) existing evidence for Denmark (Buus et al., 2025) suggests TC support operates primarily through demand channels.

Critically, knowledge of demand conditions and their realized level are distinct objects—a key feature of our analysis that we develop further below.

3.2 Export Revenue

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

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

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

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

are the demand shifters among unsupported and supported firms, respectively. We decompose equation (2) into three components: α^U_{jt} common to all firms in a given market-year pair, α^S_{jt}; common to supported firms in the same market-year pair; and e_{ijlt}, which varies across firms:

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

Here, e_{ijlt} accounts for unexpected, firm-, market-, and year specific revenue shocks:

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

Although e_{ijlt} is unknown prior to entry, we do not restrict how the information set $\mathcal{J}_{ijlt}$ relates to the predictable component of revenue, $(\alpha^U_{ijlt} + \alpha^S_{ijlt}s_{ijt})r_{ihlt}$. Firms may have systematically better information about specific markets based on characteristics such as size, export experience, TC contact, or network connections to TC-supported firms. Similarly, information sets $\mathcal{J}_{ijlt}$ and $\mathcal{J}_{i'jl't}$ can differ arbitrarily across firms i and i' depending on their firm networks and other firm-level mechanisms for information transmission and spillovers. Appendix A provides assumptions on the distribution of demand shifters and variable trade costs under which

the mean independence condition (4) holds.

3.3 Export Profits and the Decision to Export

Firm i earns export profits $\pi_{ijlt} = \eta^{-1} r_{ijlt} - f_{ijt}$ if it exports to market j in year t. Firms export when expected profits are positive: $\mathbb{E}[\pi_{ijt}|\mathcal{J}_{ijlt}, s_{ijt}, dist_j, \nu^T_{ijt}] \geq 0$. Let D_{ijlt} be an indicator for whether firm i exports to market j in year t. The export probability for unsupported firms follows a probit model:

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

where ϕ and Φ denote the standard normal probability density function and cumulative distribution function, respectively, and $\mathbb{1}\{\cdot\}$ is an indicator function. For supported firms, the export decision follows the same form with two differences: supported firms face larger expected demand, $\alpha^U_{jt} + \alpha^S_{jt}$, and potentially lower fixed costs, $\beta^S_0 + \beta^S_1 dist_j + \nu^S_{ijt}$.

Specification (5) presents four identification challenges. First, as is common in the literature, export data alone cannot separately identify $(\sigma_T, \beta^T_0, \beta^T_1)$ from η. We therefore set $\eta = 5$, a mid-range value standard in the literature (Anderson and Wincoop, 2004; Parro, 2013; Simonovska and Waugh, 2014).

Second, equation (5) requires integrating over ν^T_{ijt}, which depends on the firm's expected revenue in market j in year t—and thus its information set. Researchers rarely observe firm expectations or information sets. We employ moment inequality estimation to relax standard informational assumptions without imposing them in estimation.

Third, firms may endogenously self-select into TC support, potentially biasing fixed cost estimates. We use the TC outreach program to recover unbiased estimates fixed cost among supported firms by characterizing fixed costs among firms that are quasi-randomly contacted by the TC.

Fourth, TC services likely bundle informational, cost, and demand components. For instance, TC agents simultaneously improve firm information and expand access to buyers in export markets. By structurally estimating model parameters, we disentangle these features of TC support in the firm's export decision, including indirect benefits that unsupported firms receive through informational spillovers over firm networks.

3.4 Discussion and Extensions

The benchmark model permits rich variation in demand, cost, and information across firms, markets, and time. However, it necessarily makes simplifications. Notably, it abstracts from dynamic entry costs (Das et al., 2007; Alessandria and Choi, 2007; Alessandria and Choi, 2014; Alessandria et al., 2021) and assumes no demand differences across firm networks, although it does allow demand to differ between supported and unsupported firms.

We face a trade-off between model parsimony and specification concerns. Parsimonious specifications yield tighter confidence bands and greater power for moment inequality specification tests (Bugni et al., 2015; Dickstein and Morales, 2018) to reject hypotheses about firms' information sets. However, if the model is insufficiently rich, we risk erroneously rejecting hypotheses due to model-imposed restrictions.

Our benchmark specification builds on Dickstein and Morales, 2018 as a natural starting, but we impose no parameter restrictions across directly supported and unsupported firms. We address entry cost concerns by estimating an alternative model with differential entry costs across firm export histories and reexamining the information tests through this augmented model. Regarding demand across firm networks, while we assume no systematic differences by network location, we find no evidence of demand variation across indirectly supported and unsupported firms. For notational simplicity, we therefore abstract from this possibility in our exposition.[9]

[9]See Appendix A for further discussion of this alternative demand structure. Table 3 documents the lack of evidence supporting demand spillovers across firm networks.

4 Data

We use two data samples in our study. An extended sample spanning all manufacturing industries provides suggestive reduced-form evidence of informational spillovers across firm networks. To reduce computational burden, our estimation sample focuses on the machinery manufacturing industry (NACE 28). We use the machinery sample to estimate model parameters, test for informational spillovers, and conduct counterfactual experiments.[10]

We construct each dataset by merging several administrative registers from Statistics Denmark. First, we obtain firm characteristics from the Firm Statistics Register and Firm Accounts Statistics, which cover the population of Danish private firms.

Second, we obtain TC export support data recording purchases by destination and year, whether contact was firm-initiated or TC-initiated, and whether approached firms declined services. Third, we obtain firm-destination export data from Statistics Denmark's International Trade in Goods register, including the value of exports to each importer in each destination-year.

4.1 Estimation Sample: Machinery Manufacturers

We estimate the model using a balanced sample of Danish machinery manufacturers (NACE 28) from 2010 to 2015. We focus on machinery for two reasons: it was the largest manufacturing industry by export value during this period, accounting for 27% of total manufacturing exports in 2010, and machinery firms were frequent buyers of TC export services. We restrict our analysis to 2010–2015 to minimize the influence of the Great Recession. Restricting the sample to firms with positive values for all variables required in estimation (domestic sales, capital, etc.) yields a balanced panel of 532 firms.

The TC does not offer export support services to all destinations, and the export data do not allow us to observe buyers in EU markets. We therefore construct two estimation samples. The first (benchmark) sample includes eight major export destinations outside the EU with at least

[10] In on-going work (Buus et al., 2006), we employ the broad sample under stronger estimation assumptions to further characterize mechanisms driving spillovers across firm networks.

50 Danish exporters in all years and regular TC support activity. These non-EU destinations offer greater potential for meaningful informational frictions due to lower integration. However, Danish exports are heavily concentrated in the EU, resulting in few destination-market-year observations for directly supported firms. While our primary focus is indirectly supported firms in the benchmark sample, the second sample includes EU destinations to validate the informational content of TC support among directly supported firms.

Table 1 presents summary statistics on export and TC support rates, along with differences in domestic and export sales. While exporting is common—particularly to larger and closer destinations—TC support is rare. In the first sample, only 216 firms receive TC support for the most frequently supported destinations.

Columns (4)–(5) confirm that exporters are substantially larger than non-exporters and that export sales from any destination represent a small fraction of domestic sales. Consistent with existing evidence, column (6) shows that supported firms are larger than average Danish producers. Figures 2a and 2b reveal the magnitude of these differences: supported firms have nearly twice the domestic sales and substantially larger destination-specific export sales compared to unsupported firms, despite TC support targeting export rather than domestic performance. Buus et al., 2025 document that these differences primarily reflect selection into TC outreach and that the primary effect of TC support is a large, destination-specific increase in export demand.

4.2 TC outreach across firms

Table 1 presents summary statistics on firms receiving TC calls. Following Buus et al., 2025, TC outreach is quasi-random: while TC employees understand the general size and importance of Danish producers, their call patterns are otherwise random.[11] This quasi-random outreach is valuable for two purposes: it guards against bias in parameter identification and allows us to test the informational nature of TC support.

We corroborate the quasi-random nature of TC outreach using our estimation sample. We classify firms into four size quartiles based on prior-year ($t-1$) revenues. Within each size

[11]For instance, Buus et al., 2025 show that firms with names starting with earlier alphabet letters receive significantly more TC calls.

group, we compare domestic and export sales between firms called by the TC and firms not called. Figures 2c and 2d show that while large firms are more likely to receive TC calls than small firms, there are no significant differences in sales outcomes within each size group.

Figures 2a and 2b (right-most bars) repeat this analysis but compare supported versus unsupported firms rather than called versus non-called firms. We find larger differences by support status, particularly for export sales, likely reflecting that roughly half of supported firms self-select into TC programs. However, the export sales difference is statistically significant only for the smallest firms—a group that also has the smallest absolute sales gap.

4.3 Firm networks

We construct two firm networks based on geography and worker mobility.[12]

4.3.1 Employment Networks

We construct employment networks using employer-employee matched data. An unsupported firm-destination-year observation is indirectly linked to a TC-supported firm if at least one current employee previously worked for a firm that received TC support for the same destination.[13] This definition implicitly assumes that employees retain knowledge acquired at supported firms when they transition to unsupported firms. Using this network definition, we find that 2.2 percent of firm-year-destination observations are indirectly supported by the TC.

4.3.2 Geographic networks

We alternatively construct geographic networks by linking any two firms in the same geographic unit. As a benchmark, we define peer firms as those co-located in the same zip code. A zip code is "supported" if at least one firm in it received TC support in the previous year. We extend

[12] Alternative network definitions, such as strategic partnerships or common buyers, yielded samples too small for statistical testing.

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

this analysis by investigating spillovers across firms in the same wider municipality, using the same definition of support.[14]

Expanding the regional definition offers two advantages. First, it allows us to investigate information decay across geographic units; we expect information differences to be sharpest among tightly co-located firms. Second, it mitigates concerns about small sample sizes. While many zip codes contain supported firms, few unsupported firms have supported peers in the same zip code. We observe 632 firm-destination-year observations in supported zip codes, approximately 3 percent of the total. In contrast, 42 of Denmark's 98 municipalities have at least one supported firm in at least one sample year. This broader geographic definition increases the indirectly supported sample to 8 percent of firm-destination-year observations among unsupported firms, roughly tripling the size compared to the zip code network.

We have over 21,000 unsupported firm-destination-year observations for our information tests; even the 3 percent of zip code observations provides nearly 1,000 cases. However, the much larger number of observations among unsupported firms in unsupported locations raises concerns that differential results may reflect differences in testing power rather than true spillovers. To address this, we employ two approaches. First, we use the EU-inclusive sample, which increases observations across all firm types, although for markets where information frictions are likely weaker. Second, we conduct random assignment placebo tests across network structures to establish the robustness of informational spillovers.

4.4 TC outreach across firm networks

If the TC were aware that support programs create informational spillovers, they might intentionally target well-connected firms. However, the TC outreach mandate contains no such targeting directive, and we find no statistical evidence of this behavior.

[14]Unlike employment networks, geographic networks lack an explicit transmission mechanism for information. However, existing evidence confirms that geographic proximity matters for export entry (Fernandes and Tang, 2014), and information spillovers can operate through unobserved local buyer-seller networks, such as those in Eaton et al., 2022. The data do not provide direct information on buyer-seller relationships.

Panel (a) of Figure 3 compares firm sizes in municipalities that receive TC calls to those that do not. Differences are negligible overall and within firm size groups. Panel (b) shows the same comparison for supported versus unsupported municipalities. Again, indirectly supported firms do not differ significantly across municipalities by size.

Figure 3 overall indicates that TC-generated export information arrives quasi-exogenously to unsupported firms in supported municipalities. Similar patterns hold for all network definitions.

4.5 Extended Sample: All Manufacturing Industries

We construct an extended sample spanning all manufacturing industries from 2002–2021 to provide suggestive reduced-form evidence of informational spillovers. This broader sample allows us to characterize spillovers over a longer time period and across a wider set of firms than our machinery-focused estimation sample.

We employ two approaches to identify indirectly supported firms. First, using employer-employee matched data from 2008–2021, we track worker movements between all manufacturing firms. We identify workers exposed to TC support by matching their employment histories to TC support records from 2002–2015. These workers may transfer information when they transition to new employers. Second, using firm location data from 2002–2021, we construct a geographic network by identifying firm-destination pairs where unsupported firms are co-located with firms from the same industry that received TC support for that destination.

Across both network approaches, we focus on indirectly supported firm-destination pairs—those where unsupported firms gain information through employee transitions or geographic proximity—and exclude directly supported pairs.[15]

[15] See Munch and Schaur, 2018 and Buus et al., 2025 for evaluations of direct TC support effects on firm entry and performance.

4.6 Reduced-Form Evidence

This section provides reduced-form evidence of informational spillovers from supported to unsupported firms using an event study specification and the extended sample. For employment networks, we estimate:

$$D_{ijt} = \alpha_{ij} + \delta_{jt} + \gamma \text{ Size}_{it} + \sum_{k=-5,\ldots,-2,0,\ldots,5} \beta_k \mathbf{1}\{\text{event time}_{ijt} = k\} + \varepsilon_{ijt}^{worker} \quad (6)$$

where D_{ijt} is an indicator variable capturing the export status of firm i in destination j at time t. Event time $k = 0$ is the year unsupported firm i hires a worker with TC-acquired information about destination j. We include firm-destination fixed effects α_{ij} to isolate within-pair variation, destination-year fixed effects δ_{jt} to control for destination-specific demand shocks, and Size_{it} (log employment) to condition on firm size. The coefficients β_k measure the differential export propensity of indirectly supported firms relative to comparable firms without supported peers, at different event times.

We employ a similar event-study specification for geographic spillovers:

$$D_{ijt} = \alpha_{ij} + \delta_{jl(i)t} + \eta_{g(i)t} + \gamma \text{ Size}_{it} + \sum_{k=-5,\ldots,-2,0,\ldots,5} \beta_k \mathbf{1}\{\text{event time}_{ijt} = k\} + \varepsilon_{ijt}^{geo} \quad (7)$$

where l indexes industries and g indexes zip codes. Event time $k = 0$ is the year when peer firm $i' \neq i$ from the same zip code ($g(i) = g(i')$) receives TC support for destination j. To account for within-industry, location-specific demand shocks, we include industry-destination-year fixed effects $\delta_{jl(i)t}$ and zip code-year fixed effects $\eta_{g(i)t}$.

In both specifications, event time is winsorized at $k = -5$ and $k = 5$, and we restrict the sample to firm-destination pairs active throughout the event window.[16] Results are presented in Figure 4.

Both event studies show that before a peer firm receives TC support, indirectly connected and unconnected firms have similar export propensities. After peer TC support arrival, indirectly supported firms' export propensity to the same destination increases monotonically.

[16] When an ij pair experiences multiple events over the sample period, we use the first one.

Five years after support, indirectly supported firms are 4–5 percentage points more likely to export to supported destinations than unconnected firms (4 pp for geographic networks; 5 pp for worker networks). These findings strongly suggest that spillovers from TC support reach indirectly supported firms through their peers.

These results have three important limitations. First, the point estimates are statistically significant at the 5 percent level in the zip code network but only marginally significant in the worker transition network. Second, we cannot distinguish whether spillovers operate through information, demand, or both. Third, it remains unclear whether expanding TC outreach would generate substantially greater export entry or firm profits. To address these central questions about industrial policy in international markets, we estimate the structural model.

