What Do Market-Access Subsidies Do? Experimental Evidence from Tunisia*

Nadia Ali
Giacomo De Giorgi
Aminur Rahman
Eric Verhoogen

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ONLINE APPENDIX

A Theory

A.1 Optimal Market Penetration as a Function of Product Scope

We derive the optimal market penetration as a function of G using an envelope theorem for arbitrary choice sets from Milgrom and Segal (2002). Using the approximations in (10), profit can be written:

$$\pi(G,n) \quad = \quad \Theta n\left(\frac{G^{1-\alpha(\sigma-1)}}{1-\alpha(\sigma-1)}\right) - a\ln\left(\frac{1}{1-n}\right)\frac{G^{1+\delta}}{1+\delta} \tag{A1}$$

Define $V(n)$ as the value function corresponding to the upper envelope of the profit functions: $V(n) = \sup_{G\in\mathbb{N}} \pi(G,n)$. Let $G^*(n) = \{G \in \mathbb{N} : \pi(G,n) = V(n)\}$, i.e., the optimal G for a given n. Theorem 2 of Milgrom and Segal (2002) implies $\frac{dV(n)}{dn} = \frac{\partial\pi(G,n)}{\partial n}$ for $G \in G^*(n)$. We thus have the first-order condition:

$$\frac{\partial\pi}{\partial n} = \Theta\left(\frac{G^{1-\alpha(\sigma-1)}}{1-\alpha(\sigma-1)}\right) - a\left(\frac{1}{1-n}\right)\frac{G^{1+\delta}}{1+\delta} = 0$$

Solving for the optimal n for a given G:

$$n^*(G) = 1 - \frac{a\Lambda}{\Theta}G^{\delta+\alpha(\sigma-1)}$$

which is (12).

A.2 Optimal Product Scope and Market Penetration in the Relaxed Problem

In this section, we solve for optimal product scope and market penetration in the relaxed problem. Here we can apply a standard envelope theorem to derive the partial derivative of total profits with respect to $\widetilde{G}$ for a given (optimized) value of n. The first-order condition is:

$$\frac{\partial \widetilde{\pi}(\widetilde{G}, n)}{\partial \widetilde{G}} = \Theta n \widetilde{G}^{-\alpha(\sigma-1)} - a \ln\left(\frac{1}{1-n}\right) \widetilde{G}^{\delta} = 0 \tag{A2}$$

Together, (12) and (A2) imply (13). To see this, note that (A2) can be rewritten:

$$\widetilde{G}^{\delta+\alpha(\sigma-1)} = \frac{\Theta n}{a \ln\left(\frac{1}{1-n}\right)} \tag{A3}$$

Using (12) and re-arranging:

$$-\frac{\Lambda}{1-n} e^{-\frac{\Lambda}{1-n}} \quad = \quad -\Lambda e^{-\Lambda} \tag{A4}$$

Given that $0 < \Lambda < 1$, there are two solutions to (A4) corresponding to the two branches of the Lambert W function (Corless et al., 1996). One is simply $n = 0$; this is inconsistent with entry. The solution consistent with entry is:

$$-\frac{\Lambda}{1-n} = W_{-1}\left(-\Lambda e^{-\Lambda}\right) \tag{A5}$$

This solution holds for $-\frac{1}{e} \leq -\Lambda e^{-\Lambda} < 0$, which is implied by $0 < \Lambda \leq 1$. Re-arranging (A5) gives:

$$\widetilde{n}^{*} = 1 - \frac{\Lambda}{|W_{-1}\left(-\Lambda e^{-\Lambda}\right)|} \tag{A6}$$

The solution for $\widetilde{G}$, (13), then follows from (12).

A.3 Optimal Product Scope and Market Penetration in the Integer-Constrained Problem

In this section, we return to the integer-constrained problem and derive explicit solutions for product scope and market penetration as functions of market-access costs, a, for a given level of productivity, ϕ. To begin, let $a_1, a_2, \ldots$ be the values of a at which $\widetilde{G}^{*}$ happens to take on integer values, i.e. $\widetilde{G}^{*}(a_k) = k$ for $k \in \mathbb{N}$. Using (13), we can solve explicitly for these values:

$$a_k = \frac{\Theta}{k^{\delta+\alpha(\sigma-1)} \, |W_{-1}\left(-\Lambda e^{-\Lambda}\right)|} \tag{A7}$$

Consider two such values, a_{k+1} and a_k, where $a_{k+1} < a_k$. By the definition of a_k, $k+1$ is the optimal scope at a_{k+1}, and k is optimal at a_k, hence:

$$\widetilde{\pi}(k, n^*(k))|_{a=a_k} \quad > \quad \widetilde{\pi}(k+1, n^*(k+1))|_{a=a_k} \tag{A8}$$

$$\widetilde{\pi}(k, n^*(k))|_{a=a_{k+1}} \quad < \quad \widetilde{\pi}(k+1, n^*(k+1))|_{a=a_{k+1}} \tag{A9}$$

Between a_{k+1} and a_k there is a single critical value, call it $\widehat{a}_k$, below which $k+1$ is the optimal integer product scope and above which k is optimal. This is the value of a for which:

$$\widetilde{\pi}(k, n^*(k)) = \widetilde{\pi}(k+1, n^*(k+1)) \tag{A10}$$

We can solve for this value explicitly. With a fair amount of algebra, (A10) can be rewritten:

$$\widehat{a}_k \ln \widehat{a}_k + \left[\ln\left(\frac{\Lambda}{\Theta}\right) + J\right]\widehat{a}_k + \frac{\Theta H}{\Lambda} = 0 \tag{A11}$$

where

$$H := \frac{\left((k+1)^{1-\alpha(\sigma-1)} - k^{1-\alpha(\sigma-1)}\right)}{\left((k+1)^{1+\delta} - k^{1+\delta}\right)}$$

$$J := (\delta + \alpha(\sigma-1)) \frac{\left((k+1)^{1+\delta}\ln(k+1) - k^{1+\delta}\ln k\right)}{(k+1)^{1+\delta} - k^{1+\delta}} - 1$$

Re-arranging,

$$-\frac{\Theta H}{\Lambda \widehat{a}_k} e^{-\frac{\Theta H}{\Lambda \widehat{a}_k}} = -He^J$$

Again using the Lambert W function (Corless et al., 1996):

$$-\frac{\Theta H}{\Lambda \widehat{a}_k} = W_i\left(-He^J\right)$$

Re-arranging again, we have:

$$\widehat{a}_k = \frac{\Theta H}{\Lambda |W_i(-He^J)|}$$

It can be shown that $-\frac{1}{e} < -He^J < 0$. In this range, the Lambert W function can take on two values, $W_0(\cdot)$ and $W_{-1}(\cdot)$, but only $W_{-1}(\cdot)$ yields a solution for $\widehat{a}_k$ between a_{k+1} and a_k. Hence we have (14).

The optimal product scope is $k+1$ in the range $[a_{k+1}, \widehat{a}_k)$ and k in the range $[\widehat{a}_k, a_k)$. Thus the range of market-access costs can be partitioned into a set of intervals $[\widehat{a}_{k+1}, \widehat{a}_k)$ within which $k+1$ is the optimal integer product scope. Within each of these intervals, optimal market penetration is given by (12) and is declining in a.

To solve for the cutoff for entry into the destination, $\widehat{a}_0$, we note that $H = 1$ for $k = 0$ and that $\lim_{k \to 0} J = -1$. Since $W_{-1}(-\frac{1}{e}) = -1$, we have that $\widehat{a}_0 = \frac{\Theta}{\Lambda}$.

