Catalogue no. 18-001-X
ISBN 978-0-660-71604-6

Reports on Special Business Projects

Assessing the economic impact of Accelerated Growth Service program participants, 2017 to 2019

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Release date: October 7, 2024

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Published by authority of the Minister responsible for Statistics Canada

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Cette publication est aussi disponible en français.

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Acknowledgments

The author would like to thank Mahdia Khodja, Jacqueline Ha, Rachana Devkota, Alessandro Alasia, Sébastien Larochelle-Côté and the dissemination team at Statistics Canada, as well as two anonymous referees, for their valuable comments on an earlier version of this paper. Any remaining errors are the author's.

Assessing the economic impact of Accelerated Growth Service program participants, 2017 to 2019

by **Mahamat Hamit-Haggar**

Executive summary

The Centre for Special Business Projects (CSBP) of Statistics Canada carried out this project for the Accelerated Growth Service (AGS) to study the impact of the advisory services AGS provides to small and medium-sized enterprises.

Using the AGS client dataset and comparable non-clients, CSBP examined the performance of the client to determine whether AGS advisory services had a significant impact on business performance. The performance metrics compared were revenue growth, employment growth, profit growth, growth of exports as a percentage of revenue, and research and development (R&D) expenditure growth. Performance measures were assessed for each cohort separately.

The main findings of the analysis include the following:

- Overall, the study found that AGS clients performed better in the marketplace than non-clients.
- AGS clients demonstrated higher growth in revenue, employment, R&D spending and exports as a percentage of revenue compared with similar businesses that did not receive support.
    - For the 2017 cohort, the results showed that AGS clients that received advisory services had premiums of 5.81% for revenue, 11.82% for employment, 8.21% for profits, 3.25% for exports as a percentage of revenue and 8.21% for R&D expenditures, relative to the control group three years after the initial year of the advisory services.
    - Non-clients outperformed AGS clients in the first year following advisory service support in growth in exports as a percentage of revenue.
    - For the 2018 cohort, the results revealed that AGS clients tended to have higher growth in the one- and three-year periods following advisory service support across most indicators, except for profits and exports as a percentage of revenue.
    - One year and three years after receiving advisory service support, businesses showed higher revenue growth (3.36% and 5.27%, respectively), employment growth (1.24% and 2.19%, respectively) and R&D expenditure growth (5.73% and 12.11%, respectively).
    - Businesses that benefited from advisory service support from AGS in 2019 showed higher growth in revenue, employment, profits, exports as a percentage of revenue and R&D expenditures than non-clients in the first year following support.
    - Non-clients demonstrated higher employment growth and profit growth compared with AGS client businesses in the three years following advisory service support.

Introduction

The Accelerated Growth Service (AGS) is an advisory service composed of a network of regionally based innovation advisors (IAs) who provide expert advice to help businesses (usually small and medium-sized enterprises [SMEs]) "find, and take advantage of, everything that government can do for them—from financing to technical advice to foreign market expertise."[1]

Those firms that meet the eligibility criteria are then nominated to the Growth Service, approved by the AGS Directorate and assigned an IA who develops a customized service plan according to the unique needs of each firm. Over the span of 18 months (can be shorter if clients complete all their service plan recommendations or longer if they pause their AGS engagement), IAs check in with their assigned companies at specific intervals to assess clients' progress and determine whether their growth needs still align with the service plan's recommendations.

Objective

The AGS commissioned the Centre for Special Business Projects (CSBP) of Statistics Canada to undertake a study on the impact of its programs to understand whether its advisory services to firms had a significant impact on firm performance. To answer this question, an appropriate analysis was conducted to compare the performance of firms that use AGS advisory services with that of a control group made up of firms with similar characteristics (e.g., same region, sector, business size, annual revenue, sales, debt). The object of this study is to answer the following research question: Are AGS clients growing faster than their non-AGS counterparts? Five metrics were used to assess the long-term goal of the AGS for its participating firms to achieve accelerated growth and thereby increasing economic growth, in general.

The five metrics used to assess firm performances are

- employment growth
- revenue growth
- growth in exports as a percentage of revenue
- research and development (R&D) expenditure growth
- profit growth.

To evaluate whether the likelihood of receiving advisory service support is correlated with business performance, propensity score matching (PSM), combined with a difference-in-difference (DID) estimator, is applied. This study applies the PSM approach to assess the performances of AGS advisory services.

The PSM approach is widely used when evaluating economic policies. The key advantage of PSM (over standard regression methods) is that it is less demanding with respect to the modelling assumptions. The PSM technique does not require a functional form of assumptions for the outcome equation. Further, with matching, there is no need for the assumption of constant additive treatment effects across individuals. Instead, the individual causal effects are unrestricted, and individual effect heterogeneity in the population is permitted.

Literature review: Propensity score matching

A large body of literature in empirical economics, sociology and other areas has relied heavily on the PSM method introduced by Rosenbaum and Rubin (1983) to assess the average causal effect of an intervention on some outcome variable, by controlling for differences in observed characteristics across beneficiary and non-beneficiary groups. The rationale for the PSM method is to find a group that is as similar as possible to the group of beneficiaries but that was not enrolled in the program. Studies applying treatment effect estimators typically aim to assess the average causal effect of the intervention on some outcome variable (e.g., employment, earnings), by controlling for differences in observed characteristics across treated and non-treated subsamples.

1. Accelerated Growth Service

Czurylo (2023) applied a PSM dynamic DID approach to study whether tax increment financing (TIF) districts see an increase in jobs because of this designation, and whether the residents in neighbourhoods designated as TIF districts see employment benefits from the designation. The findings are that TIF designation increases the number of jobs in a selected census block by approximately 15% over five years. However, the employment levels of residents living in or around TIF districts show no increase because of the designation.

Meriküll and Paulus (2023) studied the impact of COVID-19 job retention support on employment. This study used firm-level administrative data from the Estonian Business Register and Tax and Customs Board, which covered the whole population of non-financial private sector firms from 2019 to 2020. They created a control group from firms that were as severely hit as those that received the support. Using matching techniques, the results demonstrated that the support given to firms had a positive effect on employment, with approximately one in five jobs being saved.

Granja et al. (2022) investigated the impacts of the Paycheck Protection Program (PPP), a large and unique small business support initiative, as part of the crisis response to the COVID-19 pandemic in the United States. The PPP provided loans to SMEs through private sector lenders, and the program was managed by the US Small Business Administration. The findings suggested that the impact of the program was very small for short- and medium-term employment compared with the program's size. They argue that the loans were not well targeted, that loans flowed to less affected regions, and that many SMEs used the loan to pay for expenses other than payrolls and to build up saving buffers.

Cancino et al. (2015) examined the impact of government support programs (SERCOTEC's Seed Capital Program) on the development of young SMEs that have growth potential in Chile. To analyze the impact of this Seed Capital Program, they used a counterfactual scenario, together with combined PSM and DID methods. A total of 682 businesses were surveyed (378 in the treatment group and the remainder in the control group), of which only 164 provided complete responses to the surveys (89 from the treatment group and 75 from the control group). The results indicate that the program had variable impacts on sales and a positive impact on the number of employees hired. However, it did not have a significant impact on raising capital after the subsidy.