5 Estimation

5.1 Empirical Model

The observable component of export revenue, $r^o_{ijt} = (\alpha^U_{jt} + \alpha^S_{jt} s_{ijt}) r_{iht}$, captures market and year-specific demand conditions for both supported and unsupported firms. However, TC support is relatively rare, limiting our ability to identify market-year-specific demand shifters for supported firms. We therefore restrict the observable component to $r^o_{ijt} = (\alpha^U_{jt} + \alpha^S_{j} s_{ijt}) r_{iht}$, where α^S_j varies across markets but is constant over time.

We assume $\mathbb{E}[e^S_{ijlt}|\mathcal{J}_{ijlt}] = 0$, $\mathbb{E}[e^U_{ijlt}|\mathcal{J}_{ijlt}] = 0$ and $\mathbb{E}[e_{ijt}|\mathcal{J}_{ijlt}] = 0$ which ensures $\mathbb{E}[r_{ijt}|\mathcal{J}_{ijlt}] = \mathbb{E}[r^o_{ijt}|\mathcal{J}_{ijlt}]$. While this structure holds across all informational settings, identifying TC support effects requires additional assumptions on how firm-level information $\mathcal{J}_{ijlt}$ relates to observable revenues r^o_{ijt}.

We assume firms possess a partial information set that includes a minimal core set but may also include additional firm- and country-specific information, such as market demand. Following Dickstein and Morales, 2018, we assume firms employ three core information components: prior-year domestic revenues r_{iht-1}, prior-year sectoral exports to destination j R_{jt-1}, and distance to the market $dist_j$. We also assume firms to know their own TC support status.

Firms' information sets may differ by TC support status, size, location, peer networks, or

other factors. While each firm makes export decisions based on expected revenues conditional on its information set, $\mathbb{E}[r_{ijt}|\mathcal{J}_{ijlt}]$, estimating model parameters and conducting counterfactuals nonetheless requires some restrictions on $\mathcal{J}_{ijlt}$ (Manski, 1993).

5.2 Information and Identification

Despite known estimation bias from informational misspecification (Yatchew and Griliches, 1985; Dickstein and Morales, 2018), strong informational assumptions remain common in the literature.[17] However, if information is partially non-excludable and spills over differently across firm networks, these assumptions are unlikely to hold. In settings with multiple overlapping or unknown information networks, researchers rarely observe the covariates underlying firms' decisions.

Yet, under the assumption that each firm has access to at least a 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 two types of moment inequalities to obtain tighter confidence bounds on fixed cost parameters: (i) odds-based and (ii) revealed preference moment inequalities. We briefly describe each type below; we employ the full set of moment inequalities for both supported and unsupported firms.[18]

Let Z denote an arbitrary covariate in the firm's information set $Z \subseteq \mathcal{J}ijlt$. We define conditional odds-based moment inequalities ($mob^{l,T}$ and $m_{ob}^{u,T}$) and revealed preference moment

[17] Standard assumptions for modeling firm export decisions are that (i) all firms use the same covariates when deciding whether to export and (ii) researchers observe the information set, up to a structural error. Key advantages include point identification of parameters, comparability with established findings, and clear policy implications.

[18] Detailed discussion of each moment inequality type is in Appendix B.2.

inequalities ($m_{rp}^{l,T}$ and $m_{rp}^{u,T}$) as follows:[19]

$$\mathcal{M}^T(Z_{ijt};\theta^T) = \mathbb{E}\left[\begin{array}{l} m_{ob}^{l,T}(D_{ijt}, r_{ijt}^o, dist_j, s_{ijt});\theta^T \\ m_{ob}^{u,T}(D_{ijt}, r_{ijt}^o, dist_j, s_{ijt});\theta^T \\ m_{rp}^{l,T}(D_{ijt}, r_{ijt}^o, dist_j, s_{ijt});\theta^T \\ m_{rp}^{u,T}(D_{ijt}, r_{ijt}^o, dist_j, s_{ijt});\theta^T \end{array}\middle| Z_{ijt}\right] \geq 0, \tag{8}$$

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

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

$$m_{ob}^{u,T}(\cdot) = (1-D_{ijt})\frac{\Phi((\theta_2^T)^{-1}(\eta^{-1}r_{ijt}^o - \theta_0^T - \theta_1^T dist_j))}{1-\Phi((\theta_2^T)^{-1}(\eta^{-1}r_{ijt}^o - \theta_0^T - \theta_1^T dist_j))} - D_{ijt} \tag{10}$$

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

$$\begin{aligned} m_{rp}^{u,T}(\cdot) &= D_{ijt}(\eta^{-1}r_{ijt}^o - \theta_0^T - \theta_1^T dist_j) \\ &\quad + (1-D_{ijt})\theta_2^T \frac{\phi((\theta_2^T)^{-1}(\eta^{-1}r_{ijt}^o - \theta_0^T - \theta_1^T dist_j))}{1-\Phi((\theta_2^T)^{-1}(\eta^{-1}r_{ijt}^o - \theta_0^T - \theta_1^T dist_j))}. \end{aligned} \tag{12}$$

Consider the upper bound of the odds-based moment condition for an unsupported exporter ($s_{ijt} = 0$) who exports ($D_{ijt} = 1$), denoted $m_{ob}^{u,T}$. If firm i exports, it must expect positive profits: $\eta^{-1}\mathbb{E}[r_{ijt}|\mathcal{J}_{ijlt}] - \beta_0^U - \beta_1^U dist_j - \nu_{ijt}^U \geq 0$. Taking expectations conditional on $(D_{ijt}, \mathcal{J}_{ijlt}, dist_j, s_{ijt})$, yields

$$\mathbb{E}\left[(1-D_{ijt})\frac{\Phi(\sigma_U^{-1}(\eta^{-1}\mathbb{E}[r_{ijt}|\mathcal{J}_{ijlt}] - \beta_0^U - \beta_1^U dist_j))}{1-\Phi(\sigma_U^{-1}(\eta^{-1}\mathbb{E}[r_{ijt}|\mathcal{J}_{ijlt}] - \beta_0^U - \beta_1^U dist_{ijt}))} - D_{ijt}\middle|\mathcal{J}_{ijlt}\right] \geq 0. \tag{13}$$

[19]We maintain the standard assumption that ν_{ijt}^T are structural errors varying across (i,j,t) with unbounded support. Implementing revealed preference moment inequalities (11) and (12) requires assuming a distribution for ν_{ijt}^T up to a scale parameter σ_T.

Although condition (13) holds at the true parameter vector $\theta = \theta^*$, it cannot be used for identification because we do not observe $\mathcal{J}_{ijlt}$. Following Dickstein and Morales, 2018, we apply Jensen's inequality to derive weaker but feasible moment inequalities that hold at $\theta = \theta^*$:

$$\mathbb{E}\left[(1 - D_{ijt})\frac{\Phi(\sigma_U^{-1}(\eta^{-1}\mathbb{E}[r_{ijt}|Z_{ijt}] - \beta_0^U - \beta_1^U dist_j))}{1 - \Phi(\sigma_T^{-1}(\eta^{-1}\mathbb{E}[r_{ijt}|Z_{ijt}] - \beta_0^U - \beta_1^U dist_j))} - D_{ijt}\Big| Z_{ijt}\right] \geq 0 \qquad (14)$$

Here, observable expectations $\mathbb{E}[r_{ijt}|Z_{ijt}]$ replace the unobserved $\mathbb{E}[r_{ijt}|\mathcal{J}ijlt]$, and the moment conditions are conditioned on the instrument vector Z_{ijt} rather than the unobserved information set $\mathcal{J}_{ijlt}$. Similar established arguments justify the other moment conditions used for identification.

5.3 Estimation and Selection

For computational purposes, we use a fixed set of unconditional moment inequalities defined by positive-valued instrument functions, $g^T(\cdot)$:

$$\mathbb{E}\left[\left\{\begin{array}{l} m_{ob}^{l,T}(D_{ijt}, r_{ijt}, s_{ijt}, dist_j; \theta^T) \\ m_{ob}^{u,T}(d_{ijt}, r_{ijt}, s_{ijt}, dist_j; \theta^T) \\ m_{rp}^{l,T}(D_{ijt}, r_{ijt}, s_{ijt}, dist_j; \theta^T) \\ m_{rp}^{u,T}(D_{ijt}, r_{ijt}, s_{ijt}, dist_j; \theta^T) \end{array}\right\} \times g^T(Z_{ijt})\right] \geq 0. \qquad (15)$$

The inequalities are conditioned on the instrument vector, Z_{ijt}. We estimate fixed costs separately for supported and unsupported firms to allow model parameters to vary across support status.

Estimating moment inequalities by support status raises two key concerns. First, firms may endogenously select into TC support. Second, firm characteristics and information may systematically differ across firms and markets. For instance, the likelihood of TC outreach calls differs by firm size (Section 4.2). Accordingly, we stratify the instrument $g^T(Z_{ijt})$ by firm size, lagged aggregate export revenue, and distance to market.

To address endogenous selection, we exploit quasi-random TC outreach. As documented in Buus et al., 2025, outreach is a strong instrument for support status. We therefore re-estimate our benchmark specification using outreach status instead of support status to recover export fixed costs and quantify self-selection bias.[20]

6 Results

We present results in the following order. First, we document the estimated model parameters. Second, we use model specification tests from Bugni et al., 2015 to show that TC-supported firms possess systematically better information than unsupported firms. Third, we show that unsupported peers of supported firms are better informed about export demand than unsupported firms without supported peers. Finally, we quantify how informational spillovers contribute to Danish export growth.

6.1 TC Demand Premia

We recover export demand shifters by OLS estimation of equation (3). Table 2 reports demand shifters by destination. The first column presents average annual market demand for unsupported firms (α_{jt}^{U}), and the middle column presents the demand premium for TC-supported firms (α_{j}^{S}).

Unsupported demand shifters are almost always statistically significant. Supported demand premia are statistically significant in popular export destinations but small and insignificant in unpopular destinations.

Two empirical patterns emerge. First, supported firms enjoy substantially larger export market demand than unsupported firms with comparable domestic sales. Table 2 shows that supported firms' export market demand is nearly twice as large in Norway, approximately three times as large in India and Japan, four times as large in China and the USA, and five times as large in Australia compared to unsupported firms.[21] However, the demand increase is not

[20] See Appendix B.3 for details.

[21] These support premia are consistent with evidence in Buus et al., 2025.

universal: TC support has no estimated effect in Russia or Turkey.

Second, estimated market demand differences across destinations align with economic size differences. China and the US represent large export markets for both supported and unsupported firms, with export demand multiples of smaller markets regardless of support status. These differences in market size and support effects suggest that firms likely possess varying information about different export destinations.

A potential concern is whether support-driven demand premia spill over across firms or markets. Buus et al., 2025 investigate whether TC programming generates *demand* spillovers (as opposed to information spillovers) across firms but find no evidence of such spillovers. To further investigate, we re-estimate equation (3) to distinguish demand premia for indirectly supported firms from unsupported firms.

Results in Table 3 show network-specific demand premia for each industry-destination pair. In 22 of 23 cases, the network demand premium is statistically insignificant.[22] In 17 of 23 cases, the premium is smaller than 2 percent, and in over half the estimated coefficient is negative. These results align with existing evidence and support the assumption that network *demand* spillovers are negligible.

6.2 Fixed Export Costs

Table 4 reports moment inequality estimates of fixed cost parameters (β_0^U, β_1^U, σ_U, β_0^S, β_1^S, σ_S), while Table 5 reports implied fixed costs for exporters to Norway, the United States, and China. In each table, the first column reports estimates for unsupported firms and the third column reports estimates for supported firms. Columns two and four present alternative estimates using called versus uncalled firms instead of supported versus unsupported firms, allowing us to address endogenous selection into TC support.

Fixed costs for both supported and unsupported firms are substantial, increase with distance,

[22]The sole significant estimate is a negative network premium for Japan through employee networks. Positive network premia appear only for China, and these are always insignificant. The large estimated spillover for Norway in the zip code network is driven by a single zip code; removing it yields a coefficient near zero.

and vary little across firms. Export entry costs represent 12–24 percent of typical annual export revenue across destinations. As expected, fixed costs rise with distance. For unsupported exporters, average fixed cost estimates range from 336–493 thousand DKK (60–88 thousand USD) for Norway, 450–648 thousand DKK (80–115 thousand USD) for the United States, and 454–655 thousand DKK (81–117 thousand USD) for China.

By comparison, Das et al., 2007 estimate average export-entry costs in Colombia at 344–430 thousand USD using maximum likelihood estimation. Castro et al., 2016 find that export-specific fixed cost expenditures may imply substantially smaller estimates. Our unsupported firm fixed cost estimates align most closely with moment inequality estimates from Dickstein and Morales, 2018, who show that maximum likelihood estimates suffer significant bias in informationally opaque markets.[23]

Columns three and four of Tables 4 and 5 report fixed cost parameters for supported firms, which are modestly lower than for unsupported firms. We expect TC support to be more valuable for distant, informationally opaque markets, while common neighboring destinations experience fewer information frictions. Consistent with this expectation, the estimated coefficient on distance declines noticeably for supported firms.

Roughly half of supported firms contact the TC for export support, potentially biasing estimates if these firms are systematically different (in export propensity, market knowledge, or entry costs). Following Buus et al., 2025, we repeat the estimation using TC calls rather than support status to guard against selection bias. Results appear in the last row of Tables 4 and 5.

Fixed cost estimates using TC calls are generally similar to benchmark estimates for supported firms, though confidence sets are modestly wider. The estimates maintain plausible magnitudes and consistent ranking across destinations, indicating the moment inequality approach produces robust fixed cost estimates for both firm types. The modest impact of using TC calls rather than support status reflects the quasi-random nature of TC outreach: Figure 2 shows that within firm size groups, differences between supported and unsupported firms are

[23] Standard maximum likelihood estimates for unsupported firms appear in Appendix C. Since Dickstein and Morales, 2018 already document how informational assumptions affect fixed cost estimates, we do not pursue this further.

small and insignificant. We caution that in either case the moment conditions always account for firm size differences, leaving modest differences across supported and unsupported firms, none of which are statistically significant. Although these differences are further reduced by using TC outreach calls, quasi-random TC outreach only has a small impact on estimated fixed costs.

6.3 Information, Networks and TC Support

Under rational expectations, any variable in the firm's information set is a valid instrument in our moment inequalities. We test whether variables in Z_{ijt} belong to the firm's information set using the model specification test from Bugni et al., 2015. Specifically, we test the null hypothesis that the revenue forecast error ε_{ijt} satisfies $\mathbb{E}[\varepsilon_{ijt}|Z_{ijt}] = 0$, where $\varepsilon_{ijt} \equiv r^o_{ijt} - \mathbb{E}[r^o_{ijt}|\mathcal{J}_{ijt}]$. Rejection of this null hypothesis indicates that variable $Zijt$ was not part of the firm's information set when deciding whether to export to market j.[24]

Consider the moment inequalities for identifying unsupported firm parameters: $\bar{\mathcal{M}}^U(X_{ijt}, Z_{ijt}, \theta^U; \hat{\alpha}^U)$ where $\hat{\alpha}^U \equiv \hat{\alpha}^U_{jt}; \forall j, t$ and $X_{ijlt} = (D_{ijt}, dist_j, r^o_{ijlt})$. The identified set Θ_0 comprises all values of θ^U satisfying $\bar{\mathcal{M}}^U(X_{ijt}, Z_{ijt}, \theta^U; \hat{\alpha}^U) \geq 0$. The model is correctly specified when Θ_0 is non-empty, motivating the hypothesis test:

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

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

We first test what supported and unsupported firms know about export markets, examining differences across firm and market characteristics. These tests establish the baseline finding that supported firms possess systematically better export market information than unsupported firms. We then test whether unsupported peers of supported firms gain export market information through indirect network connections to TC programs.