Note from (12) that $n^* = 0$ at $\widehat{a}_0$. For a given G, n^* is declining in a. Hence for $\widehat{a}_1 \le a < \widehat{a}_0$, where $G = 1$, $n^* > 0$. For all other cutoffs $\widehat{a}_k$, we have $n^* > 0$ for $a \to \widehat{a}_k^-$ (i.e. as a approaches $\widehat{a}_k$ from the left). To see this, note that combining (12) and (14) we have:

$$\begin{aligned}
n^*(G)|_{a\to\widehat{a}_k^-} &= 1 - \frac{\Lambda}{\Theta}\frac{\Theta H}{\Lambda|W_{-1}(-He^J)|}k^{\delta+\alpha(\sigma-1)} \\
&= 1 - \frac{H}{|W_{-1}(-He^J)|}\frac{k^{1+\delta}}{k^{1-\alpha(\sigma-1)}} \\
&= 1 - \frac{1}{|W_{-1}(-He^J)|}\frac{\left(\frac{k+1}{k}\right)^{1+\delta}-1}{\left(\frac{k+1}{k}\right)^{1-\alpha(\sigma-1)}-1} > 0 \text{ for } k \in \{1,2,3,\ldots\} \qquad \text{(A12)}
\end{aligned}$$

where the inequality follows from (9) and (11) and the fact that $|W_{-1}(-He^J)| > 1$. Hence we have $n^* > 0$ for $a \in [0, \widehat{a}_0)$. That is, unlike in Arkolakis et al. (2021), the constraint that market penetration be non-negative does not bind for any value of market-access costs for which the firm has positive product scope.

A.4 Impact on Exports

Using (6), (7), and (12), we can write total firm exports to a destination as follows:

$$\begin{aligned}
E &= \sum_{g=1}^{G} px_g = \sum_{g=1}^{G} p_g^{1-\sigma} nTP^{\sigma-1} \\
&= \sum_{g=1}^{G}\left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma}\left(\frac{\tau g^\alpha}{\phi}\right)^{1-\sigma}\left[1-\frac{a\Lambda}{\Theta}G^{\delta+\alpha(\sigma-1)}\right]TP^{\sigma-1} \\
&= \sigma\Theta\left[1-\frac{a\Lambda}{\Theta}G^{\delta+\alpha(\sigma-1)}\right]\sum_{g=1}^{G} g^{-\alpha(\sigma-1)}
\end{aligned}$$

Using the approximation in (10),

$$E = \left[\Theta - a\Lambda G^{\delta+\alpha(\sigma-1)}\right]\frac{\sigma G^{1-\alpha(\sigma-1)}}{1-\alpha(\sigma-1)} \qquad \text{(A13)}$$

which is (15). The fact that $n^* > 0$ for all $a \in [0, \widehat{a}_0)$ (see Appendix A.3) implies that the term in brackets is positive. Equations (16) and (18) follow immediately.

B Details: Tasdir+ Program and Randomization

B.1 Program Overview

The Tasdir+ program, known officially as the Fund for Competitiveness and Export Development Support [*Fonds d'Appui à la Compétitivité et au Développement des*

Exportations], was created in 2014 with a budget of USD 23.5 million. The program was housed in the *Centre de Promotion des Exports (CEPEX)* [Export Promotion Center]. The Tasdir+ program included 4 waves of matching grants (*Lots*, in French). In *Lot 1* (launched in 2015), 106 firms were selected; in *Lot 2* (launched in 2017), 194 firms were selected. The selection was not randomized in these waves. In collaboration with the World Bank, we helped Tasdir+ implement a randomized selection process in *Lots 3* and *4*. Each wave had application "rounds"; there were four rounds in *Lot 3* and one in *Lot 4*. The randomization sample (across the five randomized rounds) included 487 firms.[1]

In each wave, the program conducted a communication campaign to invite firms from around the country to apply. In *Lots 3* and *4*, our team supported these efforts, including by hiring a consultant to help Tasdir+ identify firms likely to be eligible for the program and contacting these firms to share information about the program and to assist them with completing the Tasdir+ application.

As part of the Tasdir+ application, firms were required to submit a business plan (with the possibility of modifying the plan later). The maximum budget for the business plan was TND 300,000 (USD 100,000).[2] Firms chose between two types of plan: one for standard export activities, referred to as an "Export Development Plan" (*appui a l'export*), and one for setting up a foreign office, referred to as a "Foreign Affiliate Plan" (*implantation a l'étranger*).

Tasdir+ used the three calendar years preceding the program year as a time frame for various eligibility criteria. These were 2015-2017 for Rounds 1-4 and 2016-2018 for Round 5. We refer to these years as the "reference period." As noted in the main text, when referring to pre-program information from a single year, we follow Tasdir+ practice in using 2017 as the reference year for Rounds 1-4 and 2018 for Round 5.[3]

The business plan had to list up to three target countries, of which ≥ 50% had to be new destinations. Tasdir+ defined a new destination as a country to which the firm did not export in the last year of the reference period.

The eligible actions for business plans were organized by Tasdir+ into six categories (*rubrics* in French). The categories and actions are listed in Table 1 in the main text. In their applications, firms indicated their estimated budget, timeline, and desired objective for each chosen action.

[1]Parallel to the randomized selection process, Tasdir+ continued to use the traditional non-randomized method for a separate set of firms. In total, 122 firms in *Lot 3* and 21 firms in *Lot 4* were offered the program based on the traditional, non-randomized selection method; these firms are not part of our study.

[2]The average exchange rate of Tunisian dinars to US dollars over our study period was approximately 3 TND/USD.

[3]When determining eligibility, Tasdir+ staff used as the reference year the most recent calendar year for which finalized accounting data were available. Finalized accounting data are often not available until late spring of the following year. Hence even as late as Round 4 in May 2019, 2017 was still used as the reference year.

Tasdir+ staff reviewed the applications to determine eligibility. To be eligible, a firm had to fulfill a number of criteria: (1) be privately owned; (2) be legally based in Tunisia; (3) not be a retailer or wholesaler, with the exception of importing and exporting firms, known locally as "trading firms"; (4) not be an artisanal firm; (5a) (for non-agriculture/fishing firms) have a "liquidity ratio," defined as assets over liabilities averaged for the reference period, greater than or equal to 1 in Rounds 1-4, and greater than or equal to 0.9 in Round 5;[4] (5b) (for agriculture/fishing firms) have five or more permanent employees or at least one export operation during the reference period;[5] (6) be established prior to Jan. 1, 2015 for Rounds 1-4 or Jan. 1, 2017 for Round 5.

When applying, firms self-classified into six sectors defined by the Tasdir+ program: (1) agriculture/fishing, (2) trading, (3) food processing, (4) non-food manufacturing, (5) information and communication technology (ICT), and (6) services.

Our team conducted a survey of the eligible firms in collaboration with a local survey firm. Firms were invited to complete the survey online, through the Tasdir+ program's web portal. The survey firm followed up in person with firms that did not complete the survey online. The baseline surveys took place in August 2018 (Round 1), November 2018 (Round 2), February 2019 (Round 3), May 2019 (Round 4), and November 2019 (Round 5). The follow-up surveys took place in July-December 2020 (Rounds 1-3) and March-December 2021 (Rounds 4-5).

In each round, randomization took place in a public meeting. We describe the randomization in detail in Appendix B.3 below.

Following randomization, firms assigned to treatment were able to revise their business plan in consultation with Tasdir+ staff (the business plan type, used in stratification, could not be changed). Tasdir+ staff reviewed the plan to ensure that, for instance, the number of new destinations was $\geq 50\%$ and that firms' text descriptions of actions corresponded to the declared action types and desired objectives.

Treatment firms were then approved by the Tasdir+ steering committee (*Comité de Pilotage*).[6] The treatment period of 12 months, referred to as the "business plan period", started on the date of approval by the steering committee. Each firm signed a contract with CEPEX to enroll officially.

In order to remain in the program, firms were technically required to meet two conditions. First, the firm had to implement at least one action within the first three months of its business plan period. Second, it had to spend 30% of its approved budget

[4] The Tasdir+ program relaxed the liquidity threshold in round 5 in order to increase the number of eligible firms. This change was implemented prior to Round-5 randomization.

[5] For agriculture/fishing firms, the liquidity criterion was replaced by the employment/export criterion because many agricultural firms did not have formal accounting of assets and liabilities.

[6] In principle, the steering committee could have exercised discretion at this stage, but in practice it approved all firms assigned to treatment.

within the first six months of its business plan period. The Tasdir+ rationale for these conditions was to encourage inactive firms to exit the program to free up unused funds for future applicants. In practice, the program was stricter in enforcing these conditions as the end of the program neared. In Rounds 1-4, 24% of firms were removed for failing to meet these conditions; in Round 5, which largely coincided with the covid-19 pandemic, 68% of firms were removed.