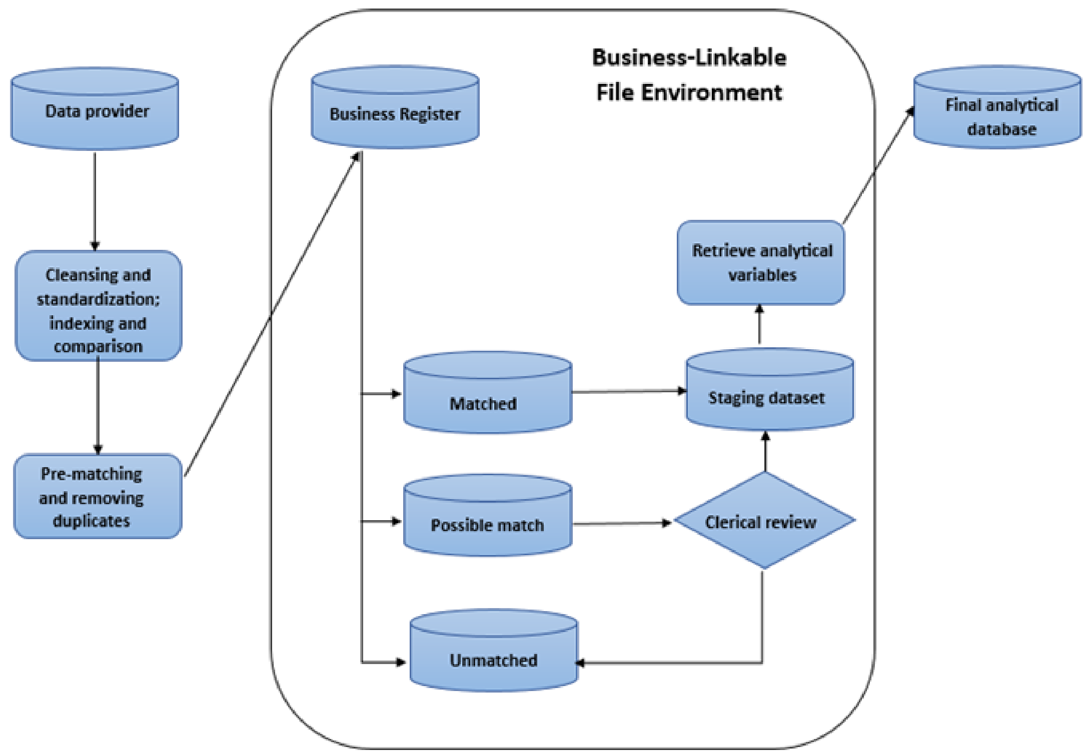
Kelly and Kim (2018) compared the performance of venture capital (VC)-backed and non-VC-backed firms using Canadian data, linking information on VC financing with firm-level administrative data. For this study, a control group was created based on PSM. The results show that R&D expenditures attracted VC, increasing significantly for VC-backed firms compared with non-VC-backed firms in the short term. Further, this study indicated that VC-backed firms had increased growth in wages and scale during a five-year period. Overall, VC financing correlated with the acceleration of the innovation and commercialization process, along with larger growth in wages and scale.

The next section of this report provides a guide to the process of linking the business microdata to the Business Register (BR) and then to other business microdata databases through the Business Linkable File Environment (B-LFE).

Matching Accelerated Growth Service clients to the Business Register

Figure 1 illustrates the overall procedure used to match the client list to the BR and the creation of the final database for the analysis. The list of AGS advisory services was matched to the BR using the deterministic record linkage method.

Figure 1
General process for record linkage to the Business Register



Source: Adapted from Christen et al., 2012

In deterministic record linkage, a pair of observations is said to be linked if the two observations match perfectly on each of the identifier elements (linkage keys). Mostly, the unique identifier in deterministic record linkage is the Business Number. If the linkage key is the business name, all characters of the business name must match perfectly. In principle, with deterministic matching of businesses from a complete BR, 100% of the observations should be systematically matched. In practice, the matching of the client list and the BR may not reach 100% because of missing or poor-quality information on some specific records, or other legitimate reasons, such as time lags between the registration of the business and the creation of the Business Number in the BR.

To match observations, CSBP first trimmed the list by removing duplicates and then standardized the format of the names and the addresses in the list received. A cleaning procedure greatly increased the number of good matches by removing extraneous text (such as accents and punctuation) and addressed frequently encountered inconsistencies between the two sources (e.g., differences in capitalization, use of “LIMITED” or “INC”). The cleaned list was then matched to the BR, and unique identifiers for each business were obtained.

In most cases, the match for each client record was achieved using the cleaned client list and the BR. For each observation, the best of the tentative matches on the BR was determined using a score function. This score function measures the quality of a match based on fields derived from the business name, street name, street number, city, province, incorporation number and postal code. Once the mathematical algorithm determined the observation pairs to be matched, unmatched or potentially matched (see Figure 1), match quality was then evaluated. A clerical review was performed to evaluate whether the records correspond to true matches or to false matches. This step consists of distinguishing true matches from false matches.

Matching results

For the present study, AGS provided CSBP with a list of the 1,000 businesses that benefited from AGS advisory services from 2017 to 2023. This file contained one row for each business. The information provided for these businesses included the reference year for each program cohort, the enterprise name, the Canada Revenue Agency Business Number, the register ID, the enterprise address or township, the postal code, and the province or territory of the enterprise.

Table 1 provides the match rate by year. The match rate is calculated as the total number of successful matches to the BR divided by the total number of clients for which matching was attempted. As shown in Table 1, a high match rate was found for all years considered in the analysis. The match rate, depending on the year, ranged from 94% to 99%. The average match rate for all years combined was approximately 98%. Overall, these results show that the match rates were sufficiently high. This study focused on the 2017 to 2019 cohorts.

Table 1
Matching rate to Business Register, by year

Reference year	Initial	Number of records	Matching rate (%)
2017	150	141	94
2018	205	201	98
2019	159	156	98
2020	131	129	99
2021	103	101	98
2022	186	183	98
2023	66	65	99
Totals	1000	976	98

Source: Author' computation

Data from the Business Linkable File Environment

After the AGS client businesses were matched to the BR, the next step consisted of describing the data sources used to create the research database. To create the research database, variables were extracted from the B-LFE. The B-LFE brings together Statistics Canada's microdata holdings from both administrative and survey sources. Specifically, the following microdata holdings were the sources of the final research database:

1. Statistics Canada Business Register (BR)—2014 to 2021. Maintained by the Data Integration Infrastructure Division at Statistics Canada, this file contains a structured list of businesses engaged in the production of goods and services in Canada. It also serves as the base for the B-LFE and is the ultimate source for North American Industry Classification System (NAICS) codes.
2. Payroll Deduction Account (PD7) File—2014 to 2021. This file, derived from payroll tax administrative data, contains, among other items, an enumeration of the number of employees in Canada for each payroll account. Each payroll account is uniquely identified by its 15-digit Business Number, which is an extension of the standard 9-digit Business Number.
3. General Index of Financial Information—2014 to 2021. Maintained by the Enterprise Statistics Division at Statistics Canada, these files contain financial information derived from tax data.
4. Research and Development in Canadian Industry—2014 to 2020. Maintained by the Centre for Innovation, Technology and Enterprise Statistics at Statistics Canada, these files contain R&D information derived from the Survey of Research and Development in Canadian Industry and tax data.
5. Exporter Register—2014 to 2021. Maintained by the International Accounts and Trade Division at Statistics Canada, these files contain the values of business merchandise exports.