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

6.3.1 Are TC supported firms better informed?

This section presents hypothesis tests validating that supported firms are better informed than unsupported firms and characterizing information differences across firm types.

Table 6 reports p-values for each information test. We first test whether firms know a minimal information set: prior-year aggregate exports to destination j ($R_{j,t-1}$), distance ($dist_j$), and prior-year domestic sales (r_{iht-1}). Each column indicates whether the specification test rejects the null hypothesis that these variables are in the firm's information set.

Panel A shows we cannot reject that firms know the minimal information set, regardless of TC support status. Panel B tests whether firm information sets are rich enough to perfectly predict observed export profits. Specifically, we test whether firms know both the minimal information set and the observable revenue component $r^o_{ijt} = \alpha_{jt} r_{iht}$. We strongly reject this hypothesis at conventional significance levels for all firms. This rejection confirms that the Bugni et al., 2015 test has statistical power in our setting, as it correctly rejects an implausibly rich information specification.

Panel C tests whether firms know prior-year export market demand shifters in addition to the minimal information set. For unsupported firms, the relevant shifter is $\alpha^U_{j,t-1}$; for supported firms, it is $\alpha^U_{j,t-1} + \alpha^S_j$. We reject that unsupported firms know the country demand shifters but fail to reject this hypothesis for supported firms. This suggests that supported firms possess knowledge of export market demand conditions when making export decisions, while unsupported firms do not.

We verify these conclusions are robust to sample composition. The large imbalance between unsupported and supported firms reflects TC program size. Including EU destinations does not alter conclusions from Panels A–C (see Appendix D). Table A7 qualitatively replicates Table 6.

We next consider the same information test, whether a firm knows the minimal information set and the export demand shifter, but disaggregate our sample across firm size and destination popularity.[25] To be clear, in the first column and first row of panel D the null hypothesis we test

[25] 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.

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.

Panel D reveals two clear patterns. First, we rarely reject that unsupported firms know export market conditions, except for large firms exporting to popular destinations. Second, we almost always fail to reject this hypothesis for supported firms, indicating they consistently possess market knowledge.

Panel E repeats these tests by destination. Danish firms know export conditions in Australia, Norway, Japan, and the USA—the nearby, popular markets with largest p-values. Conversely, unsupported firms lack knowledge of China, India, Russia, and Turkey. Supported firms, however, know export conditions in all destinations.

Panel F examines whether self-selection into TC support affects information acquisition. Approximately 50 percent of supported firms receive quasi-random TC outreach (Section 4.2); the remainder self-select.

Comparing firms that accept versus decline TC calls, we fail to reject that both know export conditions. Notably, unsupported firms declining calls despite high subsidies likely already possess relevant information or cannot apply it. In contrast, uncalled unsupported firms lack market knowledge, while uncalled self-selected supported firms possess it.

An important caveat is that we do not distinguish new from incumbent exporters. Prior research suggests new exporters face higher entry costs (Das et al., 2007). Among unsupported firms, we re-estimate entry costs comparing firms with prior export experience to any sample destination against first-time exporters.[26] Appendix Tables A3 and A4 show modestly lower entry costs for experienced exporters. Information tests in Appendix Table A8 confirm that new exporters cannot reject knowing the minimal information set but strongly reject knowing lagged export demand shifters. Experienced exporters fail to reject both hypotheses, though the

[26] Insufficient data precludes analogous analysis for supported firms.

latter is marginal. Thus, firms with prior export experience are better informed than newcomers, though not perfectly so.

Overall, the information tests consistently show that supported firms know export market conditions across most destinations and firm types, while unsupported firms rarely do.[27] These findings validate the conventional narrative and confirm TC support improves firm information. It is also consistent with exit surveys of supported firms where a large fraction (36%) report that TC services improve knowledge of export markets.

However, improved firm knowledge does not necessarily indicate market failure or establish that TC information constitutes a public good. To investigate these questions, we examine informational spillovers across firm networks.

6.4 Does export market information spillover to unsupported firms?

An advantage of our approach is that we do not need to specify firm information networks for model estimation. With estimated model parameters, we now test the nature of information spillovers across firm networks.

We test whether unsupported firms in supported locations have better information than those in unsupported locations. Column 1 of Panel A, Table 7, reproduces the p-value for the null hypothesis that unsupported firms know export market demand conditions—a hypothesis we clearly reject. Columns 2–3 repeat this test, restricting the sample to unsupported firms in progressively smaller supported regions: Column 2 uses municipal boundaries; Column 3 uses zip codes. Across all specifications, we fail to reject that unsupported firms in indirectly supported locations possess market knowledge. The contrast between Columns 2–3 and Column 1 is consistent with informational spillovers through geographic networks.

Geographic networks provide a natural starting point but lack an explicit transmission mechanism. To identify a specific mechanism, the final column of Panel A tests employment-based networks. We again fail to reject that unsupported firms indirectly linked to the TC through employee transitions know export market conditions. This finding indicates that employee mo-

[27] Results are qualitatively identical in both the benchmark and EU-inclusive samples; see Appendix D. Findings hold across exporters with and without prior export experience.

bility is an important mechanism through which industrial policy generates broader economic benefits.[28]

Panel B verifies that findings are not confounded by firms with direct TC contact. We distinguish firms receiving quasi-random TC calls from those without contact. This ensures our sample of unsupported firms genuinely lack direct TC engagement.

The first row shows we fail to reject that called firms possess market knowledge. Given that TC export support is documented to significantly increase export profits (Buus et al., 2025), a potential explanation for this finding is that called firms which turn down offers TC already know export demand conditions, as indicated by our information tests.

The second row examines uncalled firms across each network. While we clearly reject that uncalled unsupported firms know export conditions (Column 1), we fail to reject this hypothesis for indirectly supported firms across all networks (Columns 2–4). The p-values in the second row of Panel B are nearly identical to Panel A, confirming that spillover effects are robust to controlling for direct TC contact.

A natural concern is that p-values increase as network scope narrows. This pattern could reflect two mechanisms. First, informational spillovers may decay with weaker network links—we expect closer proximity (same zip code) to facilitate stronger information transmission than wider geographic scope. Second, the fraction of informed firms declines in narrower network definitions, potentially reducing statistical power to detect spillovers.

We provide two pieces of evidence that statistical power is not driving our results. First, even with the widest network definition, we fail to reject that unsupported firms are well-informed. Second, we conduct placebo tests on the sparsest network definitions: supported zip codes and employment networks. We randomly draw zip codes until the placebo sample size matches the number of indirectly supported firms in the actual data.[29] We use the same pro-

[28] This parallels Hastings et al., 2017, who find that sales force intensity affects firm profits through demand channels. In our case, we find no significant effect of TC-supported employee transitions on demand but do find effects on export entry decisions.

[29] Since approximately 5 percent of firms are actually in supported zip codes, random placebo samples largely contain firms without supported peers.

cedure for employment networks, drawing random networks and setting the number of "treated" firms to match the actual data.

Panel C reports the mean p-value of 50 separate placebo tests for each firm network. For all placebos, we clearly reject the null hypothesis that firms lack export market knowledge. This demonstrates that when firms are genuinely uninformed, we have sufficient statistical power to detect it. In stark contrast, we fail to reject the null hypothesis for actual indirectly supported firms across all network definitions, suggesting genuine informational spillovers rather than lack of power.

6.4.1 Are TC information spillovers destination-specific?

This subsection tests whether TC spillovers are destination-specific or reflect broader export demand characteristics. We employ a destination-specific placebo test.

We first identify which location-destination-year combinations received TC support. Next, we identify all locations that had at least one supported destination in a given year. Finally, we create a placebo treatment by selecting destination-year pairs in these supported locations, but only for destinations where firms in that location did not actually receive TC support. This placebo identifies "counterfactually treated" destination-location pairs to test whether information effects are specific to the destinations firms actually export to or reflect broader market knowledge.[30]

Panel D, Table 7, reports results. For both geographic and worker networks, we reject that firms know export market conditions under the placebo assignment. These results confirm that TC-generated information is destination-specific rather than reflecting general export market knowledge.

[30]This procedure yields three samples: (i) unsupported firm-destination pairs counterfactually linked to supported destinations, (ii) unsupported firm-destination pairs never linked to any destination, and (iii) unsupported firm-destination pairs genuinely indirectly supported. We test the unconnected sample (ii) to verify power to detect information, and exclude sample (iii) to avoid confounding placebo and realized spillovers. See Appendix XX for details.

6.4.2 Export market information spillovers across firms and geography

To characterize information spillover heterogeneity, Table 8 disaggregates unsupported firms by size and market popularity, with columns distinguishing network types and rows distinguishing null hypotheses. Columns 1–3 replicate Panels D–E from Table 6, testing whether unsupported firms know export market conditions. The null is strongly rejected except for large firms and popular destinations (US, Japan, Norway).[31]

Panel A shows that large unsupported firms with supported peers in the same zip code fail to reject knowledge of export conditions in unpopular markets. Panel B confirms this for specific destinations: Australia, China, India, and Turkey. In contrast, using municipality-level networks (Column 2), we reject knowledge for large firms across unpopular markets, though Panel C shows information spillovers for Australia, China, and India when municipality peers have support. Overall, stronger spillovers appear in narrower networks and less popular markets.

Employment networks (Column 3) show similar patterns: unsupported firms with previously connected workers fail to reject knowledge of export conditions, while those without such connections do reject. Spillovers are particularly strong for unpopular, distant, or informationally opaque destinations (Australia, China, India, Russia, Turkey), regardless of firm size.

Notably, employment networks yield stronger and more consistent spillover evidence than geographic networks. This suggests that export information, while non-excludable, remains partially rival—requiring direct past TC contact for transmission. This raises a critical question: what specific information diffuses across firm networks? We address this next.

6.5 What do firms learn through information networks?

Our benchmark model aggregates export-relevant information into a limited set of covariates, with export market demand shifters being most important. While theoretically grounded, de-

[31] Full results appear in each table. For brevity, we highlight subgroups with meaningful differences. Appendix Table A10 presents p-values adjusted for multiple testing.

mand shifters lack intuitive interpretation. To address this, we decompose them using data on firm-level buyer counts by destination and year. Appendix A shows that demand shifters can be separated into two additively separable components: the number of buyers a firm reaches in a destination and the average quality of those buyers, measured by average sales per buyer.

Table 9 presents results by network type. Unsupported firms broadly lack knowledge of either component. In regional networks, both components spill over to unsupported firms, though information about buyer quantity spillovers more consistently than buyer quality. Buyer quality spillovers appear only for firms in the same zip code as supported peers. Employment networks show both components spillover when workers have prior TC connections.

Two findings warrant emphasis. First, unsupported firms connected to supported firms—through geography or worker links—learn both buyer quantity and quality, contrasting sharply with unsupported firms generally (who reject both components) and indirectly supported firms at broader aggregation levels (who reject buyer quality).

Second, examining buyer quality spillovers across geographic networks reveals information decay: unsupported firms in the same zip code as supported firms cannot reject knowledge of typical buyer quality, but we reject this hypothesis at wider geographic scales. This decay is economically significant: buyer quantity variation explains approximately 68 percent of demand shifter variation, with buyer quality explaining the remainder. Thus, information spillovers in less connected networks remain far from complete.

6.6 Are information spillovers economically important?

We conduct counterfactual experiments using the estimated model to evaluate the value of information spillovers in export markets. We compare two scenarios: one where unsupported firms lack knowledge of export demand shifters (baseline) and one where firms in supported networks receive informational spillovers while unsupported firms do not. Results for each network structure appear in Table 10.

Panel A of Table 10 considers information spillovers among employee networks. Average export propensity shows no significant change, but mean export profits increase, indicating information spillovers improve sorting: less profitable firms avoid entry while more profitable

firms expand. In aggregate, these spillovers increase exports to non-EU countries by 0.2–0.6 percent, generating additional export profits of 1.6–2.5 million DKK (0.22–0.35 million USD).

Panels B and C consider zipcode and municipality networks, respectively. Information to unsupported firms in supported zip codes increases export participation by 0.2–0.3 percent, concentrated among large firms and popular destinations. Mean export profits rise 0.1–0.2 percent—modest because improved information induces marginal entrants with below-average profitability.[32] Despite representing few firms, indirectly supported firms increase aggregate exports 0.6–1.3 percent annually.

Widening the geographic scope to municipalities mechanically increases gains since more unsupported firms benefit while subsidy costs remain constant. Export participation growth approximately doubles, mean export profits double, and aggregate export growth reaches 1–2 percent annually through information spillovers alone.

We incorporate decay consistent with information tests: zip code firms receive full spillovers; municipality-level firms learn only buyer quantity; firms outside these areas receive no spillovers. Results fall between Panels B and C. Export propensity changes resemble zip code estimates, but mean export growth parallels municipality results. Aggregate gains from information spillovers are substantive even when less connected firms only receive partial information.

6.7 Is the TC support program a worthwhile public investment?

Following Hahn et al., 2026, we compute the marginal value of public funds (MVPF) to evaluate TC support relative to its cost to the Danish government. MVPF equals the ratio of beneficiary willingness to pay to net government cost. Willingness to pay includes post-tax profits from directly and indirectly supported firms minus service outlays paid by these firms. Net government cost includes the subsidy cost and the deadweight loss (DWL) from raising funds, minus

[32]Luco, 2019 finds information disclosure disproportionately benefits smaller markets; Ater and Rigbi, 2023 finds larger effects for premium chains. Our results suggest large firms and popular markets benefit most from information disclosure.

additional tax revenues (Buus et al., 2025):

$$MVPF^{standard} = \frac{\text{Additional post-tax profits} - \text{Private support outlays}}{\text{TC subsidy} + \text{DWL} - \text{Additional tax revenues}}$$

Typically, additional tax revenues less than fully offset program costs. In our setting, additional tax revenues *exceed* TC subsidy and DWL costs, implying infinite MVPF by standard metrics—indicating exceptional program performance.

However, standard MVPF obscures information spillovers' relative importance. We therefore consider two alternative specifications. First, we reclassify tax revenues as public gains (numerator) rather than cost offsets (denominator):

$$MVPF_1^{alt} = \frac{\text{Additional post-tax profits} - \text{Private support outlays} + \text{Additional tax revenues}}{\text{TC subsidy} + \text{DWL}}$$

Second, we exclude tax revenues entirely—a conservative benchmark:

$$MVPF_2^{alt} = \frac{\text{Additional post-tax profits} - \text{Private support outlays}}{\text{TC subsidy} + \text{DWL}}$$

In this case we treat the additional tax revenues generated by the TC program as having no value to Danish citizens. While extreme it provides a conservative benchmark for program evaluation. Values for $MVPF_1^{alt}$ and $MVPF_2^{alt}$ are reported in panels A and B of Table 11, respectively.

