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Abstract

We evaluate a place-based policy aimed at commercial service providers in Sweden. In 2016, the Swedish government introduced a special operating support for grocery stores in remote rural areas with the intention to slow down the process of grocery store closures. We investigate the effects of the support in a Regression Discontinuity Design (RDD) framework by using a distance criterion that determined if stores qualified for the support. Stores located at least 15 kilometres away from another store could apply for the support whereas stores located closer to each other could not. Thus, the local causal effect of receiving the support can be estimated. The results indicate a 15-20 percent increase in store survival rates due to the support. For surviving stores, the effects on employment are negative, possibly due to labour being replaced by capital investments. Such labour substitution appears to be more pronounced for smaller stores.

JEL classification: H25; L81; L88; R38

Keywords: place-based policy, regression discontinuity design, commercial services

1. Introduction

Place-based policies have long been used in Europe to mitigate spatial disparities in incomes and employment. The EU cohesion policy budget is around one-third of the EU budget and consists of investments in transport infrastructure, research and development, and firm support in less developed regions (Ehrlich and Overman, 2020). Most European countries also have national policies for reducing spatial disparities and in Sweden, place-based policies are found within several policy areas such as infrastructure, education, and agriculture. In addition, regional development support to firms and projects using EU as well as national funding is available (Swedish Government, 2022). The special operating support targeted at grocery stores in rural areas is one type of regional development support and has the aim to provide basic commercial services for business and citizens in remote rural areas (Swedish Government, 2015).

Knowing if the aims of place-based policies are reached and whether they contribute to reduced spatial disparities is important for decision makers. However, evaluating these policies is difficult, and few studies manage to overcome the challenges involved since policies are most often non-randomly assigned. Firm support e.g., may be assigned to low-performing firms or to regions where firms are geographically dispersed, and growth is low. If low-performing firms are given support estimated effects will tend to be biased downwards. On the other hand, if high performing firms are more likely to apply for support, results may not be generalizable to non-applicants. Furthermore, spill-over effects on non-receiving firms make it difficult to find unaffected control groups.

This paper exploits the quasi-experimental setting of the Swedish special operating support for grocery stores in remote rural areas. Grocery stores that are 15 kilometres or further from another grocery store are eligible for support whereas grocery stores that are closer than 15 kilometres apart are not. Assuming that grocery stores just below the cut-off are good counterfactuals for grocery scores just above the cut-off allows us to use a regression discontinuity design (RDD). The aim is to investigate the causal effect on survival and economic outcomes (employment, turnover and investments). Theoretically, the support could be used for increasing the amount of capital in the firm or the amount of labour, depending on the expected marginal products of the factors. But how the support is used is an empirical question. We contribute to the scarce literature evaluating place-based policies aimed at firms. Commercial service providers are often seen as important to the attractiveness of rural areas (Öner, 2017) but studies investigating the effects of government support on outcomes of service providers in rural areas are limited. To the best of our knowledge, this is the first study to use RDD to evaluate regional support to service providers.

In 2016 the Swedish government introduced the special operating support as part of its regional policy. The budget was initially set at 35 million SEK (approximately 3.5 million euros) per year for the period 2016-2019 with the intention to provide a long-term support. In addition to the distance criterion the grocery store had to have a diverse selection of groceries and gross turnover was not to exceed 11 million SEK (approximately 1.1 million euros). Furthermore, the store was supposed to be open all year around and provide another type of service such as a fuel, pharmacy, postal or payment service (SAERG, 2017). These types of services are typically combined with sales of groceries in remote areas in Sweden (SAERG, 2021). In 2016, the average support was 179 000 SEK (approx. 17 900 euros). Given that most stores were small, with an average of two employees and a median turnover of 4.4 million SEK (approx. 0.4 million euros), the support was substantial. In 2018 the budget for the support increased to 70 million SEK (approx. 7 million euros) per year and the requirement about the longest distance to the closest grocery store was lowered to 10 kilometres (SAERG, 2019).

Data come from two sources. Data about the special operating support come from the Swedish Agency for Economic and Regional Growth (SAERG) and contain information about all grocery stores that received the support in 2016-2018 and distances to the closest grocery store. This data is merged with firm data from Statistics Sweden that contain information about coordinates of workplaces and economic data for these such as turnover, employment, value added and investments. Additional control stores that did not receive the operating support are found in the data from Statistics Sweden.