Creation of the potential comparison group

The underlying concept of an economic impact study is that, once a proper counterfactual is identified, the comparison of outcomes across the two groups (beneficiaries and counterfactuals) allows for an assessment of the observed changes associated with the intervention (or the treatment effect), while controlling for other confounding factors. The key methodological challenge of this type of study is the identification of the counterfactual, i.e., a control group of enterprises that is as similar as possible to the group of beneficiaries.

A pool of potential candidates was constructed to make the matching exercise less onerous prior to running the matching algorithm. To achieve this, the operating entity number for each of the AGS advisory service beneficiary enterprises matched to the BR was used to extract detailed financial and employment information from the B-LFE. The information compiled in this database included the enterprises' total income, total revenue, total sales, total assets, total expenses, total liabilities, debt ratio, profit margin, R&D expenditures, export values and employment, as well as some basic enterprise characteristics, such as the age of the business, NAICS industry, operating address and country of control.

For each AGS client, a list of potential comparable businesses was selected from the B-LFE to form a database comprising AGS clients and a pool of potential candidates (i.e., a group of enterprises that are reasonably similar to one or more beneficiaries). This process was implemented for each cohort (i.e., 2017, 2018 and 2019 cohorts). Thus, the selection of potential candidates was limited to enterprises that had the same enterprise characteristics considered and fell in the same value range. Specifically, potential candidates were selected if they had any of the same six-digit NAICS codes reported by the beneficiaries, and if their values were in the same range as the beneficiaries for employment, income, assets, debt ratio and profit margin.

This study also ensures that the potential comparable business selected for each AGS advisory service is an enterprise that does not belong to any observed AGS group. In other words, an enterprise that was a beneficiary of any of the AGS programs considered in this study from 2014 to 2021 is automatically excluded from being a potential matching candidate.

After matching the client list to the BR and selecting key variables from the B-LFE, a series of PSM modelling methods was applied to perform the economic impact analysis.

The PSM method entails a number of procedures, which can be summarized as follows:

- First, the propensity score was run to obtain the predicted probability of being treated given a set of pre-treatment covariates.
- Second, the nearest neighbour matching algorithm was executed.
- Third, the balance of the covariates after matching was examined.
- Fourth, the treatment effect was computed.

Modelling methods

The analytical approach used in this study applies an econometric technique to assess the performance of AGS advisory service recipient enterprises. In brief, the approach relies on the identification of a sample of businesses that did not receive support (the counterfactual), but which present similar characteristics to those of the AGS program. The two groups are compared on a set of business performance indicators to establish the relative performance of beneficiaries against the control group.

Estimation of the propensity scores

This subsection presents the methodology used to estimate the propensity score. To estimate the propensity score, the study applies a logistic regression model (Cox & Snell, 1989). More specifically, the following equation is estimated:

$$\log\left(\frac{\pi_{it}}{1-\pi_{it}}\right) = \beta_0 + \beta_k X_{it} + \varepsilon_{it} \qquad (1)$$

The dependent variable considered in this study is a binary variable taking the value of 1 if an enterprise is an AGS participant and 0 otherwise. π_{it} is the probability of reporting the characteristic of interest for individual i. The first term in the left-hand side of equation 1 represents the log of the odds of receiving support. The term in the right-hand side, β_0 is the intercept, and the matrix X_{it} contains a set of control variables. β_k stands for the corresponding coefficients, and the last term, $\varepsilon_{it} \sim N(0, \sigma_\varepsilon{}^2)$ is the error term assumed to have a mean of 0 and a variance to be estimated.

There is a lack of consensus in the applied literature as to which variables to include in the propensity score model. Possible sets of variables for inclusion in the propensity score model include the following: all measured baseline covariates, all baseline covariates that are associated with treatment assignment, all covariates that affect the outcome (i.e., the potential confounders), and all covariates that affect both treatment assignment and the outcome (i.e., the true confounders) (Heckman et al., 1998; Bryson et al., 2002). Furthermore, Bryson et al. (2002) indicate that the inclusion of irrelevant variables may increase variance of the estimates, but that omitting important variables can seriously increase bias in the resulting estimates. Using Monte Carlo simulations, Cuong (2013) shows that efficiencies can be gained if all the variables, including those that do not affect the program participation, are controlled for in the PSM.[2]

Therefore, this study controls for revenue growth, employment growth, profit growth, R&D expenditure growth, export value growth, asset growth, expense growth, age and age squared of the business, and industrial classification (NAICS) of the business.

Nearest neighbour matching algorithm

After estimating the previous equation, the next step is to decide which observations are close matches. To select a comparison for each advisory service beneficiary from the pool of candidates with the closest absolute propensity score, the nearest neighbour matching approach is applied with a caliper to match each AGS client to the single non-beneficiary with the most similar propensity score. This method combines two matching approaches: nearest neighbour matching and caliper matching (Cochran & Rubin, 1973). The closest neighbour is selected within a predetermined common-support region. More specifically, we choose a caliper of 0.1 standard deviation.[3,4] The method can be expressed as follows: let a non-beneficiary j with propensity score p_j in the control sample I_0 be a match for a participant i with propensity score p_i in the treatment group if the absolute difference between their propensity scores is the smallest.

$$C(p_i) = \min_j \left\| p_i - p_j \right\|, j \in I_0 \ and \left\| p_i - p_j \right\| < \varepsilon, \varepsilon = 0.1 \qquad (2)$$

The selection process without replacement is performed, i.e., a candidate could be matched to only one AGS-supported business (one-to-one matches). In other words, the beneficiary of advisory services from AGS and the non-beneficiary are randomly ordered, with the first AGS beneficiary being matched with the non-beneficiary with the most similar overall revenue growth, employment growth, profit growth, R&D expenditure growth, export value growth, asset growth, expense growth, age and age squared, and industrial classification (NAICS). Once a non-beneficiary has been selected to be matched to a given AGS client, that non-beneficiary is no longer considered as a potential match for an AGS client. Accordingly, matched pairs are removed from the AGS advisory service list and the pool of non-beneficiaries; following this, the process is repeated for the remaining cases.

Balance check

Matching is considered successful when significant differences of covariates among AGS advisory service recipients and non-AGS businesses are removed. The balance check is meant to illustrate the reduction in bias after the matching process. The expected result after applying nearest neighbour matching would be a significant reduction in differences of mean between the two groups for the pre-treatment covariates. A balanced matched sample suggests that the two groups are successfully balanced with respect to observed baseline characteristics.

Treatment effects

Once the control group (counterfactual) was identified correctly, the impact of treatment on the treated businesses (the “causal effect” of the AGS program) is estimated by computing mean differences across both groups. As explained by Wooldridge (2010), the average treatment effect is simply given by the ordinary least squares estimate of β. This is the basic DID model.

$$\hat{\beta} = (\overline{Y}_{G=1,T=1} - \overline{Y}_{G=1,T=0}) - (\overline{Y}_{G=0,T=1} - \overline{Y}_{G=0,T=0}) \qquad (3)$$

2. All PSM was performed using the R package MatchIt (Stuart et al., 2011).
3. Rosenbaum and Rubin (1985) suggested a caliper of one-quarter of a standard deviation.
4. Recent studies have shown that the use of strata removes 95% of the bias attributable to the confounding of treatment status with a covariate (Caliendo & Kopeinig, 2008; Epstein et al., 2012).

Where $\overline{Y}_{G=1,T=1}$ is the sample average post-treatment outcome for the treated observations, and $\overline{Y}_{G=1,T=0}$ is the sample average pre-treatment outcome for the treated observations.