Results appear in Table 11, Panels A–B. Even our conservative MVPF measures show high returns to public funds. Across experiments, MVPF ranges from 7.3 (no spillovers, $MVPF_2^{\text{alt}}$) to 10.9 (full municipality-level spillovers, $MVPF_1^{\text{alt}}$). The final three columns of Panel A decompose gains across stakeholders. Gains largely accrue to directly supported firms (71.5-74.4%) and government (23.5%), while share of gains accrued through information spillovers is relatively modest (2.1-5.0%). Panel B reinforces this finding by highlighting that regardless of network structure information spillovers never account for more than 6.6 percent of $MVPF_2^{alt}$.

This result is expected: the impact of TC support on export demand among TC supported is large (Buus et al., 2025) and swamps the absolute level of gains from information spillovers.

Nonetheless, by accounting for a small fraction of a highly profitable program, the gains from information spillovers are substantive. Information spillovers alone generate up to 55 percent of the gains needed to achieve a MVPF of 1, a benchmark indicating that the gains match program costs, even when using our conservative evaluation metrics, $MVPF_1^{alt}$ and $MVPF_2^{alt}$.

6.8 How does TC outreach shape information spillovers?

We examine how outreach strategies shape TC support benefits. We counterfactually provide export demand information to an additional 216 unsupported firms, doubling machinery industry program size. For each experiment, we vary information spillover assumptions and outreach strategy, focusing on employment networks where information transmits through worker transitions.

In panel A of Table 12 contacted firms learn demand conditions ($\alpha_{j,t-1}^U$) with no spillovers to peers. In Panel B contacted firms receive full demand information; indirectly supported firms learn only buyer quantities. In Panel C both contacted and connected firms receive full information. We abstract from direct demand effects and fixed cost reductions to isolate information provision gains. We assume all contacted firms accept support.

We evaluate four outreach strategies. First, random selection serves as a baseline. Second, size-stratified random selection within size bins (matching Figure 2c) captures targeting large firms where profit gains are largest.[33] The second strategy approximates the actual TC approach. Third, exclusive targeting of largest firms creates a size-based pecking order. Fourth, targeting the most-connected firms (by employment links) recognizes that firm connectivity imperfectly correlates with size.

Surprisingly, all experiments show declining export participation with program expansion (Column 1). This reflects improved sorting: firms avoid unprofitable markets while profitable firms enter. This selection effect is strongest when targeting large firms—where information most precisely identifies profitable opportunities. Random targeting produces smaller selection effects.

Allowing spillovers (Panels B–C) reinforces selection effects but similarly across size-based

[33] Absolute gains from support, $\alpha_j^S r_{iht}$, scale with domestic revenues.

strategies. For example, adding full spillovers to random outreach increases the export decline from −0.35 to −4.55 percent (4.2 pp additional decline), while targeting largest firms shows −6.7 to −9.9 percent (3.2 pp additional decline).

Targeting connected firms yields qualitatively different results. Without spillovers, substantial exit occurs but smaller than size-targeting. Critically, adding spillovers has minimal impact on participation—despite most firms receiving information indirectly through connected firms. This suggests connected-firm targeting exhausts spillover potential.

Column 2 shows mean export profits rise substantially with improved sorting, particularly under size-targeting strategies. Column 3 reveals minimal aggregate export growth with random, size-stratified, or size-targeted outreach, regardless of spillover assumptions. Gains come from reduced fixed costs among exiting firms rather than net entry.

This finding parallels Atalay et al., 2023 and Bartelme et al., 2025, showing modest industrial policy gains. However, we exclude direct demand and cost effects, so expansion's cost-benefit remains indeterminate on information grounds alone. Critically, size-based strategies cannot justify expansion on public benefits alone.[34]

Connected-firm targeting with full spillovers differs strikingly. Gains are consistently positive and economically substantial, exceeding program expansion costs at the lower bound. This experiment uniquely demonstrates that strategic program design and network structure are essential for maximizing public benefits from export support.

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

Table 12 reports the impact of broad or targeted TC outreach. The first column again reports the percentage change in the number of exporters due to TC outreach. Perhaps surprisingly, in

[34]Relaxing the assumption that all firms accept support would further reduce aggregate gains.

almost every case the experiments find that the number of exporters declines with further TC outreach. Again, this result reflects a change in selection into export markets: firms are more likely to refrain from entering unprofitable export markets, while profitable firm-market pairs are more likely to see new entry. On net, the change export propensities are negative.[35]

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

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

Targeting the most connected firms yields substantially different findings. In the absence of network spillovers, targeting connected firms induces substantial net exit and a large rise in mean export profits. However, these changes are smaller in magnitude than a program targeting the largest firms by size, confirming that the largest firms are not necessarily the most connected

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

firms. Unlike the other outreach strategies, adding spillovers in panels B and C has a very small impact on either the propensity to export or mean export profits relative to Panel A for an outreach approach targeting connected firms. This difference is substantive as the largest number of firms are receiving TC information indirectly in the outreach strategy targeting the most connected firms.

Column 3 of Table 12 documents the change in aggregate exports for the machinery industry. Strikingly, we find little evidence of significant growth in aggregate exports from expansion of the TC programs when the TC pursues random, binned random (actual), or size-targeted (largest) outreach strategies. Regardless of the network spillover assumption, the predicted impact of TC expansion is always small or even slightly negative. In this case, any aggregate gains are largely achieved by saving fixed export costs among firms which refrain from export markets.[36]

This result is reminiscent of Atalay et al., 2023 and Bartelme et al., 2025 where gains to industrial policy are modest at best, though it is important to recall that we are omitting the direct demand boost or fixed cost savings to supported firms. In this sense, our experiment cannot fully determine whether the benefits to expansion outweigh the costs. It can, however, clearly conclude that expansion is not justified on the basis of public benefits alone. In the absence of said justification, it is prudent to question the appropriate degree of public subsidy to these widespread programs.

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

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

7 Concluding Remarks

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

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

Finally, we quantify the aggregate gains from policy driven information spillovers. We find that information spillovers alone increase aggregate exports from the Danish machinery industry by 1-2 percent per year. This tax revenue generated by additional profits through TC support suggest that the current program is self-financing and the absolute gains from information are economically substantive.

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

References

Aghion, P., J. Cai, M. Dewatripont, L. Du, A. Harrison, and P. Legros. "Industrial Policy and Competition". *American Economic Journal: Macroeconomics* 7.4 (2015), 1–32.

Alessandria, G. and H. Choi. "Do Sunk Costs of Exporting Matter for Net Export Dynamics?*". *The Quarterly Journal of Economics* 122.1 (Feb. 2007), 289–336.

— "Establishment heterogeneity, exporter dynamics, and the effects of trade liberalization". *Journal of International Economics* 94.2 (2014), 207–223.

Alessandria, G., H. Choi, and K. J. Ruhl. "Trade adjustment dynamics and the welfare gains from trade". *Journal of International Economics* 131 (2021), 103458.

Ali, N., G. De Giorgi, A. Rahman, and E. Verhoogen. *What Do Market-Access Subsidies Do? Experimental Evidence from Tunisia*. Working Paper 33985. National Bureau of Economic Research, 2025.

Allen, T. "Information Frictions in Trade". *Econometrica* 82 (2014), 2041–2083.

Anderson, J. E. and E. van Wincoop. "Trade Costs". *Journal of Economic Literature* 42.3 (2004), 691–751.

Atalay, E., A. Hortaçsu, M. Runyun, C. Syverson, and M. F. Ulu. *Micro- and Macroeconomic Impacts of a Place-Based Industrial Policy*. Working Paper 31293. National Bureau of Economic Research, 2023.

Ater, I. and O. Rigbi. "Price Transparency, Media, and Informative Advertising". *American Economic Journal: Microeconomics* 15.1 (2023), 1–29.

Atkin, D., A. K. Khandelwal, and A. Osman. "Exporting and Firm Performance: Evidence from a Randomized Experiment*". *The Quarterly Journal of Economics* 132.2 (Feb. 2017), 551–615.

Bai, J., P. J. Barwick, S. Cao, and S. Li. *Quid pro quo, knowledge spillover and industrial quality upgrading*. NBER Working Papers 27644. National Bureau of Economic Research, Inc, 2022.

Bartelme, D., A. Costinot, D. Donaldson, and A. Rodríguez-Clare. "The Textbook Case for Industrial Policy: Theory Meets Data". *Journal of Political Economy* (2025).

Bernard, A. B. and J. B. Jensen. “Why Some Firms Export”. *Review of Economics and Statistics* 86.2 (2004), 561–69.

Bisztray, M., M. Koren, and A. Szeidl. “Learning to import from your peers”. *Journal of International Economics* 115 (2018), 242–258.

Blonigen, B. A. “Industrial Policy and Downstream Export Performance”. *The Economic Journal* 126.595 (July 2015), 1635–1659.

Bugni, F. A., I. A. Canay, and X. Shi. “Specification tests for partially identified models defined by moment inequalities”. *Journal of Econometrics* 185.1 (2015), 259–282.

Buus, M. T., J. R. Munch, J. Rodrigue, and G. Schaur. “Do Export Support Programs Affect Prices, Quality, Markups and Marginal Costs? Evidence from a Natural Policy Experiment”. *The Review of Economics and Statistics* 107.1 (Nov. 2025), 1–45.

— *Push or Pull? Spillovers Across Firm Networks: Evidence from Employee-Employer Linked Data*. 2006.

Cai, J. and A. Szeidl. “Interfirm Relationships and Business Performance*”. *The Quarterly Journal of Economics* 133.3 (Dec. 2017), 1229–1282.

Carballo, J., I. Marra De Artinano, and C. Volpe Martincus. *Information Frictions, Investment Promotion, and Multinational Production: Firm-Level Evidence*. Working Papers ECARES 2023-02. ULB – Universite Libre de Bruxelles, 2023.

Castro, L., B. G. Li, K. E. Maskus, and Y. Xie. “Fixed Export Costs and Export Behavior”. *Southern Economic Journal* 83.1 (2016), 300–320.

Chaurey, R., G. Nayyar, S. Sharma, and E. Verhoogen. *Social Learning among Urban Manufacturing Firms: Energy-Efficient Motors in Bangladesh*. Working Paper 34296. National Bureau of Economic Research, 2025.

Choi, J. and A. A. Levchenko. *The Long-Term Effects of Industrial Policy*. Working Paper 29263. National Bureau of Economic Research, 2021.

Ciliberto, F. and E. Tamer. “Market Structure and Multiple Equilibria in Airline Markets”. *Econometrica* 77.6 (2009), 1791–1828.

Criscuolo, C., R. Martin, H. G. Overman, and J. Van Reenen. “Some Causal Effects of an Industrial Policy”. *American Economic Review* 109.1 (2019), 48–85.

Das, S., M. J. Roberts, and J. R. Tybout. "Market Entry Costs, Producer Heterogeneity, and Export Dynamics". *Econometrica* 75.3 (2007), 837–873.

Dickstein, M. J. and E. Morales. "What do Exporters Know?*". *The Quarterly Journal of Economics* 133.4 (July 2018), 1753–1801.

Eaton, J., D. Jinkins, J. R. Tybout, and D. Xu. *Two-Sided Search in International Markets*. Working Paper 29684. National Bureau of Economic Research, 2022.

Fernandes, A. P. and H. Tang. "Learning to export from neighbors". *Journal of International Economics* 94.1 (2014), 67–84.

Feyrer, J., E. T. Mansur, and B. Sacerdote. "Geographic Dispersion of Economic Shocks: Evidence from the Fracking Revolution". *American Economic Review* 107.4 (2017), 1313–34.

Fink, C., A. Mattoo, and I. C. Neagu. "Assessing the impact of communication costs on international trade". *Journal of International Economics* 67.2 (2005), 428–445.

Freund, C. and D. Weinhold. "The effect of the Internet on international trade". *Journal of International Economics* 62.1 (2004), 171–189.

Goldberg, P. and N. Pavcnik. *The Effects of Trade Policy*. NBER Working Papers 21957. National Bureau of Economic Research, Inc, 2016.

González, A., J. C. Hallak, L. Iacovone, S. Llamas, and M. Rossi. *Helping Differentiated-Goods Producers Succeed in Exports Markets through Good Exporting Practices: Experimental evidence from Argentina*. Documentos de trabajo del Instituto Interdisciplinario de Economía Política IIEP (UBA-CONICET) 2025-97. Universidad de Buenos Aires, Facultad de Ciencias Econímicas, Instituto Interdisciplinario de Economía Política IIEP (UBA-CONICET), 2025.

Görg, H., M. Henry, and E. Strobl. "Grant Support and Exporting Activity". *Review of Economics and Statistics* 90.1 (2008), 168–74.

Hahn, R. W., N. Hendren, R. D. Metcalfe, and B. Sprung-Keyser. "A Welfare Analysis of Policies Impacting Climate Change". *American Economic Review* (2026). Forthcoming.

Hanlon, W. W. "The Persistent Effect of Temporary Input Cost Advantages in Shipbuilding, 1850 to 1911". *Journal of the European Economic Association* 18.6 (Dec. 2019), 3173–3209.

Hastings, J., A. Hortaçsu, and C. Syverson. “Sales Force and Competition in Financial Product Markets: The Case of Mexico’s Social Security Privatization”. *Econometrica* 85.6 (2017), 1723–1761.

Head, K. and J. Ries. “Immigration and Trade Creation: Econometric Evidence from Canada”. *Canadian Journal of Economics* 31.1 (1998), 47–62.

Hortaçsu, A., F. Luco, S. L. Puller, and D. Zhu. “Does Strategic Ability Affect Efficiency? Evidence from Electricity Markets”. *American Economic Review* 109.12 (2019), 4302–42.

Hortaçsu, A. and S. L. Puller. “Understanding strategic bidding in multi-unit auctions: a case study of the Texas electricity spot market”. *The RAND Journal of Economics* 39.1 (2008), 86–114.

Juhász, R. “Temporary Protection and Technology Adoption: Evidence from the Napoleonic Blockade”. *American Economic Review* 108.11 (2018), 3339–76.

Juhász, R., N. Lane, and D. Rodrik. “The New Economics of Industrial Policy”. *Annual Review of Economics* 16.Volume 16, 2024 (2024), 213–242.

Juhász, R., M. P. Squicciarini, and N. Voigtländer. “Technology Adoption and Productivity Growth: Evidence from Industrialization in France”. *Journal of Political Economy* 132.10 (2024), 3215–3259.

Kamal, F. and A. Sundaram. “Buyer–seller relationships in international trade: Do your neighbors matter?” *Journal of International Economics* 102 (2016), 128–140.

Lane, N. “Manufacturing Revolutions: Industrial Policy and Industrialization in South Korea*”. *The Quarterly Journal of Economics* 140.3 (May 2025), 1683–1741.

Lashkaripour, A. and V. Lugovskyy. “Profits, Scale Economies, and the Gains from Trade and Industrial Policy”. *American Economic Review* 113.10 (2023), 2759–2808.