Results show that the support increased the survival rate of stores in rural areas. Stores that received the operating support in 2016 were 15-20 percent more likely to operate also in 2018, compared to a situation where the support had not been available. The effect on employment is negative, meaning that stores that received support did not increase the number of employees to the same extent as stores that did receive the support. A plausible interpretation is that the support caused labour to be replaced by capital investments. There is no general effect on turnover, indicating that the support did not affect the size of the stores. Dividing the sample into small and large stores shows that labour substitution is more pronounced for small stores.

The remainder of the paper is organized as follows. Section 2 provides a literature review and section 3 give more details about the special operating support. Section 4 explains the data and presents some descriptive statistics and section 5 describes the methodology in detail. The results are presented in section 6 and section 7 concludes.

2. Literature review

In the literature review we focus on place-based policies aimed at firms and different aspects of commercial service providers in rural areas. Place-based policies have been evaluated by i.a. Bronzini and de Blasio, 2006; Devereux et al., 2007; Bernini and Pellegrini, 2011; Bennmarker et al., 2009; Blomquist and Nordin, 2017; Andini and de Blasio, 2016; Cerqua and Pellegrini, 2014; Decramer and Vanormelingen, 2016; Brachert et al., 2019 and Criscuolo et al., 2019.The EU cohesion policy, which in part is aimed at specific firms, have also been evaluated by e.g., Becker et al. (2010, 2012, 2013). There are a few studies that use RDD to evaluate place-based policies, some of these studies are briefly discussed in the following. Cerqua and Pellegrini (2014) evaluate Law 488/92 (L488), the main Italian regional policy and exploit the selection process that entails the ranking of firms where treatment is assigned by multiple rankings with different cut-off points. The results show that the policy had a positive impact on employment, investments, and turnover of receiving firms, whereas the effect on productivity is mostly negligible. Decramer and Vanormelingen (2016) use RDD to analyse the effects of an investment subsidy program aimed at small and medium size firms in Flanders. Subsidies were awarded according to a ranking system with a sharp cut-off point. Positive effects were found on investment, employment, output, and productivity on firms that were granted the subsidy, but the effects were relatively small and only found for small firms. Brachert et al. (2019) use RDD to investigate regional support in Germany. The government used a scoring system based on indicators such as unemployment, incomes, and the quality of infrastructure to determine if firms in a district was eligible for the support. The support was available in districts with scores below a certain cut-off and districts above the cut-off were used as controls. Results show that the support had positive effects on output and productivity but no effects on employment and wages. Finally, Cerqua and Pellegrini (2022) evaluate effects on the labour market of Law 488/92 (L488) in Italy using a RDD design with multiple cut-offs. The results show that most new employees were young people and students rather than people from other firms or regions.

Ehrlich and Seidel (2018) investigate subsidies (given to firms as well as public projects) that were aimed at West-German regions close to the East-German border before the unification of Germany in 1990. Regions receiving subsidies are compared to bordering regions (also in West Germany) that did not receive subsidies. The results shows that the subsidies increased economic activity, also many years after they ended. However, there was also a substantial decrease of economic activity in the bordering regions, casting doubt on the efficiency of the subsidies. Significant displacement effects are also found in Einiö and Overman (2016) investigating the effects of spatially targeted support (mainly to firms) in the UK.

There are few studies evaluating public policies aimed at commercial service providers in rural areas. Cleary et al. (2018) investigate how the profitability of large stores in non-metro areas (semi-urban and rural areas) in the US are affected by two public policies. Results show that support to low-income households (in terms of benefit cards) as well as subsidies to the stores reduce the market size needed for a store to be profitable. Thus, both policies are regarded as successful in increasing access to grocery stores in semi-urban and rural areas.

The effects of access to grocery stores in rural areas on different outcomes such as migration (Amcoff et al., 2011), place attractiveness (Öner, 2017)) and child well-being (Bullinger et al (2021 has received some attention in the literature. Amcoff et al. (2011) study grocery stores in rural Sweden and investigate if residents' decision to move to or from a village is affected by the existence of a local store. The results suggest that these decisions are unrelated to the closure of village stores. These results are also in line with the results in Öner (2017) who investigates the effect of access to grocery stores on place attractiveness in Sweden, where the latter is measured using house prices. Access to stores in a rural municipality does not increase the attractiveness of the place. However, access to stores in the broader labour market region has some effect on the attractiveness of rural locations (Öner, 2017). This suggests that access to grocery stores in the labour market region is more important than access to grocery stores in the smaller areas such as a village or a municipality. Finally, Bullinger et al. (2021) investigate how access to stores in the US that accept benefit cards affect child maltreatment. The authors find that one additional store that accepts benefit cards in rural areas is associated with a 4.4 percent decrease in child maltreatment. Finally, the establishment of supermarkets on the performance of existing grocery stores in rural areas have been investigated (Artz and Stone, 2006; Bergström, 2000). Sales of rural stores are shown to be negatively affected by these establishments.