Empirical results

Propensity score estimates

Probabilities of participation in the AGS program are computed by estimating a probit model. The probability of being treated (i.e., in the AGS program) is reported in Table 2. In addition to other variables, all models include an industry dummy variable intended to control for sectoral differences and a year dummy to control for the year. At first glance, one can observe that the estimates for the revenue and employment variables are significant across all cohorts. The results show that profits enter with a negative coefficient (see the profit variable for the 2017 and 2018 cohorts), but it is not statistically significant for the 2019 cohort. R&D expenditures are found to be negatively and statistically significant for the 2017 and 2018 cohorts but not statistically significant in the case of the 2019 cohort.

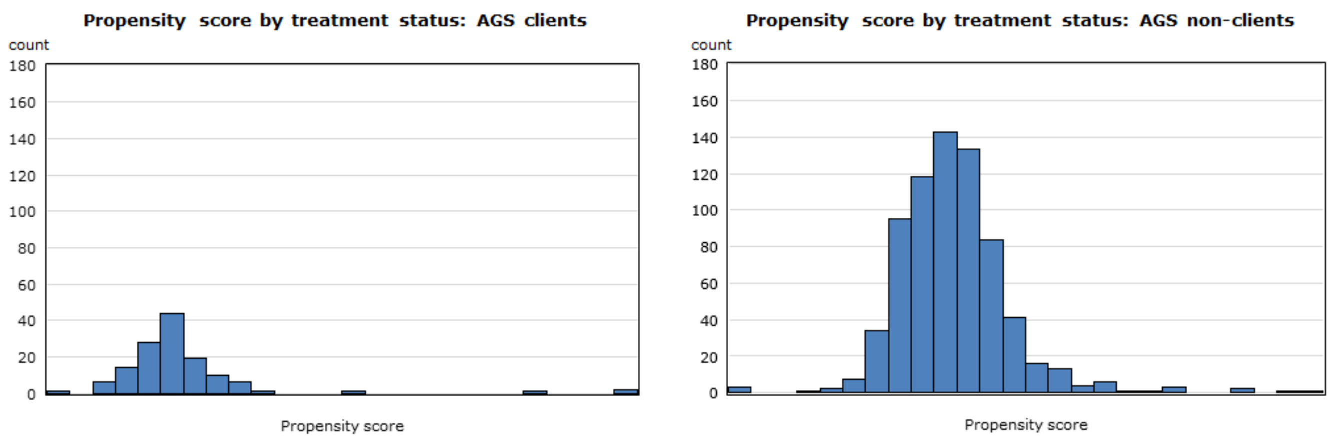
Table 2
Results from Probit analysis (AGS=1)

	Cohort 2017		Cohort 2018		Cohort 2019	
Independent variables	**Coeff.**	**P-value**	**Coeff.**	**P-value**	**Coeff.**	**P-value**
Intercept	-1.4300	0.0000	-1.4920	0.0000	-1.5500	0.0000
Revenue	0.2660	0.0330	0.0250	0.0780	-0.0770	0.0700
Employment	0.2780	0.0700	0.0570	0.0710	0.2430	0.1030
Profits	-0.1270	0.0750	-0.0790	0.0120	0.0090	0.8760
Assets	-0.0430	0.6910	-0.0930	0.3890	0.2000	0.1860
R&D Expenditures	-0.0210	0.0230	-0.0040	0.0390	-0.0210	0.2360
Expenses	-0.0930	0.5180	0.1290	0.2700	-0.1620	0.5070
Age	0.0110	0.6270	-0.0070	0.7010	0.0010	0.9810
Age*Age	-0.0010	0.4910	0.0000	0.7970	-0.0010	0.5380
Industry effects	yes	…	yes	…	yes	…
Year effects	yes	…	yes	…	yes	…
Observations	679	…	933	…	782	…

… not applicable
Note(s):
Number of observations consist of all businesses (control and potential comparison group)
Variables are in natural logs, except age variable.
Cohort 2017 spanning 2014-2017.
Cohort 2018 spanning 2015-2018.
Cohort 2019 spanning 2016-2019.
Source: Author' computation

Figure 2 depicts the propensity score distribution for the 2017 cohort. Propensity scores are calculated for every business that will undergo matching analysis. The results of the propensity scores of those businesses receiving AGS advisory services support overlap with the propensity scores of the potential comparison group, suggesting an increased likelihood of picking a good match. The probability distributions for the 2018 and 2019 cohorts are reported in the appendix.

Figure 2
Propensity score distribution, cohort of 2017



Source: Author' computation.

Nearest neighbour implementation and covariate balance check

After estimating the propensity score, we apply a nearest neighbour matching strategy on a linear propensity score without replacement. Once all the businesses are successfully matched, we assess covariate balance, which is crucial for causal comparisons. Matching is successful when significant differences in covariates among AGS clients and non-clients are removed. A suite of balance diagnostics has been proposed in the literature for PSM, including covariate adjustment using the propensity score, as well as visual inspection of the propensity score (Franklin et al., 2014). In this study, we check whether covariates are balanced across treated businesses and comparison groups by using statistical inference. Then, we proceed with visual inspection to ascertain whether the estimated propensity score achieved optimal covariate balance, by comparing the distribution of propensity scores.

Table 3 provides a summary of balance for the AGS clients and the control group for the 2017 cohort. The first three columns in Table 3 report the results for the two groups before the matching (columns 1 through 3), and the last three columns present results after performing the matching (columns 3 through 6). The results demonstrate that the standardized mean difference of the distance is 0.416 before matching, while after the matching, the standardized mean difference of the distance is 0.000. This suggests that a satisfactory balance has been achieved. Stuart et al. (2013) recommend 0.1 as an acceptable standardized mean difference threshold, and a threshold above 0.1 would lead to biased effects. As for the other variables, the standardized mean differences are below 0.1 in all cases after the matching. Results for the 2018 and 2019 cohorts are reported in the appendix.