Lawrence, R. Z. and D. Weinstein. *Trade and growth: import-led or export-led? Evidence from Japan and Korea*. 1999.

Liu, E. “Industrial Policies in Production Networks*”. *The Quarterly Journal of Economics* 134.4 (Aug. 2019), 1883–1948.

Luco, F. “Who Benefits from Information Disclosure? The Case of Retail Gasoline”. *American Economic Journal: Microeconomics* 11.2 (2019), 277–305.

Manski, C. “Adolescent Econometricians: How Do Youth Infer the Returns to Schooling?” *Studies of Supply and Demand in Higher Education*. National Bureau of Economic Research, Inc, 1993, 43–60.

Mion, G. and L. D. Opromolla. “Managers’ mobility, trade performance, and wages”. *Journal of International Economics* 94.1 (2014), 85–101.

Morales, E., G. Sheu, and A. Zahler. “Extended Gravity”. *The Review of Economic Studies* 86.6 (Feb. 2019), 2668–2712.

Munch, J. R. and G. Schaur. “The Effect of Export Promotion on Firm-Level Performance”. *American Economic Journal: Economic Policy* 10.1 (2018), 357–387.

Pakes, A., J. Porter, K. Ho, and J. Ishii. “MOMENT INEQUALITIES AND THEIR APPLICATION”. *Econometrica* 83.1 (2015), 315–334.

Pakes, A. “Alternative Models for Moment Inequalities”. *Econometrica* 78.6 (2010). Draft July 2010, 1783–1822.

Parro, F. “Capital-Skill Complementarity and the Skill Premium in a Quantitative Model of Trade”. *American Economic Journal: Macroeconomics* 5.2 (2013), 72–117.

Portes, R. and H. Rey. “The determinants of cross-border equity flows”. *Journal of International Economics* 65.2 (2005), 269–296.

Rauch, J. E. “Business and Social Networks in International Trade”. *Journal of Economic Literature* 39.4 (2001), 1177–1203.

— “Networks versus markets in international trade”. *Journal of International Economics* 48.1 (1999), 7–35.

Rauch, J. E. and V. Trindade. “Ethnic Chinese Networks in International Trade”. *The Review of Economics and Statistics* 84.1 (2002), 116–130.

Simonovska, I. and M. E. Waugh. “The elasticity of trade: Estimates and evidence”. *Journal of International Economics* 92.1 (2014), 34–50.

Steinwender, C. “Real Effects of Information Frictions: When the States and the Kingdom Became United”. *American Economic Review* 108.3 (2018), 657–96.

Van Biesebroeck, J., E. Yu, and S. Chen. “The Impact of Trade Promotion Services on Canadian Exporter Performance”. *Canadian Journal of Economics* 48.4 (2015), 1481–1512.

Volpe Martincus, C. and J. Carballo. "Beyond the average effects: The distributional impacts of export promotion programs in developing countries," *Journal of Development Economics* 92.2 (2010), 201–14.

— "Entering new country and product markets: Does export promotion help?" *Review of World Economics* 146.3 (2010), 437–67.

Volpe Martincus, C. and J. Carballo. "Export promotion activities in developing countries: What kind of trade do they promote?" *The Journal of International Trade & Economic Development* 21.4 (2012), 539–578.

Volpe Martincus, C. and J. Carballo. "Export Promotion: Bundled Services Work Better". *World Economy* 33.12 (2010), 1718–56.

— "Is export promotion effective in developing countries? Firm-level evidence on the intensive and the extensive margin of exports". *Journal of International Economics* 76.1 (2008), 89–106.

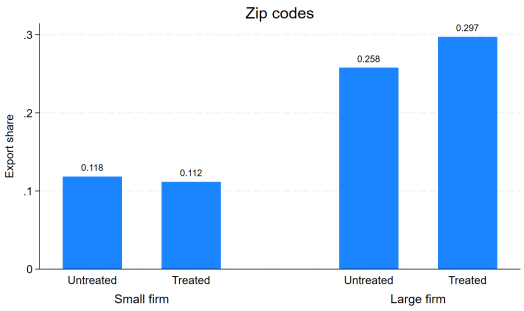
Wei, S.-J., Z. Wei, and J. Xu. "On the market failure of "missing pioneers"". *Journal of Development Economics* 152 (2021), 102705.

Yatchew, A. and Z. Griliches. "Specification Error in Probit Models". *The Review of Economics and Statistics* 67.1 (1985), 134–39.

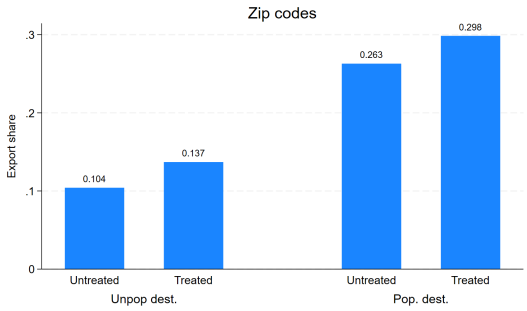
8 Figures

Figure 1: Export Share Across TC Firm Networks

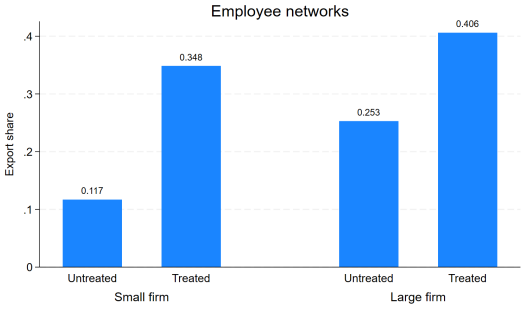
(a) Firm Size & Zipcode



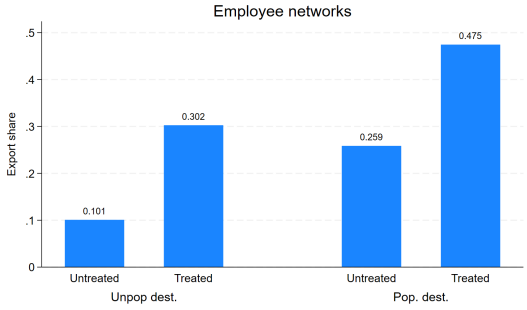
(b) Dest. Popularity & Zipcode



(c) Firm Size & Emp. Network

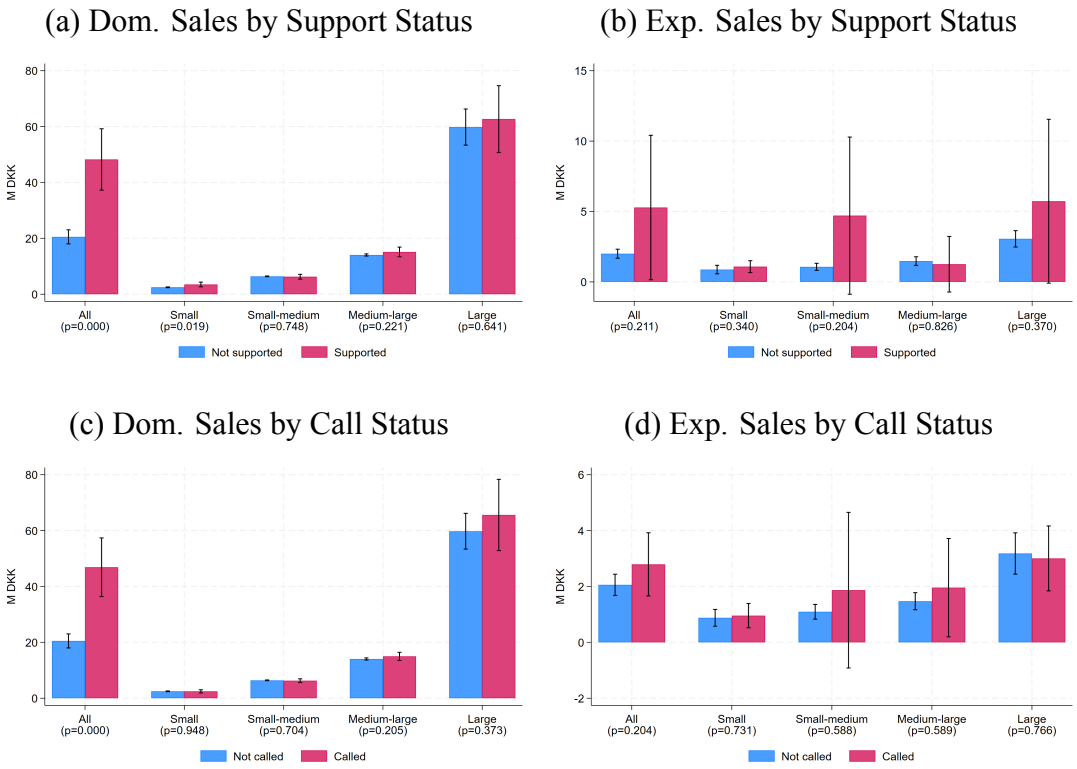


(d) Dest. Popularity & Emp. Network



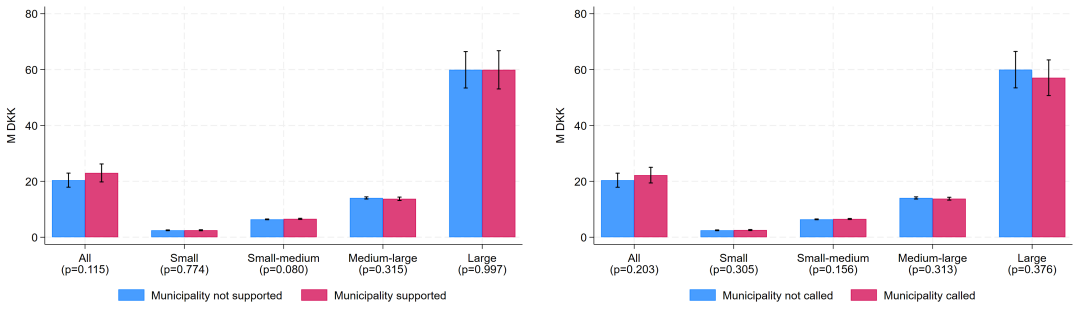
Notes: The above figures report the fraction of exporting firms unsupported by the Danish Trade Council. We separately document export share across firm size and export destination popularity for firms that have a supported neighbour in the same zipcode (panels (i) and (ii)) and firms which have hired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

Figure 2: TC Calls Across Firms and Randomization



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.

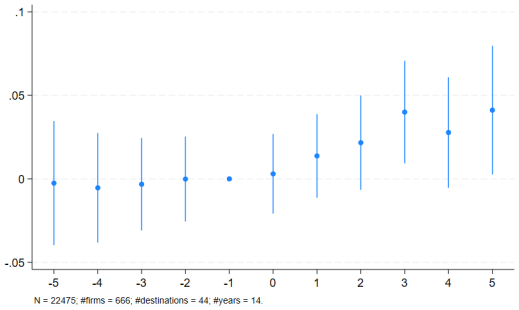
Figure 3: TC Calls Across Municipalities and Randomization



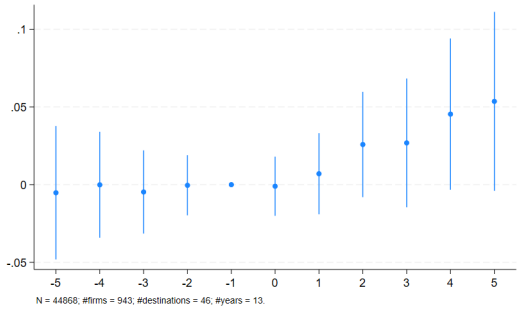
Notes: The above figures report the results from a randomization experiment where we first divide unsupported firms into four distinct groups based on lagged firm size, measured by domestic sales. We then report average domestic sales, along with corresponding confidence intervals, across municipalities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

Figure 4: Export Share Event Study Across Firm Networks

(a) Zipcode Networks



(b) Worker Transition Network



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

$$D_{ijt} = \alpha_{ij} + \delta_{jl(i)t} + \eta_{g(i)t} + \gamma \text{ Size}_{it} + \sum_{k=-5,\ldots,-2,0,\ldots,5} \beta_k \mathbf{1}\{\text{event time}_{ijt} = k\} + \varepsilon_{ijt}^{geo}$$

where D_{ijt} is export status of firm i in destination j in year t, l is industry and g is zipcode. Event time is zero for ij in the year t where $i' \neq i$ from the same zipcode ($g(i) = g(i')$) received promotion for j. The specification include firm-destination fixed effects α_{ij}, industry-destination-year fixed effects $\delta_{jl(i)t}$, and zipcode-year fixed effects $\eta_{g(i)t}$. The co-variate Size_{it} conditions the estimates on firm size, as proxied by the log number of employees in each firm. If an ij pair experienced multiple events over the sample period, we restrict attention to the first event. Event time is binned/winsorized at -5 and 5. An analogous event study exercise is documented in Panel (b) for the network of worker transitions.

9 Tables

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

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

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

Table 2: Country shifters

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

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

Table 3: Network Demand Spillover Country Shifters

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

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

Table 4: Fixed cost parameter estimates, 1,000 DKK; across support/call status

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

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

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

Country	Unsupported	Uncalled	Country	Supported	Called
USA	[450, 648]	[459, 648]	USA	[193, 433]	[187, 438]
China	[454, 655]	[463, 655]	China	[194, 440]	[117, 327]
Norway	[336, 493]	[340, 484]	Norway	[188, 442]	[113, 353]

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

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

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

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

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

Uninformed		None	Unsup. Muni.	Unsup. Zips	Unsup. Wkrs
Informed		All Unsup.	Sup. Muni.	Sup. Zips	Sup. Wkrs
Firms	Markets				
Panel A: Minimal information & country shifter					
All	All	0.029	0.230	0.415	0.345
Panel B: Minimal information & country shifter across call status					
Called	All	0.481	0.541	0.412	0.545
Not called	All	0.039	0.224	0.416	0.373
Panel C: Minimal information & country shifter for Placebo firms					
All	All	—	—	0.039	0.043
Panel D: Minimal information & country shifter for Placebo destinations†					
All	All	—	—	0.005	0.017
No. of Uninformed Obs.		0	19421	20432	20601
No. of Informed Obs.		21064	1643	632	463

Notes: Independent p-values are reported in Panel B. Adjusting p values for multiple testing had little impact reported p-values. The p-values reported in Panel C are the average p-values over 50 placebo samples. The null hypothesis is rejected in each individual placebo sample of supported zip codes. The number of un/informed observations in panel C is the total number in each group multiplied by the fraction that receive a call (or do not receive a call from the TC). Approximately 5.4 percent of firms receive a destination specific call in a typical year. (†) Panel D: In columns (3) and (4) firm-destination-year observations where indirect support is realized in the data are dropped to avoid confoundedness in testing with the placebo samples. The are 3,162 and 1,622 indirectly supported firm-destinations-year observations for zip code and workers transitions networks, respectively.