After incurring expenditures, firms submitted reimbursement requests. The required supporting documents depended on the type of action. Receipts were required for travel expenses, and contracts and proofs of payment were required for consulting expenditures. Tasdir+ staff checked whether the expenditures corresponded to actions in the approved business plans and whether the supporting documents were satisfactory. If so, CEPEX then issued a transfer order, signed by the CEPEX president, to the Central Bank of Tunisia (the *Banque Central de Tunisie (BCT)*). The BCT then disbursed the funds to the firm. The reimbursement rate was 50% for eligible expenses.

B.2 The Rebate Arm

Our experimental design originally included two treatment arms, a "Matching Grant Only" arm and a "Matching Grant + Rebate" treatment with a pay-for-performance element, in which firms that were successful in increasing exports would be eligible to be reimbursed for a greater share of eligible expenses. In practice, however, the implementation of the rebate was not successful.

Although subsidies conditioned on exports are normally inconsistent with World Trade Organization (WTO) rules, the WTO allowed for an exception in the case of some developing countries' exports of food products. Initially, in Round 1, this exception was interpreted to apply to two of the six sectors listed above: agriculture/fishing and food processing. Starting in Round 2, the interpretation was broadened to include trading companies (since essentially all trading firms exported food products). We refer to firms deemed eligible for the rebates as the "rebate-eligible sample."

The rebate was intended to be given as a supplement to the 50% subsidy in the main matching-grant program. The amount was designed to be the minimum of (a) 20% of the cumulative value of exports to new markets and (b) 40% of the firm's eligible expenses. Firms in the Matching Grant + Rebate arm could thus in principle have received reimbursement of up to 90% of their eligible expenses.

In practice, however, the design for the rebates was not implemented. Midway through our study, a government audit of the Tasdir+ program resulted in new, more stringent constraints on disbursements. These constraints included a prohibition on reimbursing more than 50% of firms' expenditures. Although 41 firms were assigned to the Matching

Grant + Rebate arm and 5 of these firms submitted rebate requests, no rebates were paid out. Firms in the Matching Grant + Rebate arm were effectively treated by Tasdir+ as if they were in the Matching Grant Only arm. In our main analysis, we treat the Matching Grant + Rebate and the Matching Grant Only as a single treatment.

B.3 Randomization

Randomization was carried out in public meetings in each round. Here we explain the randomization procedure in detail.

Because of the planned rebate arm explained above in Appendix B.2, the probability of selection in the randomization procedure differed by sector. In Rounds 1-4, in non-rebate-eligible sectors, the probability of selection (for the Matching Grant Only treatment) was 1/2. In Round 5, Tasdir+ leadership decided to increase the selection probability to 2/3. In rebate-eligible sectors, the probability of selection for Matching Grant Only treatment was 1/3 and for the Matching Grant + Rebate treatment was 1/3.[7] (When we treat the Matching Grant Only and Matching Grant + Rebate as a single treatment, the effective selection probability is thus 2/3 for these sectors.)

Non-rebate-eligible firms were stratified based on size, business plan type, and sector. For size, firms were classified as small, medium, or large based on their average sales in the reference period. The sales bounds (in TND) by size for each sector were: a) for non-food manufacturing, small = sales < 1.6 million; medium = sales between 1.6 million and 5 million; large: = sales > 5 million; b) for services and trading, small = sales < 0.3 million; medium = sales between 0.3 million and 2 million, large = sales > 2 million; for ICT, small = sales < 0.45 million; medium = sales between 0.45 million and 2 million; large = sales > 2 million.

For rebate-eligible firms, the stratification differed by round. In Round 1, there were only four rebate-eligible firms and no stratification was implemented in this round. In Rounds 2-5, rebate-eligible firms were stratified by sector and business plan type. No agreement was reached about the appropriate stratification by size for the rebate-eligible firms; as a result, the rebate-eligible sample (including trading firms in Rounds 2-5) was not stratified by size. Because of these changes, the number of strata varies across rounds. We obtained 18 strata for Round 1, 22 strata for Round 2, 20 strata for Round 3, 21 strata for Round 4, and 22 strata for Round 5.

The randomization sessions were held in public meetings at the CEPEX offices (Rounds 1-2) and the office of a national small business association (*Union Tunisienne de l'Industrie, du Commerce et de l'Artisanat* (UTICA) [Tunisian Union of Industry, Trade and Handicrafts], Rounds 3-5). Firms, Tasdir+ staff, CEPEX/UTICA leaders, and

[7] The definition of rebate-eligible sectors changed in Round 2 as described above.

reporters from local news outlets attended the sessions. The randomization was conducted in excel, following a methodology recommended by Gertler et al. (2016). Within each stratum, a random number between 0 and 1 was generated for each firm, and random numbers were sorted in decreasing order. Firms were selected highest numbers first, according to the probabilities explained above. Following each session, results were published on the CEPEX website. Although the randomization had the potential to be politically contentious, especially given the large amounts of money involved, the procedure was generally well-received in the local media (L'Économiste Maghrébien, 2018; Kapitalis, 2018). This may in part have been because the transparency of the procedure contrasted with the practices for allocating government support under the regime of former President Ben Ali (Rijkers et al., 2017).

B.4 Foreign Affiliate Plan Implementation Issues

In practice, the implementation of "Foreign Affiliate Plans" was impeded by a number of administrative and regulatory issues. To set up a foreign affiliate, firms needed to transfer money to their target destination. Capital outflows were subject to strict regulations in Tunisia and required authorizations from the Central Bank. These authorizations could take up to six months to clear. As a result, foreign-affiliate-plan firms had a difficult time initiating their business plans. Even if firms were able to transfer funds to their target destinations, they could still face issues in implementing their actions. For example, many transactions in sub-Saharan countries were conducted in cash. Tasdir+ staff considered cash transactions to be ineligible and rejected reimbursement requests for them. As a result, many foreign-affiliate-plan firms were not able to meet the two performance conditions summarized in Appendix B.1 above.

B.5 Other Issues

The covid-19 pandemic and ensuing lockdown were a blow to the Tasdir+ program on several dimensions. There was uncertainty regarding when each covid-19 wave would occur (and end), when vaccines would arrive, and when a return to normal was expected, affecting firms' ability to stick to their original business plans. Crucially, there were unexpected difficulties in implementing most eligible actions. As the pandemic worsened and the government put in place harsh restrictions on movement and gatherings, many Tasdir+-eligible actions were no longer feasible. Plans for travel, prospecting missions, and fairs were canceled as commercial flights were completely halted. Certification, marketing events, invitation of buyers and contractors, etc., were also cancelled or postponed. All rounds were exposed to the pandemic shock during their treatment period, but earlier rounds less so than later rounds. Unsurprisingly, the average matching grant realization rates (spending as a share of the approved business plan amount) decrease markedly by round. For instance, Round 5 firms have on average a realization rate of 5.7%, compared to 32.8% for Round 1 firms (Table 4).

C Details on Data Sources and Samples

C.1 *Repertoire National des Entreprises (RNE)*

The *Repertoire National des Entreprises (RNE)* [National Repertory of Firms] is a database of all formally registered private-sector firms in Tunisia, managed by the national statistical agency (*Institut National des Statistiques (INS)* [National Institute of Statistics]). It combines firm-level total quarterly employment and wages from the Tunisian social-security agency (*Caisse Nationale de Sécurité Sociale (CNSS)* [National Social Security Fund]), annual local sales, export sales, and total sales (pre- and post-tax) from the Tunisian tax agency (*Direction Générale des Impôts (DGI)* [General Tax Authority]), and annual export and import flows from Tunisian customs (*Direction Générale des Douanes* (DGD) [General Customs Authority]). The years available to us are 1996 to 2021. The RNE uses the first 7 digits of the firm's unique tax identifier to identify firms. We used this RNE unique identifier to match all 487 firms in our randomization sample to this dataset, for the years beginning in the firm's opening year and ending in 2021. In line with RNE guidelines, all analysis using this data was carried out in person at the RNE office in Tunis by one of the authors.