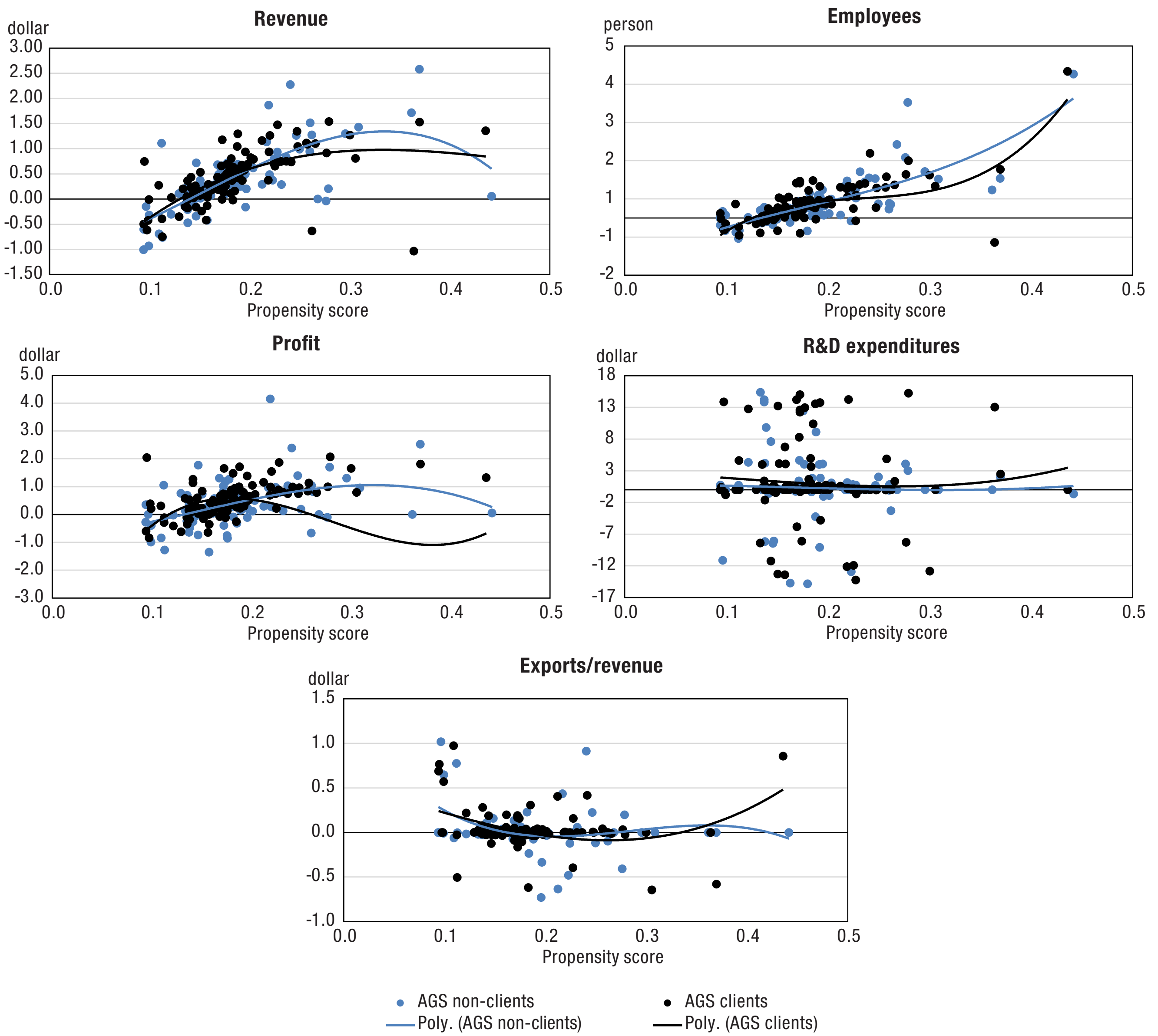
Table 3
Summary of balance (Cohort of 2017)

	Summary of Balance for All Data			Summary of Balance for Matched		
	Means Treated	**Means Control**	**Std. Mean Diff.**	**Means Treated**	**Means Control**	**Std. Mean Diff.**
Distance	0.1860	0.1600	0.4160	0.1830	0.1830	0.0000
Revenue	0.4200	0.2330	0.2890	0.4000	0.3780	0.0330
Employment	0.3500	0.1740	0.2980	0.3480	0.3440	0.0070
Profits	0.3350	0.3970	-0.0390	0.3270	0.3570	0.0190
R&D Expenditures	1.0000	1.1780	-0.0290	1.1200	0.3290	0.1290
Exports/Revenue	0.0390	0.0480	-0.0380	0.0320	0.0150	0.0740
Sample Sizes						
All	112	567	…	…	…	…
Matched	…	…	…	108	108	…
Unmatched	4	459	…	…	…	…

… not applicable
Source: Author' computation

Figure 3 displays the linear fitting for the propensity score of the two groups after matching for the 2017 cohort. In summary, the visual evidence complements the numerical evidence, indicating that the matching procedure was successful in providing an adequate comparison group for the treated group. This visual inspection reinforces our confidence in the extent to which the control group resembles AGS clients after the matching.

Figure 3
Propensity score distribution after matching, cohort of 2017



Source: Author' computation.

Treatment effects

Table 4 shows the one-year and three-year growth premiums for AGS advisory services for the 2017 cohort. The growth premium is displayed in the first column, and the *t*-statistic is in the second column. AGS-supported businesses had 0.46% higher revenue growth than the comparison group during the first year following support, while the growth differential increases to 5.81% over the three-year period. These results are statistically significant at the 5% and 10% levels, respectively. Additionally, AGS-supported businesses outperform the control group in all the metrics studied, except profits, where in the first year following AGS advisory services support, businesses posted 1.98% lower profits than the comparison group.

Table 4
Treatment effects (premium); cohort of 2017

	Average treatment effect	*t*-statistic
Revenue		
1 Year growth	0.4550	2.0970
3 Year growth	5.8070	1.8340
Employment		
1 Year growth	9.1060	2.5880
3 Year growth	11.8240	3.6580
Profits		
1 Year growth	-1.9800	1.0210
3 Year growth	8.2170	2.3290
Export/Revenue		
1 Year growth	0.5210	1.7450
3 Year growth	3.2450	2.4440
R&D Expenditures		
1 Year growth	9.1200	1.1170
3 Year growth	8.2080	2.1410

Source: Author' computation

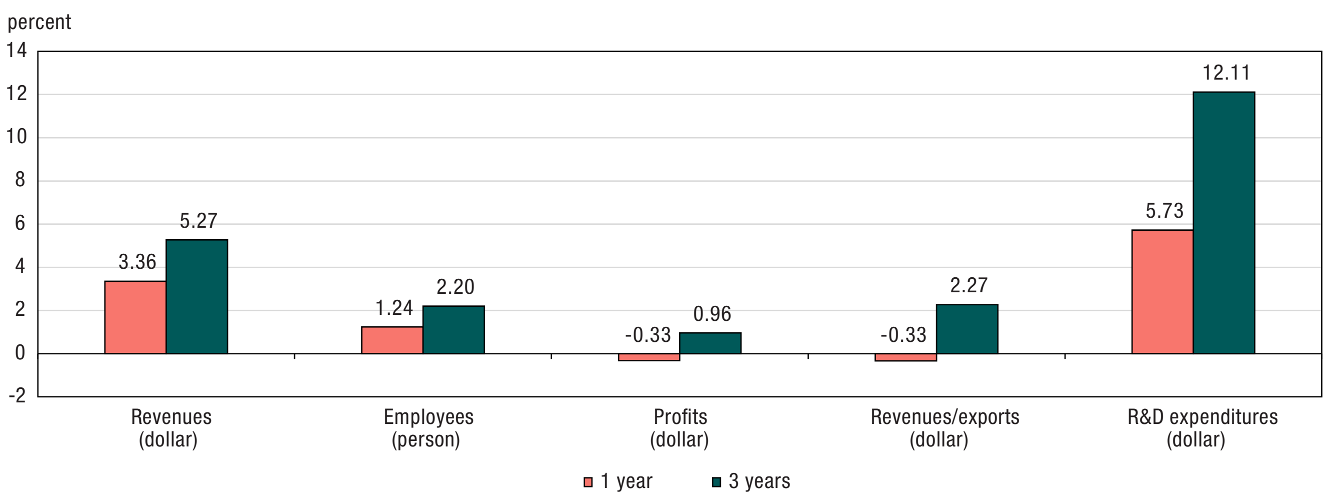
The study also found that AGS advisory service support to clients improved their ability to create jobs; generate revenue; engage in R&D activity; export; and, to a certain extent, improve profits (Figure 4 represents results for the 2017 cohort; results for the 2018 and 2019 cohorts are reported in the appendix). On average, interventions led to higher employment growth by the first year (9.11%) and third year (11.82%) following advisory service support compared with the control group. For revenue, AGS clients reported 0.46% higher revenue than the control group in the first year following advisory service support and up to 5.81% higher revenue three years following support. The effect of the intervention on R&D activity is greater in the first year following support than the third year following support. The two other performance measures, profits and exports as a percentage of revenue, also favour AGS client businesses.