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

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

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

Table 9: Testing the disaggregated content of information sets

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

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

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

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

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

Table 11: Marginal Value of Public Funds

		Beneficiary Shares (%)		
Spillovers	MVPF	Directly Supported Firms	Indirectly Supported Firms	Government Revenue
Panel A: $MVPF_1^{alt}$ Government revenue evaluated a face value				
None	[9.53, 10.17]	[76.5, 76.5]	[0, 0]	[23.5, 23.5]
Municipalities	[10.21, 10.89]	[71.5, 71.6]	[4.9, 5.0]	[23.5, 23.5]
Zip Codes	[9.99, 10.66]	[73.7, 73.7]	[2.8, 2.8]	[23.5, 23.5]
Workers	[9.91,10.63]	[73.9, 74.4]	[2.1, 2.6]	[23.5, 23.5]
Panel B: $MVPF_2^{alt}$ Abstracting from additional government revenue				
None	[7.29, 7.78]	[1, 1]	[0, 0]	—
Municipalities	[7.81, 8.33]	[93.4, 93.6]	[6.4, 6.6]	—
Zip Codes	[7.64, 8.15]	[96.3, 96.3]	[3.7, 3.7]	—
Workers	[7.58, 8.13]	[96.6, 97.3]	[2.7, 3.4]	—

Notes: The marginal value of public funds computed as the ratio of the willingness to pay for

Table 12: Impact of doubling TC outreach via information alone; broad vs targeted policy (%)

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

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

Online Appendix

Information Frictions in Export Markets

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May 2025

A Demand

A.1 Mean Independence of Firm-Specific Export Revenue Shocks

We assume that for every *unsupported* firm i in network location l and every destination market j and year t we can write decompose demand shocks[37]

$$\xi_{ijlt} = \xi_{ilt}\xi_{jt}\tilde{\xi}_{ijlt},\ \xi_{jt} = \xi^{U}_{jt},\ \text{and } \xi_{ihlt} = \xi_{ilt}\xi_{hlt} \tag{A1}$$

trade costs

$$\tau_{ijt} = \tau_{it}\tau_{jt}\tilde{\tau}_{ijt} \text{ and } \tau_{iht} = \tau_{it}\tau_{ht} \tag{A2}$$

such that

$$\mathbb{E}_{jt}\left[\left(\frac{\tilde{\tau}_{ijt}}{\tilde{\xi}_{ijlt}}\right)^{1-\eta}\middle|\mathcal{J}_{ijlt}, \tau_{it}, \xi_{ilt}, c_{it}, f_{ijt}\right] = 1. \tag{A3}$$

Under the above assumptions we can write α^{U}_{jt} and, e^{U}_{ijt} as

$$\alpha^{U}_{jt} = \left(\frac{\xi^{U}_{jt}\tau_{ht}P_{jt}}{\xi_{hlt}\tau_{jt}P_{ht}}\right)^{\eta-1}\frac{Y_{jt}}{Y_{ht}} \tag{A4}$$

$$e_{ijlt} = \left(\frac{\xi^{U}_{jt}\tau_{ht}P_{jt}}{\xi_{hlt}\tau_{jt}P_{ht}}\right)^{\eta-1}\frac{Y_{jt}}{Y_{ht}}\left(\left(\frac{\tilde{\tau}_{ijt}}{\tilde{\xi}_{ijlt}}\right)^{\eta-1} - 1\right)r_{ihlt} \tag{A5}$$

[37] This discussion closely follows Appendix A.2 from Dickstein and Morales (2018).

and domestic revenues can be expressed as

$$r_{ihlt} = \left[\frac{\eta-1}{\eta}\frac{\xi_{ilt}\xi_{hlt}P_{ht}}{\tau_{it}\tau_{ht}c_{it}}\right]^{\eta-1} Y_{ht}. \tag{A6}$$

With the exception of the terms specific to firm i in location l, $(\tau_{it}c_{it}/\xi_{ilt})$, domestic revenues r_{ihlt} are a function of variables that are constant across firms in each year. The Law of Iterated Expectations implies that we can rewrite equation (A3) as

$$\mathbb{E}_{jt}\left[\left(\frac{\tilde{\tau}_{ijt}}{\tilde{\xi}_{ijlt}}\right)^{1-\eta}\middle|\mathcal{J}_{ijt}, r_{ihlt}, f_{ijt}\right] = 1. \tag{A7}$$

Combining equation (A3) with equation (A5) yields

$$\begin{aligned}
\mathbb{E}_{jt}[e_{ijlt}|\mathcal{J}_{ijlt}, r_{ihlt}, f_{ijt}] &= \mathbb{E}_{jt}\left[\left(\frac{\xi_{hlt}\tau_{jt}P_{ht}}{\xi^U_{jt}\tau_{ht}P_{jt}}\right)^{1-\eta}\frac{Y_{jt}}{Y_{ht}}\left(\left(\frac{\tilde{\tau}_{ijt}}{\tilde{\xi}_{ijlt}}\right)^{1-\eta}-1\right)r_{iht}\middle|\mathcal{J}_{ijlt}, r_{ihlt}, f_{ijt}\right] \\
&= \left(\frac{\xi_{hlt}\tau_{jt}P_{ht}}{\xi^U_{jt}\tau_{ht}P_{jt}}\right)^{1-\eta}\frac{Y_{jt}}{Y_{ht}}r_{ihlt}\mathbb{E}_{jt}\left[\left(\frac{\tilde{\tau}_{ijt}}{\tilde{\xi}_{ijlt}}\right)^{1-\eta}-1\middle|\mathcal{J}_{ijlt}, r_{ihlt}, f_{ijt}\right] \\
&= \left(\frac{\xi_{hlt}\tau_{jt}P_{ht}}{\xi^U_{jt}\tau_{ht}P_{jt}}\right)^{1-\eta}\frac{Y_{jt}}{Y_{ht}}r_{ihlt}\left(\mathbb{E}_{jt}\left[\left(\frac{\tilde{\tau}_{ijt}}{\tilde{\xi}_{ijlt}}\right)^{1-\eta}\middle|\mathcal{J}_{ijlt}, r_{ihlt}, f_{ijt}\right]-1\right) = 0
\end{aligned}$$

A.1.1 Demand spillovers across firm networks

The previous section assumed that the destination market-specific component of demand shocks, ξ^U_{jt}, vary by destination and year but do not vary by network location. This assumption effectively rules out network demand spillovers (even though information spillovers remain possible). To incorporate network demand spillovers we instead assume that the destination market-specific component of demand shocks is indexed by network location, ξ^U_{jlt}, and distinguish indirectly connected ($l = C$) and unconnected ($l = U$) firms:

$$\xi^U_{jlt} = ((\tilde{\xi}^U_{jUt})^{\eta-1} + C_{ljt}(\tilde{\xi}^U_{jCt})^{\eta-1})^{\frac{1}{\eta-1}}$$

where $\tilde{\xi}^U_{jUt}$ is the demand shock pertaining to unsupported firms in unsupported locations, $\tilde{\xi}^U_{jCt}$ is the demand shock pertaining to unsupported firms in supported locations and C_{ljt} is an indi-

cator variable that takes the value of 1 if location l is indirectly connected to the TC and zero otherwise.

Under the above assumptions we can write base demand α^U_{jut}, the network demand premium α^U_{jct} and, e_{ijlt} as

$$\alpha^U_{jUt} = \left(\frac{\tilde{\xi}^U_{jUt}\tau_{ht}P_{jt}}{\xi_{hlt}\tau_{jt}P_{ht}}\right)^{\eta-1}\frac{Y_{jt}}{Y_{ht}} \tag{A8}$$

$$\alpha^U_{jCt} = \left(\frac{\tilde{\xi}^U_{jCt}\tau_{ht}P_{jt}}{\xi_{hlt}\tau_{jt}P_{ht}}\right)^{\eta-1}\frac{Y_{jt}}{Y_{ht}} \tag{A9}$$

$$e_{ijlt} = \left(\frac{\xi^U_{jlt}\tau_{ht}P_{jt}}{\xi_{hlt}\tau_{jt}P_{ht}}\right)^{\eta-1}\frac{Y_{jt}}{Y_{ht}}\left(\left(\frac{\tilde{\tau}_{ijt}}{\tilde{\xi}_{ijlt}}\right)^{\eta-1}-1\right)r_{ihlt} \tag{A10}$$

where domestic revenues are expressed as in equation (A6). Combining equation (A3) with equation (A10) yields

$$\begin{aligned}
\mathbb{E}_{jt}[e_{ijlt}|\mathcal{J}_{ijlt}, r_{ihlt}, f_{ijt}] &= \mathbb{E}_{jt}\left[\left(\frac{\xi_{hlt}\tau_{jt}P_{ht}}{\xi^U_{jlt}\tau_{ht}P_{jt}}\right)^{1-\eta}\frac{Y_{jt}}{Y_{ht}}\left(\left(\frac{\tilde{\tau}_{ijt}}{\tilde{\xi}_{ijlt}}\right)^{1-\eta}-1\right)r_{iht}\middle|\mathcal{J}_{ijlt}, r_{ihlt}, f_{ijt}\right] \\
&= \left(\frac{\xi_{hlt}\tau_{jt}P_{ht}}{\xi^U_{jlt}\tau_{ht}P_{jt}}\right)^{1-\eta}\frac{Y_{jt}}{Y_{ht}}r_{ihlt}\mathbb{E}_{jt}\left[\left(\frac{\tilde{\tau}_{ijt}}{\tilde{\xi}_{ijlt}}\right)^{1-\eta}-1\middle|\mathcal{J}_{ijlt}, r_{ihlt}, f_{ijt}\right] \\
&= \left(\frac{\xi_{hlt}\tau_{jt}P_{ht}}{\xi^U_{jlt}\tau_{ht}P_{jt}}\right)^{1-\eta}\frac{Y_{jt}}{Y_{ht}}r_{ihlt}\left(\mathbb{E}_{jt}\left[\left(\frac{\tilde{\tau}_{ijt}}{\tilde{\xi}_{ijlt}}\right)^{1-\eta}\middle|\mathcal{J}_{ijlt}, r_{ihlt}, f_{ijt}\right]-1\right)=0
\end{aligned}$$

where the second equality holds under the assumption that the arrival of new information in location l is as good as random.

A.1.2 Incorporating supported firms

In this section we incorporate demand differences across supported and unsupported firms. Specifically, we assume that the destination market-specific component of demand shocks among supported firm is, ξ_{jt}, is a composite of the base unsupported demand shock, ξ^U_{jt}, and a support premium, ξ^S_{jt}:

$$\xi_{jt} = ((\xi^U_{jt})^{\eta-1} + (\xi^S_{jt})^{\eta-1})^{\frac{1}{\eta-1}}$$

Under the above assumptions we can write base demand α_{jt}^U, the network demand premium α_{jt}^S and, e_{ijlt} as

$$\alpha_{jt}^U = \left(\frac{\xi_{jt}^U \tau_{ht} P_{jt}}{\xi_{hlt} \tau_{jt} P_{ht}}\right)^{\eta-1} \frac{Y_{jt}}{Y_{ht}} \tag{A11}$$

$$\alpha_{jt}^S = \left(\frac{\xi_{jt}^S \tau_{ht} P_{jt}}{\xi_{hlt} \tau_{jt} P_{ht}}\right)^{\eta-1} \frac{Y_{jt}}{Y_{ht}} \tag{A12}$$

$$e_{ijlt} = \left(\frac{\xi_{jt} \tau_{ht} P_{jt}}{\xi_{hlt} \tau_{jt} P_{ht}}\right)^{\eta-1} \frac{Y_{jt}}{Y_{ht}} \left(\left(\frac{\tilde{\tau}_{ijt}}{\tilde{\xi}_{ijlt}}\right)^{\eta-1} - 1\right) r_{ihlt} \tag{A13}$$

where domestic revenues are expressed as in equation (A6). Combining equation (A3) with equation (A13) yields

$$\begin{aligned}
\mathbb{E}_{jt}[e_{ijlt}|\mathcal{J}_{ijlt}, r_{ihlt}, f_{ijt}] &= \mathbb{E}_{jt}\left[\left(\frac{\xi_{hlt}\tau_{jt}P_{ht}}{\xi_{jt}\tau_{ht}P_{jt}}\right)^{1-\eta} \frac{Y_{jt}}{Y_{ht}} \left(\left(\frac{\tilde{\tau}_{ijt}}{\tilde{\xi}_{ijlt}}\right)^{1-\eta} - 1\right) r_{iht} \middle| \mathcal{J}_{ijlt}, r_{ihlt}, f_{ijt}\right] \\
&= \left(\frac{\xi_{hlt}\tau_{jt}P_{ht}}{\xi_{jt}\tau_{ht}P_{jt}}\right)^{1-\eta} \frac{Y_{jt}}{Y_{ht}} r_{ihlt} \mathbb{E}_{jt}\left[\left(\frac{\tilde{\tau}_{ijt}}{\tilde{\xi}_{ijlt}}\right)^{1-\eta} - 1 \middle| \mathcal{J}_{ijlt}, r_{ihlt}, f_{ijt}\right] \\
&= \left(\frac{\xi_{hlt}\tau_{jt}P_{ht}}{\xi_{jt}\tau_{ht}P_{jt}}\right)^{1-\eta} \frac{Y_{jt}}{Y_{ht}} r_{ihlt} \left(\mathbb{E}_{jt}\left[\left(\frac{\tilde{\tau}_{ijt}}{\tilde{\xi}_{ijlt}}\right)^{1-\eta} \middle| \mathcal{J}_{ijlt}, r_{ihlt}, f_{ijt}\right] - 1\right) = 0
\end{aligned}$$

where the second equality holds under the assumption that the selection of firms into support status, conditional on $(\mathcal{J}_{ijlt}, r_{ihlt}, f_{ijt})$ is as good as random. We check this assumption by using the quasi-random TC outreach as an instrument for selection to into support status.

A.2 Buyers and the Export Demand Shifter

This section builds a simple framework which distinguishes a firm-level component of export demand that captures "average buyer quality" from differences in the average number of buyers each firm faces. We abstract from network demand spillovers and for the sake of notational parsimony omit the location index throughout. Specifically, let market-specific demand shocks take the form: $\tilde{\xi}_{ijt} = \left(\sum_{b \in \Omega_{ijt}^T} (\mu_b^T)^{\eta-1}\right)^{\frac{1}{\eta-1}}$ where Ω_{ijt}^T is the set of buyers firm i reaches market j and year t, b indexes individual buyers, and μ_b^T 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, $n(\Omega_{ijt}^S) > n(\Omega_{ijt}^U)$, where $n(\Omega)$ is the cardinality of set Ω. Second, it may increase the purchase size of any particular buyer, $\mu_b^S > \mu_b^U$.