C.2 Customs Transactions

At the time of applying to Tasdir+, firms provided written authorization for CEPEX to access their customs records. For the purposes of our study, the Ministry of Finance (which oversees the Tunisian customs agency) and CEPEX signed a data-sharing agreement. This allowed us to access, for the 487 randomization-sample firms, all export and import transactions for Jan. 1, 2017-Dec. 31, 2022. Information is available at the firm-shipment-product (11-digit *Nomenclature de Dédouanement des Produits (NDP)* [Customs Clearance Product Nomenclature]) level.[8] The data include the declaration type (a 2-letter code that denotes whether the declaration is that of an export, import, re-import, etc.), the "customs regime" (a 3-digit code that denotes the sub-type of declaration, e.g. simple import, import following product transformation, simple export, etc.), origin/destination country, shipment value, net invoice price, shipment gross weight in kilograms, and declaration date. Using the firm's unique tax identifier, customs staff matched 421 firms out of the 487 randomization-sample firms in their database of firms that have ever had a trade operation. The remaining 66 firms

[8] The first six digits of this classification correspond to the Harmonized System (HS).

had never engaged in trade through customs. Of these 421 firms, 322 firms had an import or export operation during Jan. 1, 2017-Dec. 31, 2022.

In Tunisia, exporters and importers may fill out a temporary declaration for an expedited clearance by customs when the traded good is perishable or flammable. Firms are expected to fill out a complete (final) declaration at a later date. The dataset contains both temporary and final declarations. The customs agency kept track of firms that used the expedited process but did not submit the final declaration. We received from the customs agency a list of the firms in our randomization sample that fell in this group. We explain in Appendix D.3 how we used this list to deal with temporary declarations.

C.3 Tasdir+ Administrative Data

Each firm's application to the Tasdir+ program included information the firm's unique tax identifier, self-identified sector, export regime (totally-exporting or non-totally exporting), list of quality certifications, and contact information.[9] The application also included employment and data from financial statements (sales, exports, assets, and liabilities) for the reference period. Financial information in the application was verified against firms' financial statements both by the Tasdir+ team and by us. The application also listed the firm's type of business plan, the approved budget, target destinations, actions, and estimated costs and quarter of implementation for each action. The application data was the source for information on size, sector and business plan used in stratification (see Appendix B.3).

C.4 Baseline and Follow-up Survey

We conducted baseline and follow-up surveys for the randomization sample. The survey collected standard firm characteristics and also elicited information about innovative activities, including spending on marketing, consulting, certifications, and software purchases. At baseline, applicant firms were required to answer the survey before the randomization; all 487 firms in the randomization sample responded. As mentioned in the main text, response rates to the endline survey were much lower than for the baseline, in part due to the fact that CEPEX had little leverage to oblige firms to respond.[10] The follow-up survey for Rounds 1-2 included all questions from the baseline survey. as well as new questions about (1) new quality certifications, (2) participation in Tasdir+ (for treatment firms), and (3) the impact of the covid-19

[9] An export regime indicator is also available in the RNE data. We explain in Appendix D.2 how we harmonize the two variables.

[10] Lower-than-usual responses during the pandemic were documented even in established surveys like the Current Population Survey in the US (Rothbaum and Bee, 2021).

pandemic (changes in exports, sales, and employment; adaptation efforts such as remote work and supply chain diversification; and access to government support programs), and (4) feedback about Tasdir+. After experiencing low response rates in Rounds 1 and 2 (in July 2020-December 2020), we shortened the survey for firms in Rounds 3-5 (March 2021-August 2021). Of the 487 firms in the randomization sample, 332 (68%) answered the follow-up survey at least partially.

D Cleaning Procedures

In this section, we describe our cleaning procedures. In cases where variables are available from more than one source (e.g. exports, sales, employment, firm export regime), we took the RNE information as the most authoritative source, in the absence of compelling alternative information. The main reason is that the RNE reports exports for service firms, which do not appear in the customs data — a major advantage for our purposes.

D.1 Cleaning Procedure for Application Data

We checked reported sales, assets and liabilities against firms' financial statements, which were submitted with their Tasdir+ applications. If reported exports were greater than reported sales, we assumed that sales were correct and set exports equal to sales. We winsorized sales at the tails, replacing values in the lower or upper 3% tails with values at the 3$^{\text{rd}}$ or 97$^{\text{th}}$ percentiles, respectively, for the reference year (2017 for rounds 1-4, 2018 for round 5). To keep the values of exports and export shares consistent with the winsorized values of sales, we calculated "winsorized" exports from winsorized sales and directly observed values of export shares.

D.2 Cleaning Procedure for RNE Data

We first cleaned the RNE sales and exports data. Where possible, we used information from the application data (for the reference period years, 2015-18) or the customs data (for the available years, 2017-2022) to improve the measures. We used the following rules:

1. If total sales were reported as zero in the RNE, we set them to missing.
2. If both exports and local sales in the RNE were zero, we set both to missing.
3. If (i) a firm was listed as a "totally exporting" firm, (ii) had zero exports, and (iii) had positive local sales, we assumed that local sales and exports had been reversed.
4. If a firm had never exported then immediately shifted to an export share of one, we assumed that local sales and exports had been reversed.

5. If RNE sales were missing and sales in the application data were not, we used the application data to impute sales.
6. If RNE exports were missing and application exports were positive and less than or equal to RNE sales, we used application exports to impute exports.
7. If RNE exports were zero and application data exports were positive and less than or equal to RNE sales, we used application exports to impute exports.
8. If RNE exports (from corporate tax records) were missing, we used customs transactions data to impute exports.[11]
9. If exports were still missing or were zero, and the exports variable from customs available in the RNE was positive and less than total sales, we used the this variable to impute exports.

We used the newly imputed information to calculate consistent values for local and total sales. If local sales were non-missing, we added newly imputed exports to local sales to arrive at total pre-tax sales, conditional on this new value being lower than total post-tax sales in the RNE. If local sales were missing but total sales were non-missing, we subtracted newly imputed exports from total pre-tax sales to calculate local sales.

We then cleaned the RNE employment/wages information. If total employment or total wages were reported as zero, we set them to missing. Although in principle the RNE employment variable should include both permanent and temporary employees, we determined that it is closer to permanent employment reported in the application data. Hence we used permanent employment in the application data (available for the last year in the reference period) to impute missing employment in the RNE in the corresponding year.

We then imputed new values for missing values using the sequential regression multivariate imputation technique implemented by Abowd and Woodcock (2001). We grouped our key production-relevant variables of total sales, employment, and average quarterly wages. We deflated monetary variables using the Consumer Price Index (CPI) from the INS, using the CPI from July of each year. Following Verhoogen (2008), for our key production-relevant variables, we set to missing the values that changed by more than a factor of five from one year to the next. We then proceeded as follows:

1. We regressed sales on employment, a lead and lag of sales, and a lead and lag of employment and used the predicted values to replace missing values of sales.
2. We regressed employment on sales, a lead and lag of employment, and a lead and lag of sales and used the predicted values to replace missing values of employment.

[11] In doing so, we prioritized the exports we calculated from the customs transactions data, rather than the customs variables that appeared in the RNE, which appeared to be incomplete.

3. We regressed wages on employment and sales, a lead and lag of wages, and a lead and lag of employment and sales and used the predicted values to replace missing values of wages.
4. We imputed exports and local sales using the export share variable and newly imputed sales.

We winsorized sales at the tails, replacing values in the lower or upper 3% tails with values at the 3rd or 97th percentiles, respectively. To keep the values of exports and export shares consistent with the winsorized values of sales, we calculated "winsorized" exports from winsorized sales and directly observed values of export shares.

Finally, we defined consistent exports and local sales based on winsorized sales and the reported export share, and defined a consistent wage bill variable based on winsorized employment and average quarterly wages.

D.3 Cleaning Procedure for Customs Transactions

For the customs transactions data, we first classified records into import and export transactions using the 3-digit customs regime variable. In Tunisia, firms can engage in indirect export by selling to totally exporting firms. As a result, some of our observations list "totally exporting firm" as destinations. In a few cases, a unique destination country is not specified, with the country denoted as "various." These observations represent 8% of all transactions and 6% of total export value. We keep these observations for our main analysis.