Figure 4
Estimation results, growth rate averages for cohort of 2017

Note: All values are averages of growth rates.
Source: Author' computation.

Figure 5 depicts business performance for key variables, including revenue growth, employment growth, profit growth, growth in exports as a percentage of revenue, and R&D expenditure growth, for AGS clients in the 2018 cohort. The results indicate that AGS clients reported, on average, revenue growth 3.36% higher than the comparison group for the first year following advisory service support and 5.27% growth in the third year following support (for statistical significance, see Appendix Table D). AGS clients also experienced higher employment growth (2.19%) than non-clients in the third year following support. In the first year following support, AGS client businesses had employment growth 1.23% higher than the comparison group. In terms of profit growth, the analysis revealed that AGS clients recorded profit growth that was 0.33% lower than non-clients in the first year following support. Three years after support, AGS client businesses had a 0.96% growth premium in profits over non-supported businesses. The results related to R&D expenditure growth show that after the first year following support, AGS clients had growth 5.73% higher than the comparison group. Three years after support, AGS clients outpaced non-clients by 12.11% (statistically significant at the 1% level). For growth in exports as a percentage of revenue, supported businesses had a 0.33% lower growth premium in exports than non-supported businesses in the first year following advisory service support. Exports as a percentage of revenue of AGS clients grew 0.96%, on average, slightly greater than for non-AGS clients in the third year following support.

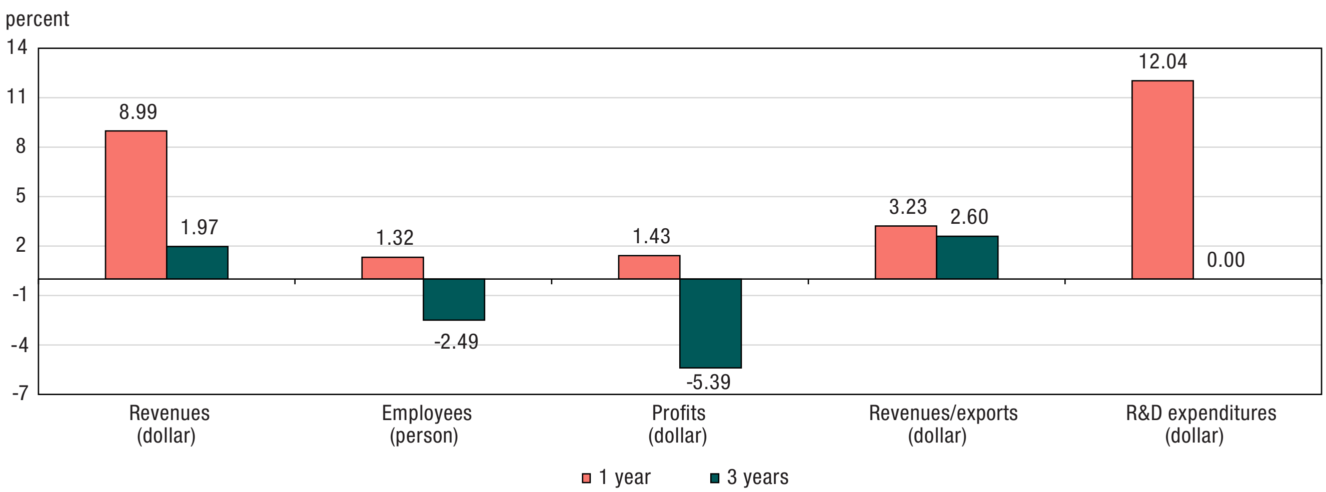
Figure 5
Estimation results, growth rate averages for cohort of 2018



Note: All values are averages of growth rates.
Source: Author' computation.

Figure 6 reports the performance differential in revenue growth, employment growth, profit growth, growth in exports as a percentage of revenue and R&D expenditure growth for the 2019 cohort. The study found that AGS clients posted revenue growth 8.99% higher than the comparison group in the first year following support. In the third year following support, AGS clients experienced revenue growth 1.97% higher than non-clients. Furthermore, AGS clients were found to have an employment growth rate that was 1.32% higher than non-clients during the first year. However, AGS client businesses underperformed by 2.49% in the third year following support compared with non-clients. With respect to R&D activity, enterprises that used AGS advisory service support showed higher R&D expenditure growth (12.04%) than similar enterprises that did not receive support in the first year (the B-LFE contains R&D data for up to 2020; as such, third-year results cannot be computed at this time). In terms of profit growth, AGS clients performed better than non-clients during the first year following support. However, three years after advisory service support, non-clients outpaced AGS clients by 5.39% on average, a statistically significant growth premium. Lastly, the value of exports as a percentage of revenue among AGS clients grew 3.22% and 2.60% higher than that of non-client businesses over the one- and three-year post-advisory service periods, respectively.

Figure 6
Estimation results, growth rate averages for cohort of 2019



Note: All values are averages of growth rates.
Source: Author' computation.

Conclusions

This report presents an analysis of the impact on businesses of advisory service support from the AGS. The impact of AGS advisory service support is assessed based on the economic performance of supported businesses relative to a similar group that did not receive support. Five measures of business performance are defined and investigated with econometric techniques for the 2017 to 2019 cohorts. The business performance measures are revenue growth, employment growth, profit growth, growth in exports as a percentage of revenue and R&D expenditure growth.

The findings reveal that AGS clients reported higher growth in revenue, employment, R&D spending and exports as a percentage of revenue compared with similar businesses that did not receive support. With respect to the 2017 cohort, the results showed that AGS clients that received advisory services had premiums of 5.81% for revenue, 11.82% for employment, 8.21% for profits, 3.25% for exports as a percentage of revenue and 8.21% for R&D expenditures over the control group three years after the initial year of support. In terms of growth premiums in the first year after receiving support, non-clients outperformed AGS clients only in exports as a percentage of revenue.

In terms of the analysis for the 2018 cohort, the results revealed that businesses that received AGS advisory services tended to have higher growth in the one- and three-year periods following support across most indicators studied, except profits and exports as a percentage of revenue. One year and three years after receiving advisory service support, businesses showed higher revenue growth (3.36% and 5.27%, respectively), employment growth (1.24% and 2.19%, respectively) and R&D expenditure growth (5.73% and 12.11%, respectively).

Businesses that benefited from AGS advisory services in 2019 showed higher growth in revenue, employment, profits, exports as a percentage of revenue and R&D expenditures than non-clients in the first year following support. Non-AGS clients displayed higher employment growth and profit growth than AGS client businesses three years after support.

Overall, the analysis shows AGS clients perform relatively better than non-clients in the marketplace. In other words, advisory services to businesses had considerable effects on various performance outcomes.