Suppose firm i reaches n_{ijt}^S buyers in market j with TC support and n_{ijt}^U buyers without TC support, $n_{ijt}^S \geq n_{ijt}^U$. Likewise, assume that for any buyer b the amount purchased if firm i has TC support, μ_{bjt}^S is no smaller than what it would have purchased without TC support, μ_{bjt}^U, $\mu_{bjt}^S \geq \mu_{bjt}^U$. We write firm i's demand shifter $\tilde{\xi}_{ijt}^T$ as

$$\xi_{ijt}^T = \left(\sum_{b \in \Omega_{ijt}^T} (\mu_{bjt}^T)^{\eta-1} \right)^{\frac{1}{\eta-1}}$$

Regardless of whether the firm uses TC support, we focus on a symmetric equilibrium where all buyers purchase the same amount so that $\mu_{bjt}^0 = \bar{\mu}_{jt}^U \; \forall \; b \in \Omega_{ijt}^U$, $\mu_{bjt}^S = \bar{\mu}_{jt}^S \; \forall \; b \in \Omega_{ijt}^S$ and $\mu_{bjt}^S \geq \mu_{bjt}^U$. We can then write $\tilde{\xi}_{ijt}^S$ as

$$\begin{aligned} \xi_{ijt}^S &= \bar{\mu}_{jt}^S (n_{ijt}^S)^{\frac{1}{\eta-1}} \\ &= (\bar{\mu}_{jt}^U + \Delta\bar{\mu}_{jt})[(n_{ijt}^U)^{\frac{1}{\eta-1}} + \Delta(n_{ijt}^{\frac{1}{\eta-1}})] \\ &= \underbrace{\bar{\mu}_{jt}^U (n_{ijt}^U)^{\frac{1}{\eta-1}}}_{\xi_{ijt}^U = \tilde{\xi}_{ijt}^U} + \underbrace{\bar{\mu}_{jt}^U \Delta(n_{ijt}^{\frac{1}{\eta-1}}) + \Delta\bar{\mu}_{jt}(n_{ijt}^U)^{\frac{1}{\eta-1}} + \Delta\bar{\mu}_{jt}\Delta(n_{ijt}^{\frac{1}{\eta-1}})}_{\xi_{ijt}^S} \end{aligned} \tag{A14}$$

where $n_{ijt}^T = n(\Omega_{ijt}^T)$ and $\Delta x = x^S - x^U$ for any variable x. The first term in equation (A14) is the demand shifter that would apply to firm i in the absence of TC support, ξ_{ijt}^U. The demand shock ξ_{ijt}^U in turn has two components, the number of buyers among unsupported firms in destination j, $(n_{ijt}^U)^{\frac{1}{\eta-1}}$, and average buyer quality among supported firms in destination j, $\bar{\mu}_{ijt}^U$, measured as average sales per buyer. These two subcomponents are features of our empirical work

It is also possible to theoretically decompose the TC demand premium, ξ_{ijt}^S into similar subcomponents. The second term in equation (A14) decomposes the TC demand premium into a component that increases demand through a greater number of buyers, $\bar{\mu}_{jt}^S \Delta(n_{ijt}^{\frac{1}{\eta-1}})$, a component that increases demand through larger orders per buyer, $\Delta\bar{\mu}_{jt}(n_{ijt}^U)^{\frac{1}{\eta-1}}$, and an inter-

action term representing the joint gains from having a greater number of high quality buyers, $\Delta\bar{\mu}_{jt}\Delta(n_{ijt}^{\frac{1}{\eta-1}})$.

A.3 From demand to revenues

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

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

Focusing on a symmetric equilibrium where firm i's buyers all purchase the same amount, $\mu_b^T = \bar{\mu}_{ijt}^T \; \forall \; b \in \Omega_{ijt}^T$, γ_{jt}^U measures the per buyer revenue (buyer quality) among unsupported firms and we can decompose the TC revenue premium, α_{ij}^S, into a component capturing a per buyer TC premium, $\alpha_{ij}^{S,\mu}$ and number of buyers premium, $\alpha_{ij}^{S,n}$

$$\alpha_{ijt}^{S} = \alpha_{ijt}^{S,\mu} + \alpha_{ijt}^{S,n} + \alpha_{ijt}^{S,j} \tag{A15}$$

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

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

$$r_{ijt} = [\alpha_{jt}^{U} + (\alpha_{jt}^{S,\mu} + \alpha_{jt}^{S,n} + \alpha_{jt}^{S,\mu n})s_{ijt}]r_{iht} + e_{ijt} \tag{A16}$$

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

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

$$\begin{aligned}
\frac{r_{ijt}}{n_{ijt}} &= \left(\frac{\xi_{iht}\tau_{ijt}P_{ht}}{\bar{\mu}^U\tau_{iht}P_{jt}}\right)^{1-\eta}\frac{Y_{jt}}{Y_{ht}}\left[(1-s_{ijt})r_{iht}+\left(\frac{\bar{\mu}^S}{\bar{\mu}^U}\right)^{\eta-1}s_{ijt}r_{iht}\right] \\
&= \left(\frac{\xi_{ht}\tau_{jt}P_{ht}}{\bar{\mu}^U\tau_{ht}P_{jt}}\right)^{1-\eta}\frac{Y_{jt}}{Y_{ht}}r_{iht}\left[1+\left[\left(\frac{\bar{\mu}^S}{\bar{\mu}^U}\right)^{\eta-1}-1\right]s_{ijt}\right]+e^n_{ijt} \\
&= (\gamma^U_{jt}+\gamma^S_j s_{ijt})r_{iht}+e^n_{ijt} \qquad \text{(A17)}
\end{aligned}$$

where the second 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 third equality applies the assumption that TC premia are time invariant.

The estimated demand coefficients capture relative buyer quality, $\frac{\gamma^S_j}{\gamma^U_{jt}}=\left(\frac{\bar{\mu}^S_j}{\bar{\mu}^U_{jt}}\right)^{\eta-1}-1$, and allow us to compute the TC quality premium $\alpha^{S,\mu}_{jt}$, the TC buyers premium $\alpha^{S,n}_{jt}$, and the TC interaction premium $\alpha^{S,\mu n}_{jt}$. 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^U_{jt} and γ^S_j from the OLS regression of equation (A17), conditional on $r_{ijt}>0$). Second, using the estimates of γ^U_{jt} and γ^S_{jt} along with our previous estimates of α^U_{jt} and α^S_{jt}, we compute $\alpha^{S,\mu}_{jt}=\alpha^U_{jt}\frac{\gamma^S_j}{\gamma^U_{jt}}$, $\alpha^{S,n}_{jt}=\frac{\alpha^S_j-\alpha^{S,\mu}_{jt}}{1+\gamma^S_j/\gamma^U_{jt}}$ and $\alpha^{S,\mu n}_{jt}=\frac{\gamma^S_j}{\gamma^U_{jt}}\frac{\alpha^S_j-\alpha^{S,\mu}_{jt}}{1+\gamma^S_j/\gamma^U_{jt}}$.

A.4 Disaggregated information tests among supported firms

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

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

markets among supported firms.

B Estimation Details

B.1 Perfect knowledge of exporter information sets

Consider a setting where the information set specified by the researcher, $\mathcal{J}^a_{ijt}$ is the same as that used by the firm for its export decision, $\mathbb{E}[r_{ijt}|\mathcal{J}_{ijt}] = \mathbb{E}[r_{ijt}|\mathcal{J}^a_{ijt}]$, including any benefits of export support. In this case, the researcher can estimate the parameter vector θ^* as the value of the unknown parameter vector θ by maximizing the the log-likelihood function[38]

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

where

$$\mathcal{P}(D_{jt} = 1|\mathcal{J}^a_{ijt}, s_{ijt}, dist_j; \theta) = \Phi(\theta_2^{-1}(\eta^{-1}\mathbb{E}[r^o_{ijt}|\mathcal{J}^a_{ijt}] - \theta_0^T - \theta_1^T dist_j)). \tag{A18}$$

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 (A18), wrongly assuming perfect foresight will induce bias in the fixed cost parameters.[39]

[38]For parsimony, there is a slight abuse of notation in equation A18 where we allow θ^T to stand in for θ^S or θ^U for supported and unsupported firms, respectively.

[39]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, $\mathbb{E}[r^o_{ijt}|\mathcal{J}_{ijt}] \sim \mathbb{N}(0, \sigma^2_e)$ and $\varepsilon_{ijt}|(\mathcal{J}_{ijt}, \nu^T_{ijt}) \sim \mathbb{N}(0, \sigma^2_\varepsilon)$, then β^T_0, β^T_1 and σ_T will be upwards biased. Dickstein and Morales, 2018 demonstrate

B.2 Moment Inequality Estimation

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

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[40]

$$\mathcal{M}_{ob}^{T}(Z_{ijt};\theta^{T}) = \mathbb{E}\left[\begin{array}{c} m_{ob}^{l,T}(D_{ijt}, r_{ijt}^{o}, dist_{j}, s_{ijt});\theta^{T} \\ m_{ob}^{u,T}(D_{ijt}, r_{ijt}^{o}, dist_{j}, s_{ijt});\theta^{T} \end{array} \middle| Z_{ijt}\right] \geq 0, \tag{A19}$$

where

$$m_{ob}^{l,T}(\cdot) = D_{ijt}\frac{1-\Phi((\theta_2^T)^{-1}(\eta^{-1}r_{ijt}^{o}-\theta_0^T-\theta_1^T dist_j))}{\Phi((\theta_2^T)^{-1}(\eta^{-1}r_{ijt}^{o}-\theta_0^T-\theta_1^T dist_j))} - (1-D_{ijt}) \tag{A20}$$

$$m_{ob}^{u,T}(\cdot) = (1-D_{ijt})\frac{\Phi((\theta_2^T)^{-1}(\eta^{-1}r_{ijt}^{o}-\theta_0^T-\theta_1^T dist_j))}{1-\Phi((\theta_2^T)^{-1}(\eta^{-1}r_{ijt}^{o}-\theta_0^T-\theta_1^T dist_j))} - D_{ijt}. \tag{A21}$$

In a full information setting conditions (A20) and (A21) are, in expectation, individually equal to zero at the true parameter vector θ^T. In our case, however, conditions (A20) and (A21) 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 (A21) 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 (A21) will hold at $\theta = \theta^*$. Similar logic applies to condition (A20).[41]

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that this result holds more broadly across different distributions for $\mathbb{E}[r_{ijt}^{o}|\mathcal{J}_{ijt}]$ and ε_{ijt}. We document below that result holds for unsupported firms. For supported firms it holds in absolute magnitude but not necessarily direction.

[40]For parsimony, conditions (A20)-(A21) 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.

[41]Intuitively, by revealed preference equation (**??**) implies that expected export prof-

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

$$\mathcal{M}_{rp}^{T}(Z_{ijt};\theta^{T}) = \mathbb{E}\left[\begin{array}{c} m_{l}^{r}(D_{ijt}, r_{ijt}^{o}, dist_{j}, s_{ijt});\theta^{T} \\ m_{rp}^{u,d}(D_{ijt}, r_{ijt}^{o}, dist_{j}, s_{ijt});\theta^{T} \end{array} \middle| Z_{ijt}\right] \geq 0, \tag{A22}$$

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 (A22), for an exporter, $D_{ijt} = 1$.[42] Expectations, conditional on $(D_{ijt}, \mathcal{J}_{ijt}, dist_{j}, s_{ijt})$, yields

$$D_{ijt}(\eta^{-1}\mathbb{E}[r_{ijt}|\mathcal{J}_{ijt}] - \beta_{0}^{T} - \beta_{1}^{T}dist_{j}) + S_{ijt} \geq 0 \tag{A23}$$

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

its 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 $\mathbb{E}[r_{ijt}^{o}\mathcal{J}_{ijt}]$ and applying Jensen's inequality, we recover equation (A21) due to the convexity of $\frac{\Phi(\cdot)}{1-\Phi(\cdot)}$.

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

with respect to the observed vector Z_{ijt}, inequality (A23) becomes weaker as long as $\frac{\phi(\cdot)}{\Phi(\cdot)}$ is convex. Under this assumption, if (A23) holds at $\theta = \theta^*$, then (A22) and (A23) will also hold at $\theta = \theta^*$.[43]

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

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

C Fixed Costs

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

C.1 Fixed Export Costs and Trade Council Support

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

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

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

The last three columns of Table A1 report fixed export cost parameters for supported firms,

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

To better understand the sources of estimation bias in our context we reconsider the likelihood function for the decision to export.[44] As in the main text, ξ^T_{ijlt} denotes the difference between the researcher's proxy for firm expected potential revenue and the firm's true expected potential export revenue, $\xi^T_{ijlt} = \mathbb{E}[r^{T,o}_{ijlt}|\mathcal{J}^a_{ijlt}] - \mathbb{E}[r^{T,o}_{ijlt}|\mathcal{J}_{ijlt}]$. Ideally $\mathbb{E}[r^{T,o}_{ijlt}|\mathcal{J}^a_{ijlt}]$ perfectly captures firm expectations and, conditional on model structure, we have discrete choice model

$$D_{ijlt} = \mathbb{1}\{\eta^{-1}\mathbb{E}[r^{T,o}_{ijlt}|\mathcal{J}^a_{ijlt}] - \beta^T_0 - \beta^T_1 dist_j - \nu^T_{ijlt} \geq 0\}, \quad \nu^T_{ijlt} \sim \mathbb{N}(0, \sigma^2_T) \tag{A24}$$

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

$$\mathcal{L}_a(\theta^T|D, \mathcal{J}^a, dist) = \tag{A25}$$
$$\textstyle\sum_{i,j,t} \Big\{ D_{ijlt} \ln\Big(\int_\nu \mathbb{1}\{\eta^{-1}\mathbb{E}[r^{T,o}_{ijlt}|\mathcal{J}^a_{ijlt}] - \theta^T_0 - \theta^T_1 dist_j - \nu^T \geq 0\} f_{\nu^T}(\nu^T|\mathcal{J}^a_{ijlt}, dist_j; \theta^T_2)\Big) +$$
$$(1 - D_{ijlt}) \ln\Big(\int_\nu \mathbb{1}\{\eta^{-1}\mathbb{E}[r^{T,o}_{ijlt}|\mathcal{J}^a_{ijlt}] - \theta^T_0 - \theta^T_1 dist_j - \nu^T \leq 0\} f_{\nu^T}(\nu^T|\mathcal{J}^a_{ijlt}, dist_j; \theta^T_2)\Big)\Big\}$$

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

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

$$\begin{aligned} D_{ijlt} &= \mathbb{1}\{\eta^{-1}\mathbb{E}[r^{T,o}_{ijlt}|\mathcal{J}_{ijlt}] - \beta^T_0 - \beta^T_1 dist_j - \nu^T_{ijlt} \geq 0\}, \\ &= \mathbb{1}\{\eta^{-1}(\mathbb{E}[r^{T,o}_{ijlt}|\mathcal{J}^a_{ijlt}] - \xi^T_{ijlt}) - \beta^T_0 - \beta^T_1 dist_j - \nu^T_{ijlt} \geq 0\}, \\ &= \mathbb{1}\{\eta^{-1}\mathbb{E}[r^{T,o}_{ijlt}|\mathcal{J}^a_{ijlt}] - \beta^T_0 - \beta^T_1 dist_j - (\eta^{-1}\xi^T_{ijlt} + \nu^T_{ijlt}) \geq 0\} \end{aligned} \tag{A26}$$

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

where the composite error $\eta^{-1}\xi^T_{ijlt} + \nu^T_{ijlt}$ accounts for both the structural error ν^T_{ijlt} and measurement error ξ^T_{ijlt}. The correct log likelihood is then

$$\mathcal{L}(\theta^T|D, \mathcal{J}^a, dist) = \tag{A27}$$
$$\sum_{i,j,t} \Big\{ D_{ijlt} \ln \Big(\int_{\chi^T} \mathbb{1}\{\eta^{-1}\mathbb{E}[r^{T,o}_{ijlt}|\mathcal{J}^a_{ijlt}] - \theta^T_0 - \theta^T_1 dist_j - \chi^T \geq 0\} f_{\chi^T}(\chi^T|\mathcal{J}^a_{ijlt}, dist_j; \theta^T_2) \Big) +$$
$$(1 - D_{ijlt}) \ln \Big(\int_{\chi^T} \mathbb{1}\{\eta^{-1}\mathbb{E}[r^{T,o}_{ijlt}|\mathcal{J}^a_{ijt}] - \theta^T_0 - \theta^T_1 dist_j - \chi^T \leq 0\} f_{\chi^T}(\chi^T|\mathcal{J}^a_{ijlt}, dist_j; \theta^T_2) \Big) \Big\}$$

where $\chi^T_{ijlt} = \xi^T_{ijlt} + \nu^T_{ijlt}$ and $f_{\chi^T}(\cdot)$ is the conditional density of χ^T_{ijlt}. The log likelihood maximizing values of θ^T will generally differ across equations (A25) and (A27) since the conditional density functions, $f_{\nu^T}(\nu^T|\mathcal{J}^a_{ijlt}, dist_j; \theta^T_2)$ and $f_{\chi^T}(\chi^T|\mathcal{J}^a_{ijlt}, dist_j; \theta^T_2)$, differ.