The customs data contain both temporary (expedited declarations associated with perishable or flammable products) and final declarations. When a final declaration was available, we dropped the corresponding temporary declaration. We received from the customs agency a list of the firms in each year that used the expedited process but did not submit the final declaration. Using the firm's unique tax identifier, we matched these firms in our dataset. In each year, we dropped all temporary declarations that were not reported by these firms.

We deflated imports, exports, and prices using the July CPI from the INS. We summed values at the firm-year level and used the raw totals to impute missing exports in the RNE for non-service firms as explained in Appendix D.2.

There were many discrepancies between total exports per firm-year reported in the customs transactions data and firm self-reports of exports from the tax agency (DGI) in the RNE. This could happen for several reasons. For example, an export operation could be realized in one calendar year but reported by the firm to the tax authority in the following fiscal year. Or some firms may count indirect exports towards their exports sales while some may not. When reconciling differences between the customs and RNE data, we gave priority to the RNE data. We re-scaled the exports variable in customs transactions to equate total exports in the customs data to the RNE total exports, while maintaining the same composition of exports across destinations and products within firms.

For service and ICT firms, which generally do not appear in the customs data (unless they also happen to export or import physical goods), we left customs outcomes as missing. For non-service firms that did not appear in the customs data, we used RNE exports to impute missing customs exports; if customs exports were still missing, we set them equal to zero and set other customs outcomes (number of destinations, number of products, number of shipments, imports) to zero.

E More on Treatment Effect Heterogeneity

In Section 6.3, we provide a simple discussion of heterogeneity by characteristics that are suggested by our theoretical model or seem particularly salient. The discussion relies on our discretion in choosing the dimensions of heterogeneity to focus on. In addition, in finite samples it becomes unfeasible to do even an exploratory analysis across several underlying characteristics at once. In this appendix, we complement the simple approach of Section 6.3 with data-driven methods to elicit the extent of heterogeneous policy responses in a more disciplined — albeit demanding for our limited sample — fashion. These Machine Learning (ML) methods have the advantage that they leave to the data the choice of which dimensions of heterogeneity to focus on. (For overviews, see Mullainathan and Spiess (2017), Athey and Imbens (2019), Chernozhukov et al. (2024), and Gaillac and L'Hour (2025).)

Here we apply two approaches: the Generalized Random Forest (GRF) framework of Athey et al. (2019), and the Generic Machine Learning (GenericML) approach of Chernozhukov et al. (forthcoming). In both cases, we use the ML methods to predict the Conditional Average Treatment Effects (CATEs). That is, in the notation of Chernozhukov et al. (forthcoming), we find a predictor $S(Z)$ of $s_0(Z) = E(Y(1)|Z) - E(Y(0)|Z)$, where $Y(1)$ and $Y(0)$ are potential outcomes under treatment and control and Z is a set of covariates. As an outcome, we focus on the intensive margin of exporting, as in Column 2 of Table 3 and Columns 2 and 4 of Tables 11-12. We first ask whether any heterogeneity can be detected and then examine the most salient dimensions of heterogeneity. Recall that our sample consists of approximately 500 firms, with only 264 firms having positive exports in the post period — a relatively modest sample, smaller than is typically recommended for such methods. We therefore see this exercise as suggestive rather than definitive.

E.1 Generalized Random Forests (GRF)

The Generalized Random Forest (GRF) algorithm (Athey et al., 2019; Wager and Athey, 2018) extends the random forest framework to estimate CATEs, among other features. The method relies on a splitting criterion that directly targets heterogeneity in the treatment effect. As a result, it may be too generous in the detection of heterogeneity. In addition, the inferential problem is not well defined for CATE estimates. (See Chernozhukov et al. (forthcoming) for a discussion of both points.) In our analysis, we use 2,000 trees with a 50% split of the sample for each tree ("honest splitting") as the default option.

We start with a large set of available covariates and we investigate the heterogeneity of the treatment effects among a restricted set based on the variable importance above a pre-specified threshold (2% in our case).[12] Figure A1 plots average CATE within quartiles of estimated CATEs. The figure displays significant heterogeneity, in particular for the comparison between Q1 and Q4. On average, the CATE is about 28 log points or about 32%, with the first quartile at about -12 log points, the second at about 2 log points, the third at about 32 log points, and the fourth at 47 log points or 60%. One caveat is that there is no guarantee that the $S(Z)$ generated by this procedure is unbiased; the confidence intervals displayed in Figure A1, which use the estimated variation in CATEs, should therefore be interpreted with caution.

In Figure A2, to get a sense of which variables are contributing most to the heterogeneity, we plot the shares of firms with particular characteristics across CATE quartiles, in the spirit of, for instance, Athey et al. (2023) Table 1. We again focus on variables with having an importance above 2%. A high share of firms with a specific characteristic in the highest quartile suggests that the characteristic is an important contributor to the large CATE. The two variables that stand out are (1) having any certification at baseline, which is positively correlated with CATE quartile, and (2) being a totally exporting firm, which is negatively correlated, consistent with Table 11 and our theoretical framework.

[12] The analysis includes the following variables: strata dummies, selection round dummies, reference-year log Exports, intended expenditures categories (Certifications, Product Marketing, Publicity/Ads), general firm characteristics (whether firm has high liquidity, defined as with below or above-median values of assets-to-liabilities ratios in reference year, whether firm is large (50+ employees), whether firm chose Export Plan subsidy, whether firm is a totally exporting firm), other indicators (whether owner responded to our survey, whether firm is importer in the reference year, whether the CEO/owner formerly lived outside of Tunisia), innovation indicators (indicators for whether the firm introduced a new product or new process, indicator for whether firm uses data in decision-making), spending types (on travel, technology, marketing, machinery, innovation, digital, consulting, certification), whether firm has foreign presence, whether firm has unit dedicated to exporting, performance metrics (whether tracks key performance indicator (KPIs), whether the firm has any certification, whether the firm targeted >2 countries in business plan), sector dummies, and a set of flag indicators for missing values in the included covariates. Variable importance is determined by how often the GRF procedure selects the variable to split the data in order to capture treatment effect heterogeneity.

E.2 Generic Machine Learning (GenericML)

We also implement the GenericML method proposed by Chernozhukov et al. (forthcoming). This approach has the advantages that it is more conservative in detecting heterogeneity and is also clearer on how to do inference on features of CATEs. At the same time, it is more demanding in terms of data and, especially in small samples such as ours, may fail to detect even economically significant heterogeneity.[13] We again proceed by choosing an initial list of variables and letting the machine pick the relevant ones.[14] Our preferred analysis uses a lasso with 100 splits and a 50% training sample as chosen options.[15] To get a sense of overall heterogeneity, Figure A3 plots Group Average Treatment Effects (GATES) for quartiles of the predicted CATEs. (We follow the notation in Chernozhukov et al. (forthcoming) and refer to the groups as G1-G4; these correspond to Q1-Q4.) The figure shows that the point estimates across quartiles are economically different — going from about -8 log points in G1 to about 32 log points in G4 — but the confidence intervals are very large and the treatment effects across quartiles are not statistically different. This overall lack of significance however masks some relevant heterogeneity across underlying covariates. Figure A4 presents the Chernozhukov et al. (forthcoming) Classification Analysis (CLAN) for a selected set of characteristics, again following their notation. The figure presents the difference in the predicted CATE across quartiles ($\delta.1$ to $\delta.4$) and the difference between top-bottom quartile ($\delta.4 - \delta.1$) We confirm the heterogeneity based on totally exporting status as well as on having any certification at baseline. There is evidence of heterogeneous effects by firm size (with smaller effects of the matching grants on larger firms, consistent with our theoretical model) and by whether the firms has any consulting expenditure at baseline. There is suggestive but not statistically significant evidence of heterogeneity by whether the firm uses data in decision-making at baseline,

Although the estimates are noisy and should be treated with caution, we see the data-driven analysis in this section as supportive of the simple split-sample approach in the main text (Section 6). In particular, it is reassuring that the results of smaller treatment effects for totally exporting firms and larger treatment effects for firms having any quality certification at baseline are largely confirmed. In addition, here there is stronger evidence of smaller effects for large firms than in Section 6.

[13]Recent applications of the method include Beam et al. (2025) and Davies et al. (2024).