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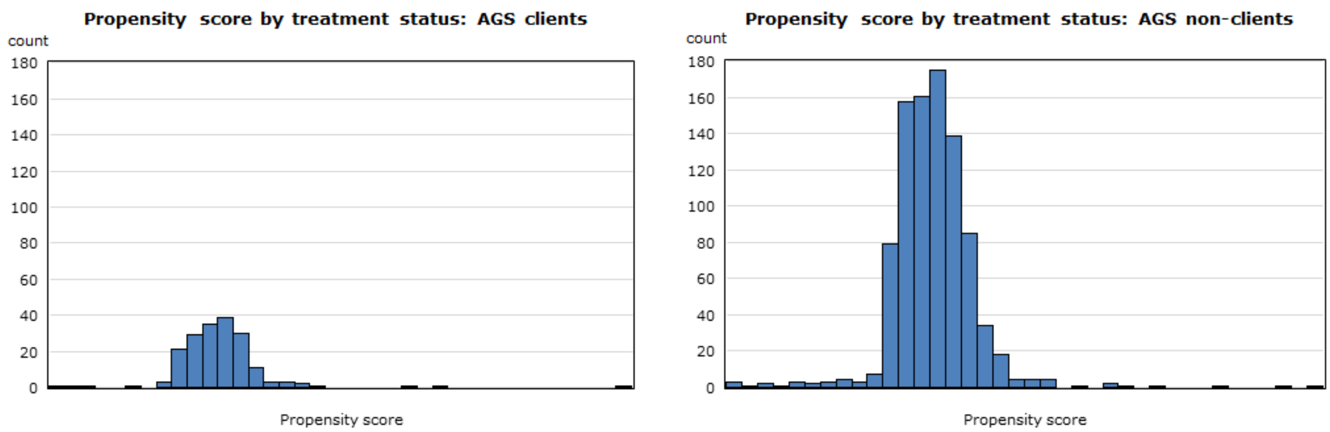
Appendix

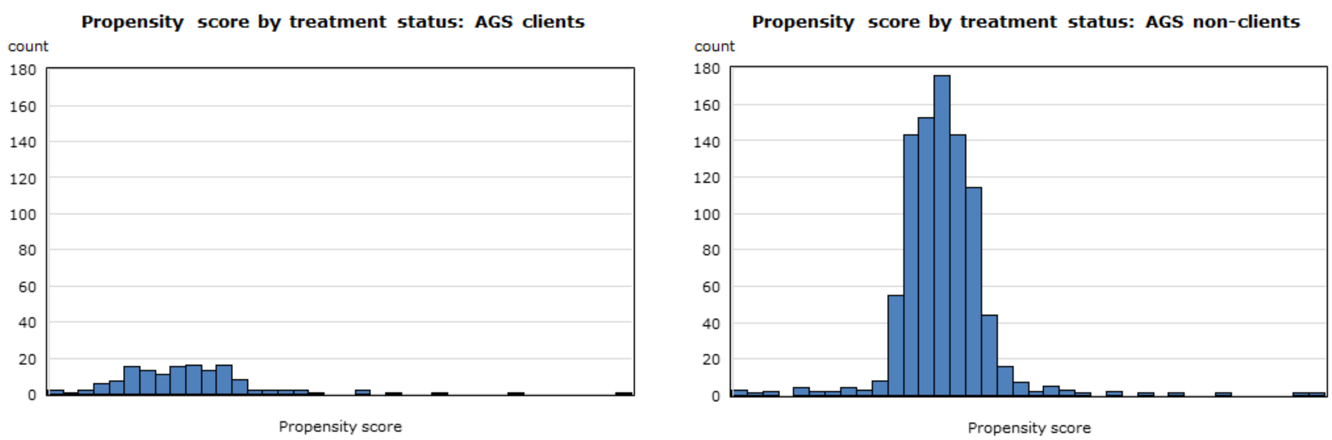
Appendix A

Figure A.1
Propensity score distribution, cohort of 2018



Source: Author' computation.

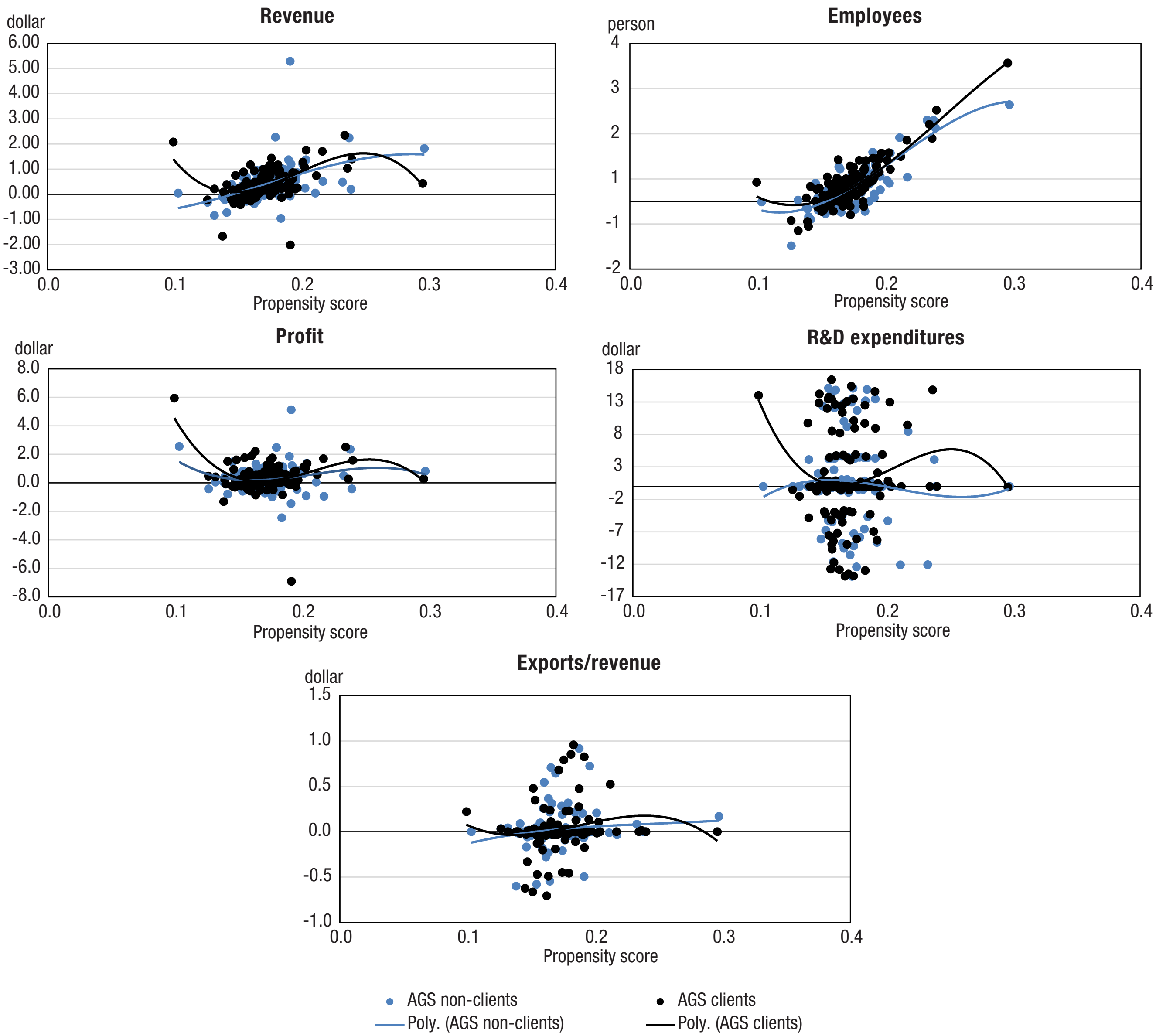
Figure A.2
Propensity score distribution, cohort of 2019



Source: Author' computation.