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

Second, the functional form of the distribution $f_{\chi^T}(\chi^T|\mathcal{J}^a_{ijlt}, dist_j; \theta^T_2)$ is unlikely to be normally distributed even when ν^T_{ijt} is normally distributed. More broadly, $f_{\chi^T}(\chi^T|\mathcal{J}^a_{ijlt}, dist_j; \theta^T_2)$ is unlikely to take the same functional form as $f_{\nu^T}(\nu^T|\mathcal{J}^a_{ijlt}, dist_j; \theta^T_2)$. In our setting ν^T_{ijlt} is assumed to be normal for both supported and unsupported firms. However, $\nu^T_{ijlt} + \xi^T_{ijlt}$ will only be normally distributed if ξ^T_{ijlt} is independent and also normally distributed. Not only is this assumption likely to fail, it is particularly likely to fail for supported firms since supported firms are likely to draw demand shocks from a highly skewed distribution. Assuming that the joint error is normally distributed when it is not is likely to introduce significant bias, as suggested by the parameter estimates in Tables A1-A2.

Last, the estimate of θ^T_2 that maximizes the likelihood function (A27) will generally be different from that which maximizes likelihood function (A25) as long as the variance of ν^T_{ijlt} and that of ξ^T_{ijlt} are different. Indeed, even if ξ^T_{ijlt} and ν_{ijlt} are independent the variance of the

structural error will converge to $\sigma_T^2 + \eta^{-2} var(\xi_{ijlt}^T)$ instead of φ_T^2. Less obviously, larger fixed cost shocks are likely to have a differential impact on the direction of fixed cost bias across firm-level support status. Among unsupported firms where export propensities are *low*, maximum likelihood estimates $of \theta_0^U$ and θ_1^U must rationalize why firms that would otherwise be profitable exporters do not export even though they are relatively likely to draw small (or negative) fixed cost shocks. Accordingly, the θ_0^U and θ_1^U are likely to be biased upwards. Among supported firms where export propensities are *high*, maximum likelihood estimates of θ_0^S and θ_1^S must rationalize why firms that would otherwise be unprofitable exporters choose to export even though they are likely to draw large, positive fixed cost shocks. In this case, the likelihood rationalizes these outcomes by choosing values of θ_0^S and θ_1^S that are biased downwards.

C.2 Dynamic Entry Costs

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

$$\pi_{ijlt}^U = \eta^{-1} r_{ijlt}^U - f_{ijt}^U - (1 - D_{ij,t-1}) F_{ijt} \tag{A28}$$

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

$$F_{ijt} = \rho_0 + \rho_1 dist_j. \tag{A29}$$

We assume that only unsupported firms are subject to first time entry costs; supported firms only incur fixed (maintenance) costs due to TC support and abstract from the dynamic problem for supported firms hereafter.[45] We maintain the assumption in Dickstein and Morales, 2018 that firms know first time entry costs when deciding whether to export to a destination and the

[45] Relaxing this assumption for supported firm returned estimates of sunk entry costs which were indistinguishable from zero among supported firms. Fundamentally, given high export propensities and destination market persistence among supported firms, we cannot credibly

evolution of firm-level information sets is independent of past export decisions

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

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

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

where ρ is the discount factor.

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

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

Notably, the estimated sunk cost for Norway overlaps zero, suggesting that entry into this neighbouring country is particularly inexpensive. We highlight that in no case to the estimated

estimate differential sunk and fixed cost parameters among supported firms.

confidence joint confidence sets ever imply negative entry costs; rather the sum of fixed and sunk costs are always estimated to bounded above zero in all cases, including Norway.

D Adding EU Export Destinations

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

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

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

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

$$f_{ijt} = (1 - s_{ijt})(\beta_0^U + \beta_1^U dist_j + \nu_{ijt}^U) + s_{ijt}(\beta_0^S + \beta_1^S dist_j + \nu_{ijt}^S) \tag{A30}$$

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

probit model[46]

$$\mathcal{P}(D_{ijt}=1|\mathcal{J}_{ijt},dist_j,s_{ijt};\theta) \;=\; \Phi\left(\frac{1}{\theta_2^T}\left(\frac{1}{\eta}\mathbb{E}[\alpha_{jt}^T r_{iht}|\mathcal{J}_{ijt}^a]-\theta_0^T-\theta_1^T dist_j\right)\right). \quad \text{(A31)}$$

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

$$f_{ijt}^{EU} = (1-s_{ijt})(\beta_0^{EU,U}+\nu_{ijt}^{EU,U})+s_{ijt}(\beta_0^{EU,S}+\nu_{ijt}^{EU,S}) \quad \text{(A32)}$$

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

$$\begin{aligned}\mathcal{P}(D_{ijt}=1|\mathcal{J}_{ijt},dist_j,s_{ijt};\theta) \;=\; & \Phi\left(\left(\frac{1}{\theta_2+\theta_3\mathbf{1}\{j\in EU\}}\right)\right. \quad \text{(A33)}\\ & \left.\times\left(\frac{1}{\eta}\mathbb{E}[\alpha_{jt}^T r_{iht}|\mathcal{J}_{ijt}^a]-\theta_0-\theta_1 dist_j\mathbf{1}\{j\notin EU\}\right)\right)\end{aligned}$$

so that the relationship between EU specific parameters is

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

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

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

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

Table A5 reports the moment inequality fixed cost parameter estimates, while Table A6 documents the implied differences in estimated fixed export costs relative to the benchmark sample. Relative to benchmark estimates there is a modest increase in the upper and lower bounds of the confidence sets for the parameters σ_U, σ_S, β_O^U, and β_0^S, though in all but β_0^U the EU-inclusive confidence sets largely overlap the benchmark confidence sets. There is a commiserate decline in the upper and lower bounds of the confidence sets of β_1^U and β_1^S, though there is again substantial overlap in the latter case. These differences in the parameter estimates are not surprising. Parameter θ_2 enters both equations (A31) and (A33), a larger estimate of which helps explain within-EU variation in exporting over a different reporting threshold. Drawing structural fixed cost shocks from a distribution with a larger variance in turn affects the relative role β_0^T and β_1^T for explaining entry behaviour across export destinations.

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

Using the EU-augmented model, we proceed to perform benchmark information tests on both unsupported and supported samples. Table A7 reports analogous results to those in main text for both samples. For both unsupported firms and supported firms we cannot reject the

separate hypotheses that they individually do not know the minimal information set. Again, for both unsupported firms and supported firms we clearly reject the separate hypotheses that they individually have perfect foresight of export market conditions. Last, while we reject the hypothesis that unsupported firms know the minimal information set and the country shifter, we cannot reject the same hypothesis among supported firms. This evidence lends further support to common narrative that supportive firms know demand conditions in export destination markets.

E Information (Specification) Tests

We employ the "Test RC" model specification test from Bugni et al., 2015 to evaluate whether firms have knowledge of demand conditions when deciding to enter export markets. We follow the implementation in Dickstein and Morales, 2018 closely; all modifications are minor in nature and this appendix is provided to give the interested reader a sense of the implementation of the specification based information tests in this setting.[47] Below we focus on tests for unsupported firms; the testing procedure for supported firms are analogous.

E.1 Computation Details

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

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

0 is correctly specified when Θ_0 is non-empty:

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

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

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

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

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

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

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

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

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

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

and

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

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

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

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

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

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

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

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

E.2 Identifying Information Spillovers

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

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

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

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

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

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

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

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

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

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

E.3 Threats to Identification

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

E.3.1 Information Spillovers vs. Confoundedness

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

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

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

Third, the placebo tests yield samples of falsely connected firms which are of the same size

as the observed set of indirectly connected firms.[48] Table **??** reports directly checks for the balancing of firm characteristics across indirectly supported firms and those from the placebo samples. The odd-numbered columns of Table Table **??** report the smallest p-value from t-tests of the difference between the observed sample of indirectly supported firms across all placebo samples in the year prior to treatment (year $t-1$ when a peer receives TC support in year t). The even numbered columns repeat this exercise for the entire sample of unsupported firms and the difference between the observed sample of indirectly supported firms and the complementary sample of unsupported firms.

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

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

E.4 Statistical Power

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

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

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

1. Randomly draw a (geographic or employment-based) network node.

2. Artificially (and incorrectly) label the randomly drawn nodes as the origin of TC support. All indirectly connected firms to the randomly drawn nodes are likewise labeled as indirectly supported firms.

3. Repeat this process until the placebo sample of indirectly supported firms reaches the sample size of the number of indirectly treated firms in the actual data.

4. Repeat all information tests on the individual placebo sample identically to the tests conducted on the actual sample.

5. Draw N placebo samples where $N = 50$ in our case.

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

E.5 Endogenous Network Targeting

A related concern pertains to the possibility that the TC targets firms which are best connected to their peers in order to facilitate informational spillovers. While there is no narrative evidence to this potential objective, we nonetheless consider the possibility that network targeting by the TC is driving our findings. Figure 3 documents that average firm size across municipalities supported or called by the TC is nearly identical to those uncalled by the TC. Along the firm size dimension, arguably the most visible firm characteristic, there is no evidence of municipality targeting with TC support. Similar results are available upon request for other network specifications and firm/destination characteristics.

F Additional Results

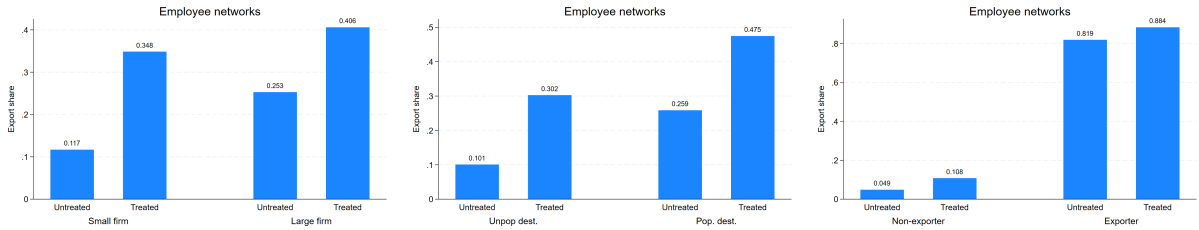
This section briefly discusses additional information test results that were omitted from the main text for brevity. Table A9 reports test whether supported firms know the number of buyers, buyer quality or their interaction premium. In each case, we cannot reject the null hypothesis that supported firms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

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

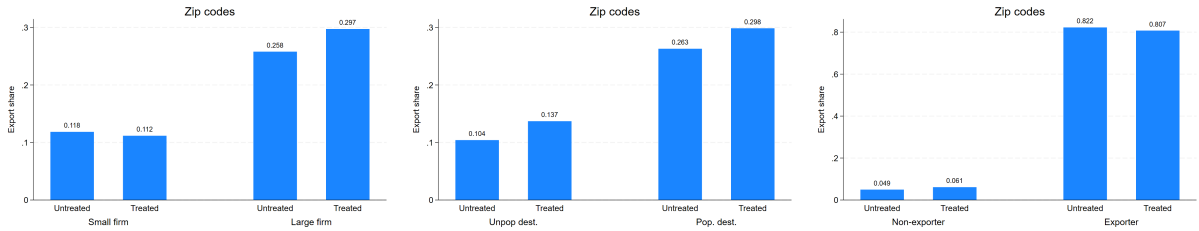
G Additional Figures

Figure A1: Export Share Across TC Firm Networks

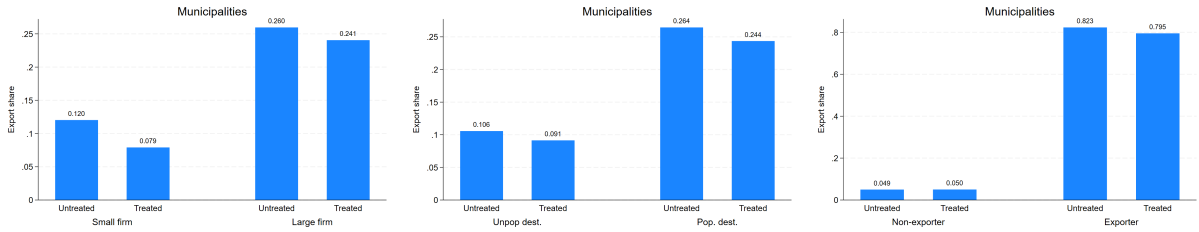
(a) Firm Size & Emp. Net. (b) Dest. Pop. & Emp. Net. (c) Exp. Status & Emp. Net.



(d) Firm Size & Zipcode (e) Dest. Popularity & Zipcode (f) Export Status & Zipcode



(g) Firm Size & Municipality (h) Dest. Popularity & Mun. (i) Export Status & Mun.



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

H Additional Tables

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

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

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

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

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

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

Table A3: Fixed Cost Parameter estimates, 1,000 DKK; by export experience

	Past non-exporters			Past exporters		
Estimator	σ_U	β_0^U	β_1^U	σ_S	β_0^S	β_1^S
Moment inequality	[15; 306]	[-226; 560]	[198; 2,284]	[337; 652]	[213; 467]	[-63; 411]

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

Table A4: Average fixed export costs, 1,000 DKK; by export experience

	Past non-exporters			Past exporters		
Estimator	USA	China	Norway	United States	China	Norway
Moment inequality	[467; 1,543]	[480; 1,602]	[-161; 580]	[402; 591]	[407; 597]	[230; 475]

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

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

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

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

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

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

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

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

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

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

Table A8: Testing the content of information sets; by export experience

Firms	Markets	Past non-exporters	Past exporters
Panel A: Minimal information			
All	All	0.367	0.758
Panel B: Perfect foresight			
All	All	0.025	0.039
Panel C: Minimal information & country shifter			
All	All	0.041	0.055
No. of Obs.		11,888	9,392

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

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

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

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

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

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

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