[14]We include the following variables: strata, flags, and selection round dummies; reference year log exports; indicators for being large (50+ employees), high-liquidity, or totally exporting firms; indicators for having introduced a new product in the year preceding the baseline, having any quality certification, using data in decision-making, and having consulting expenditures in the reference year. We experimented with two learners: random forest and lasso. The lasso learner appeared to perform best (in the sense of having the best goodness-of-fit for the CATE) and is what we use below. The random forest learner produces similar results.

[15]This analysis was carried out using the GenericML R package from Welz et al. (2022).

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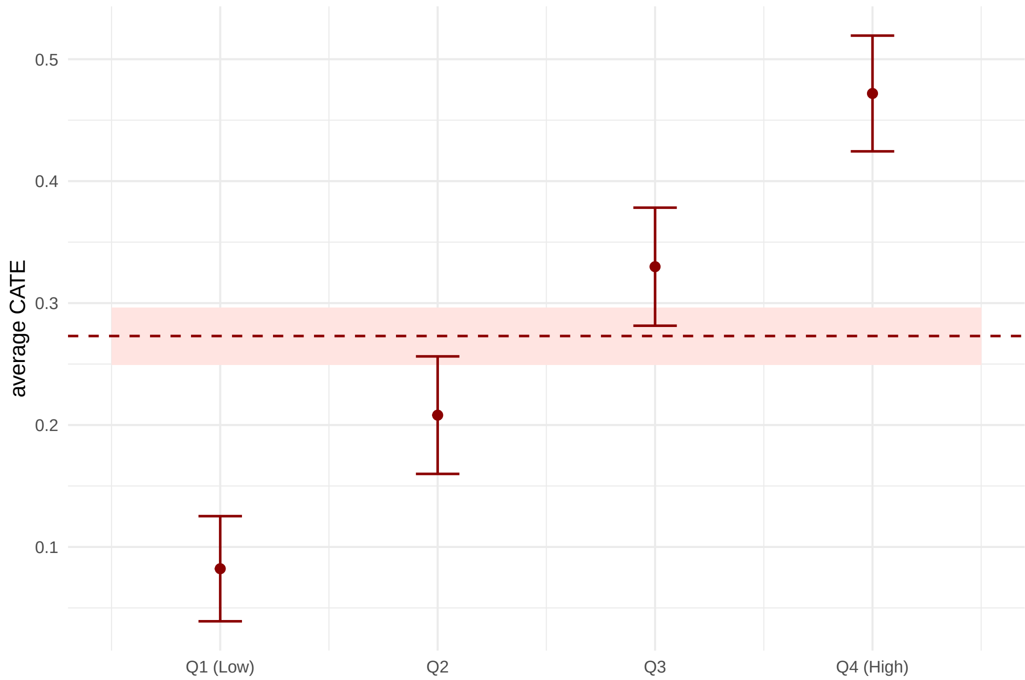
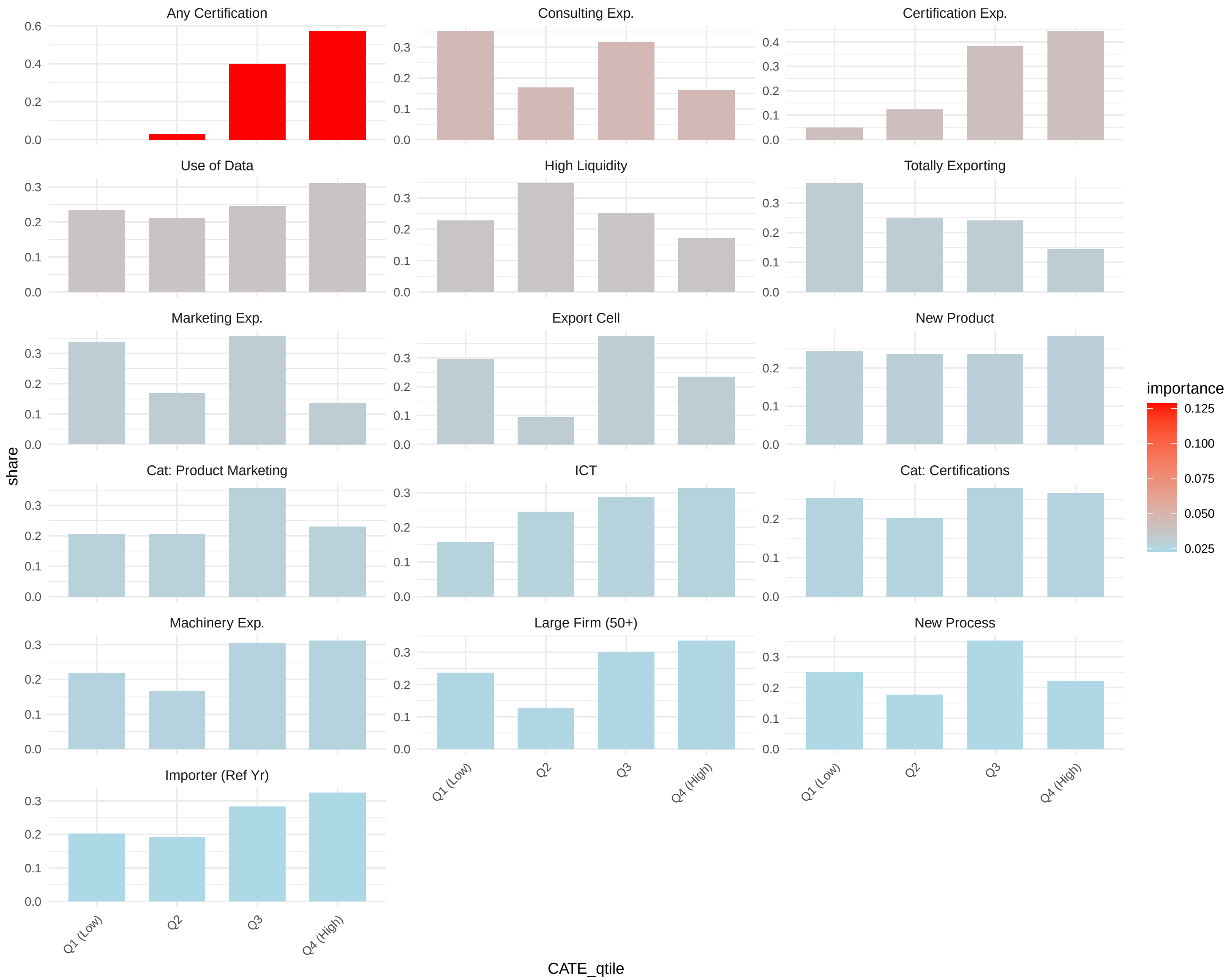
Figure A1. **CATE by Quartile from Generalized Random Forest**



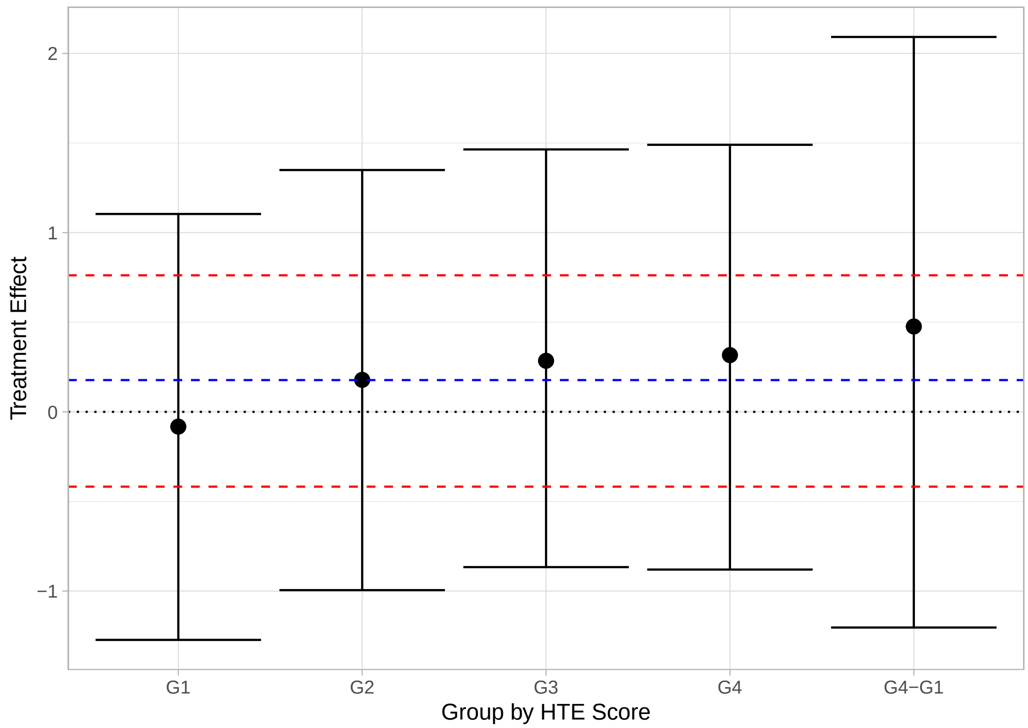
Notes: Figure presents averages of Conditional Average Treatment Effect (CATE), by quartiles of CATE, estimated with generalized random forest with 50% honest splits and 2,000 trees using the causal_forest R package (Athey et al., 2019). 90% confidence intervals are indicated for each CATE quartile. The dotted red line represents the Average Treatment Effect (ATE) and the shaded area the corresponding 90% confidence interval.