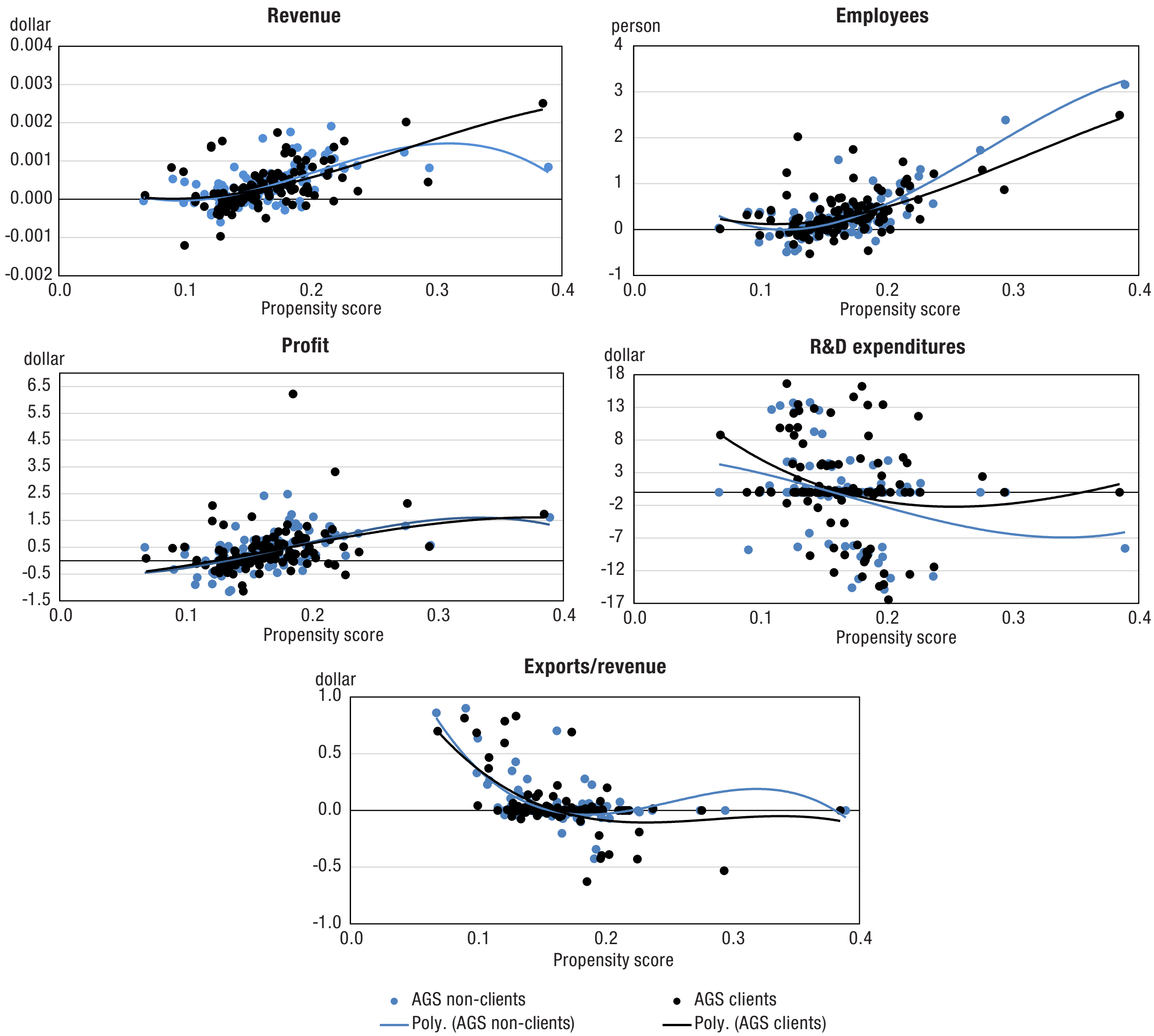
Appendix B

Figure B.1
Propensity score distribution after matching, cohort of 2018



Source: Author' computation.

Figure B.2
Propensity score distribution after matching, cohort of 2019



Source: Author' computation.

Appendix C

Table C.1
Summary of balance (Cohort of 2018)

	Summary of Balance for All Data			Summary of Balance for Matched		
	Means Treated	**Means Control**	**Std. Mean Diff.**	**Means Treated**	**Means Control**	**Std. Mean Diff.**
Distance	0.1750	0.1644	0.1748	0.1692	0.1692	0.0003
Revenue	0.3312	0.2715	0.1064	0.3439	0.3504	-0.0116
Employment	0.2638	0.2011	0.0939	0.2942	0.2589	0.0529
Profits	0.1091	0.3893	-0.1384	0.3139	0.2768	0.0183
R&D expenditures	0.7809	0.8586	-0.0121	0.8667	0.6756	0.0296
Exports/Revenue	0.0233	0.0194	0.0166	0.0176	0.0196	-0.0085
Sample Sizes						
All	155	778	…	…	…	…
Matched	…	…	…	153	153	…
Unmatched	2	625	…	…	…	…

… not applicable
Source: Author' computation

Table C.2
Summary of balance (Cohort of 2019)

	Summary of Balance for All Data			Summary of Balance for Matched		
	Means Treated	**Means Control**	**Std. Mean Diff.**	**Means Treated**	**Means Control**	**Std. Mean Diff.**
Distance	0.1759	0.1583	0.2691	0.1648	0.1648	0.0006
Revenue	0.4109	0.2802	0.1749	0.3292	0.3472	-0.0241
Employment	0.3732	0.2341	0.2300	0.3167	0.2811	0.0589
Profits	0.5241	0.3113	0.1286	0.3385	0.3162	0.0135
R&D Expenditures	0.3792	0.7761	-0.0611	0.5438	-0.3344	0.1351
Exports/Revenue	0.0139	0.0462	-0.1352	0.0319	0.0404	-0.0359
Sample Sizes						
All	126	656	…	…	…	…
Matched	…	…	…	119	119	…
Unmatched	7	537	…	…	…	…

… not applicable
Source: Author' computation

Appendix D

Table D.1
Treatment effects (Cohort of 2018 premium)

	Average treatment effect	*t*-statistic
Revenue		
1 Year growth	3.3590	2.9350
3 Year growth	5.2700	2.8560
Employment		
1 Year growth	1.2380	1.6400
3 Year growth	2.1990	2.3130
Profits		
1 Year growth	-0.3260	1.6380
3 Year growth	0.9580	2.0400
Exports/Revenue		
1 Year growth	-0.3330	0.0330
3 Year growth	2.2680	1.0560
R&D Expenditures		
1 Year growth	5.7290	2.0900
3 Year growth	12.1110	3.7660

Source: Author' computation

Table D.2
Treatment effects (Cohort of 2019 premium)

	Average treatment effect	*t*-statistic
Revenue		
1 Year growth	8.9870	1.6640
3 Year growth	1.9700	2.3190
Employment		
1 Year growth	1.3200	2.0930
3 Year growth	-2.4940	2.4960
Profits		
1 Year growth	1.4270	0.4070
3 Year growth	-5.3900	2.5450
Exports/Revenue		
1 Year growth	3.2250	0.9310
3 Year growth	2.5960	4.1520
R&D Expenditures		
1 Year growth	12.0390	1.7870
3 Year growth	…	…

… not applicable
Source: Author' computation