Figure A2. **Shares of Firms with Specific Xs by CATE Quartiles**



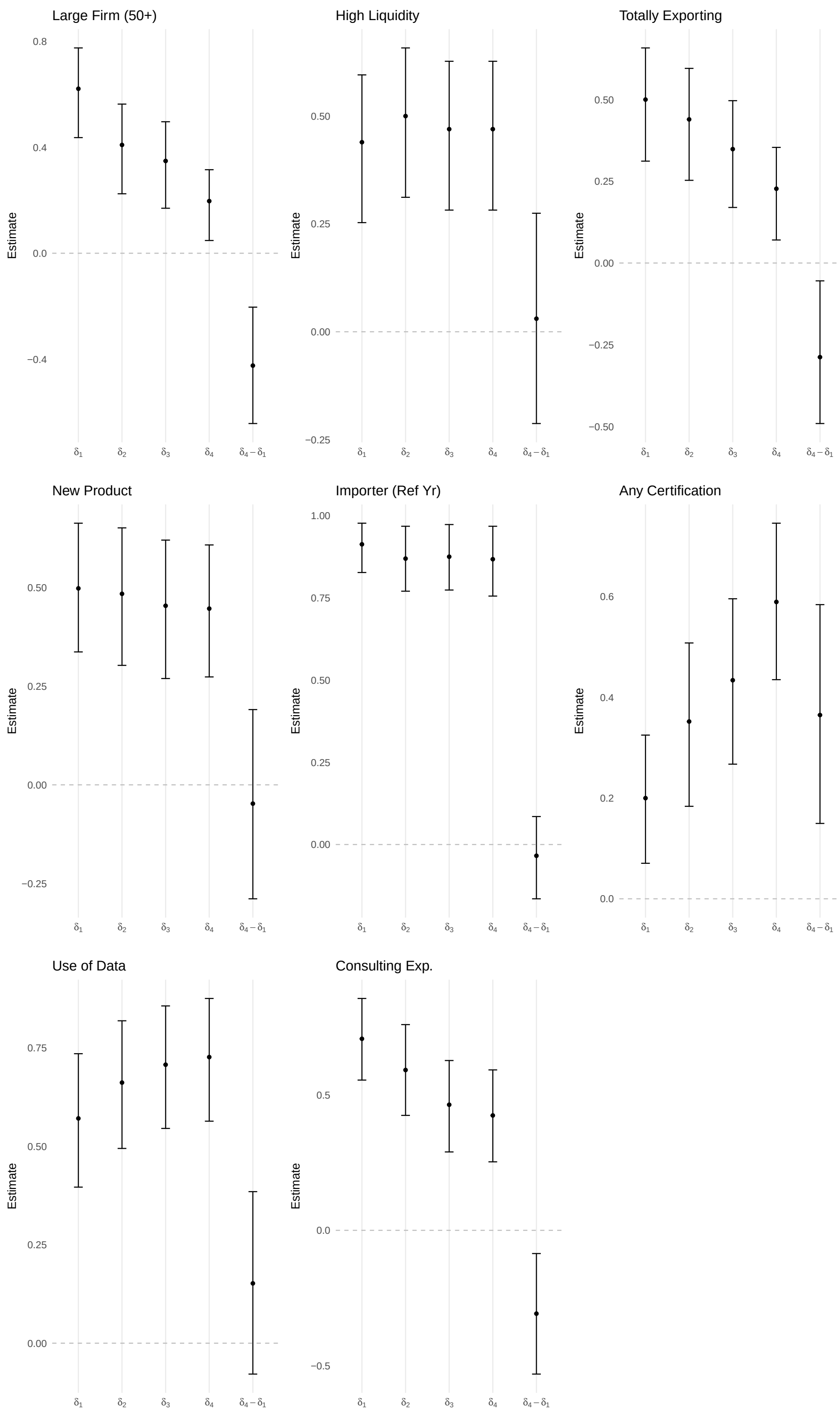
Notes: Share of firms, by quartile of CATE, with a specific characteristic, based on generalized random forest with 50% honest splits and 2,000 trees. Ordering and colors reflect the importance of each variable.

Figure A3. **Group Average Treatment Effects (GATES) from GenericML Method**



Notes: Figure plots medians and 90% confidence intervals of Group Average Treatment Effects (GATES) over four quartiles of predicted Conditional Average Treatment Effects (CATEs) for 100 splits. (G1-G4 correspond to Q1-Q4; HTE score (for "heterogeneous treatment effect score" refers to predicted CATE.) Lasso is used as causal learner. Analysis carried out using GenericML R Package (Welz et al., 2022). The dotted blue line indicates the Average Treatement Effect (ATE) and dotted red lines the 90% conference interval for the ATE.

Figure A4. **Classification Analysis (CLAN) on Covariates**



Notes: Figure presents results from a Classification Analysis (CLAN) following Chernozhukov et al. (forthcoming). For each covariate, we report the difference in the average predicted treatment effect (CATE) across quartiles ($\delta.1$ to $\delta.4$) and the difference between top and bottom quartile.

Table A1. **Balance, RNE Export Sample**

	(1) Control Mean/SD	(2) Treatment Mean/SD	(3) P-value
A. Application data			
Totally Exporting	0.26	0.27	0.76
	(0.44)	(0.45)	
Age of firm (as of randomization)	15.94	15.44	0.75
	(11.42)	(11.26)	
Domestic capital share	96.83	96.96	0.81
	(12.68)	(11.28)	
Employment	47.36	52.53	0.56
	(76.67)	(127.59)	
Sales (millions 2015 dinars)	8.12	7.66	0.72
	(16.42)	(13.89)	
Exporter	0.73	0.72	0.97
	(0.44)	(0.45)	
Exports (millions 2015 dinars)	2.51	2.40	0.95
	(7.69)	(7.02)	
B. RNE data			
Sales (millions 2015 dinars)	7.78	7.27	0.24
	(15.63)	(13.14)	
Exports (millions 2015 dinars)	2.51	2.23	0.60
	(7.48)	(6.27)	
Export share	0.38	0.41	0.58
	(0.41)	(0.43)	
N	164	213	

Notes: RNE Export Sample is firms for which sales and exports information is available in RNE both in reference year (2017 for rounds 1-4, 2018 for round 5) and in 2021. Panel A source is application data for reference year, comparable to Table 2 for the reduced sample. Panel B source is RNE data for reference year (2017 or 2018). Sales and exports from RNE data are winsorized at the 3%/97% level. Standard deviations in parentheses. P-values in Column 3 are from OLS regressions of variable on treatment indicator controlling for round and stratum fixed effects. P-value for F-test of joint null of no treatment-control differences for all variables (N=377) is 0.85. Monetary values were deflated to 2015 dinars using the CPI provided by INS. The average exchange rate over our study period is approximately 3 TND/USD. Additional details are in Appendices C and D.

Table A2. **Balance, RNE Employment Sample**

	(1) Control Mean/SD	(2) Treatment Mean/SD	(3) P-value
A. Application data			
Totally Exporting	0.23	0.24	0.89
	(0.42)	(0.43)	
Age of firm (as of randomization)	16.50	16.15	0.85
	(11.60)	(11.42)	
Domestic capital share	96.86	96.62	0.94
	(12.69)	(11.85)	
Employment	50.92	61.38	0.35
	(79.01)	(138.03)	
Sales (millions 2015 dinars)	8.76	8.89	0.98
	(17.01)	(14.81)	
Exporter	0.73	0.70	0.68
	(0.44)	(0.46)	
Exports (millions 2015 dinars)	2.64	2.72	0.75
	(7.98)	(7.60)	
B. RNE data			
Employment	59.47	64.54	1.00
	(90.97)	(93.11)	
Annual Earnings/Employee (1k 2015 dinars)	10.48	10.33	0.77
	(5.41)	(5.63)	
N	150	177	

Notes: RNE Employment Sample is subset of RNE Export Sample for which employment and earnings (from social security agency) are available in RNE in reference year (2017 for Rounds 1-4, 2018 for Round 5) and in 2021. Panel A source is application data for reference year, comparable to Table 2 for the reduced sample. Panel B source is RNE data for reference year. Employment and annual earnings from RNE data are winsorized at the 3%/97% level. Standard deviations in parentheses. P-values in Column 3 are from OLS regressions of variable on treatment indicator controlling for round and stratum fixed effects. P-value for F-test of joint null of no treatment-control differences for all variables (N=327) is 0.94. Monetary values were deflated to 2015 dinars using the CPI provided by INS. The average exchange rate over our study period is approximately 3 TND/USD. Additional details are in Appendices C and D.

Table A3. **Balance, Customs Sample**

	(1) Control Mean/SD	(2) Treatment Mean/SD	(3) P-value
A. Application data			
Totally Exporting	0.30	0.35	0.51
	(0.46)	(0.48)	
Age of firm (as of randomization)	18.63	17.92	0.75
	(12.78)	(13.13)	
Domestic capital share	94.75	96.95	0.20
	(16.29)	(11.13)	
Employment	65.84	69.09	0.86
	(91.73)	(157.75)	
Sales (millions 2015 dinars)	12.69	11.33	0.50
	(20.50)	(16.34)	
Exporter	0.81	0.79	0.69
	(0.40)	(0.41)	
Exports (millions 2015 dinars)	3.69	3.64	0.97
	(9.53)	(8.99)	
B. Customs data			
Exports (millions 2015 dinars)	3.68	3.35	0.53
	(9.21)	(8.00)	
Imports (millions 2015 dinars)	7.42	5.58	0.25
	(16.22)	(12.16)	
Destinations	3.20	3.20	0.71
	(4.44)	(4.35)	
Products	4.61	4.50	0.76
	(7.22)	(6.34)	
N	89	121	

Notes: Customs Sample is subset of non-service firms from RNE Export Sample. If a firm reported no exports in a given year, zero exports were imputed for that year, and similarly for imports. Panel A source is application data for reference year, comparable to Table 2 for the reduced sample. Panel B source is customs data for reference year. Exports and imports from customs are winsorized at the 3%/97% level. Standard deviations in parentheses. P-values in Column 3 are from OLS regressions of variable on treatment indicator controlling for round and stratum fixed effects. P-value for F-test of joint null of no treatment-control differences for all variables (N=210) is 0.79. Monetary values were deflated to 2015 dinars using the CPI provided by INS. The average exchange rate over our study period is approximately 3 TND/USD. Additional details are in Appendices C and D.

Table A4. **Balance, Survey Sample**

	(1) Control Mean/SD	(2) Treatment Mean/SD	(3) P-value
A. Application data			
Totally Exporting	0.33	0.33	0.78
	(0.47)	(0.47)	
Age of firm (as of randomization)	14.09	15.49	0.40
	(9.79)	(11.38)	
Domestic capital share	98.30	96.40	0.47
	(7.73)	(14.13)	
Employment	27.37	40.22	0.22
	(45.04)	(78.43)	
Sales (millions 2015 dinars)	2.31	6.08	0.03**
	(3.88)	(12.05)	
Exporter	0.65	0.77	0.07*
	(0.48)	(0.42)	
Exports (millions 2015 dinars)	0.89	2.46	0.09*
	(2.35)	(6.14)	
B. Survey data			
Has contract with foreign dist./ agent/partner	0.19	0.26	0.16
	(0.40)	(0.44)	
Has foreign affiliate/ representative	0.08	0.13	0.07*
	(0.28)	(0.34)	
Participated in international fair	0.45	0.45	0.96
	(0.50)	(0.50)	
Spent on certifications	0.14	0.28	0.06*
	(0.35)	(0.45)	
Spent on new technology	0.71	0.77	0.41
	(0.45)	(0.42)	
Spent on travel	0.74	0.87	0.02**
	(0.44)	(0.34)	
Spent on consulting	0.45	0.49	0.77
	(0.50)	(0.50)	
N	84	120	

Notes: Source is survey data at baseline for Survey Sample, omitting round 5 firms. (See Section 4 for details.) Standard deviations in parentheses. In applications, agricultural firms were not required to report sales or export status, hence sample size is slightly smaller for these two variables (N=198, instead of 204). P-values in Column 3 are from OLS regressions of variable on treatment indicator controlling for round and stratum fixed effects. F-test of joint null of no treatment-control differences for first four variables in Panel A and Panel B variables (N=204) has p-value 0.26; for all variables (N=198), the p-value is 0.26. See notes to Table 8 or A5 for variable definitions. Additional details are in Section 4 and Appendices C and D.

Table A5. **Survey Outcomes, ANCOVA**

	Dependent variable:						
	new contract with foreign dist./ agent/partner	new foreign affiliate/ representative	participated in int'l fair	spent on certifications	spent on new tech.	spent on travel	spent on consulting
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treated	0.12*	0.09**	0.08	0.01	0.00	0.05	0.06
	(0.06)	(0.04)	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)
Dep. var., baseline	0.05	0.01	0.33***	0.26***	0.07	0.10	0.19***
	(0.08)	(0.07)	(0.06)	(0.08)	(0.09)	(0.09)	(0.07)
R2	0.32	0.34	0.39	0.27	0.22	0.24	0.26
N	204	204	204	204	204	204	204
Strata dummies	Y	Y	Y	Y	Y	Y	Y
Round dummies	Y	Y	Y	Y	Y	Y	Y
Mean of dep. var.	0.24	0.06	0.23	0.19	0.54	0.57	0.30

Notes: Sample is Survey Sample, omitting round 5 firms. Table reports ANCOVA estimates of equation (19) in text. Dependent variable in Column 1 is indicator for whether firm contracted with distributor, local agent or partner in foreign market since July 2017 (for baseline) or since randomization (for endline). In Column 2, it is indicator for already having a foreign affiliate or representative (baseline) or having established a new foreign affiliate/representative since randomization (endline). In Column 3, it is indicator for having participated in international fair/expo since July 2017 (baseline) or since randomization (endline). In Columns 4-7, they are indicators for having positive spending in indicated category in the reference year (baseline) or in calendar year 2019. Simple OLS specifications are reported in Table 8. Means of dependent variables are for control firms at endline (2021). Additional details are in Section 4 and Appendices C and D. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6. **Survey Outcomes, Controlling for Baseline Sales, Exports**

	Dependent variable:						
	new contract with foreign dist./ agent/partner	new foreign affiliate/ representative	participated in int'l fair	spent on certifications	spent on new tech.	spent on travel	spent on consulting
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treated	0.13*	0.09**	0.10	0.03	0.02	0.10	0.09
	(0.07)	(0.04)	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)
R2	0.31	0.31	0.29	0.23	0.24	0.25	0.26
N	198	198	198	198	198	198	198
Strata dummies	Y	Y	Y	Y	Y	Y	Y
Round dummies	Y	Y	Y	Y	Y	Y	Y
Mean of dep. var.	0.24	0.06	0.23	0.19	0.54	0.57	0.30

Notes: Table is similar to Table 8, but controls for sales, exporter status, and exports from application data. Six firms in Survey Sample were agricultural firms that were not required to report sales or exports in their Tasdir+ applications. Means of dependent variables are for control firms at endline (2021). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.