3. The special operating support

In spring 2015 an investigation appointed by the Swedish government suggested a new operating support for grocery stores in the most remote areas in Sweden (Swedish government, 2015). In the years preceding the investigation, the government had observed a decline in access to commercial services. Almost 25 percent of the grocery stores in remote areas had closed between 2004-2014 (Swedish Government, 2015). The different types of service support provided at the time (investment support, investment loans, service support, home delivery support and EU rural development programme service support) had not stopped the process of store closures. Thus, in December 2015, the government decided to set aside 35 million SEK (approximately 3.5 million euros) per year in 2016-2019 for the special operating support (SAERG, 2017).

Grocery stores had to meet several requirements to be eligible for the special operating support. First, and most important for our purposes, the distance to another grocery store with a diverse range of groceries was to be 15 kilometres or more. Grocery stores on islands with no fixed land connection were also eligible. In addition, the grocery stores had to have a diverse selection of groceries and turnover of groceries was not to exceed 11 million SEK (approximately 1.1 million euros). The rationale behind this limitation was outlined in a prior investigation, which argued that stores below the 11 million SEK threshold faced greater challenges in expanding and improving profitability compared to stores above the limit (Swedish Government, 2015). Furthermore, the stores were to be open all year around and be important for another basic type of service such as a fuel, pharmacy, postal or payment service (SAERG, 2017). In 2018 the support was expanded. The budget increased to 70 million SEK per year and the required distance to the closest grocery store was lowered to 10 kilometres or more. Other requirements did not change (SAERG, 2019).

The maximum amount was set to 300 000 SEK and the size of the support was based on a formula depending on the turnover of the store. The amount increased from zero for a store with 0.5 million SEK in turnover or less, to 300 000 for a store with turnover between 5 and 7 million. If turnover was larger than 7 million SEK, the amount decreased gradually and was zero again for stores with a turnover that exceeded 11 million SEK. For instance, if a store received the maximum amount and had a turnover of 5 million SEK, the support would represent six percent of the store's turnover. In 2016 there was 180 stores that received the operating support and the average amount received was 179 000 SEK. Most grocery stores that received the support belonged to one of four major Swedish food retailers (Axfood, Menigo, ICA, COOP) (SAERG, 2018).

A survey sent out by SAERG directed at store managers who received the support in 2016 and 2017 reported that the support was mainly used for investments, hiring of staff and for increasing the assortment (SAERG, 2018). Around 60 percent of managers’ report that the support contributed to investments such as changing refrigerators or freezers, check-out systems or recycling machines. Many managers, especially those representing somewhat larger stores, report that the support made it possible to increase the number of staff. Some stores also reported that they increased opening hours. When asked about what would happen if the support was not available anymore over 50 percent of managers answered that they would have to decrease the number of staff hours and over 40 percent answered that they would have to close the store (SAERG, 2018).

The motivation for using the distance rule was to prevent unfair competition, meaning that if one store received support, it should not negatively impact another close-by store. Another motivation was to be able to be able to identify areas were access to groceries and other commercial services was limited. To establish an appropriate distance threshold, the aforementioned investigation scrutinized distances between grocery stores in different parts of the country (Swedish Government, 2015).

Three different distances were considered: 10, 15 and 20 kilometres. The shortest distance, 10 kilometres, was considered too short since some grocery stores in this class were close to densely populated areas. The longest distance, 20 kilometres, was considered too long since some grocery stores in vulnerable areas would not be included. Hence, the investigation recommended 15 kilometres (Swedish Government, 2015). As mentioned above, the distance rule was changed to 10 kilometres or more in 2018. The SAERG then argued that the support had been successful and could be used to mitigate the loss of place attractiveness more widely (SAERG, 2019).

4. Data and descriptive statistics

Data about grocery stores that received operating support in 2016-2018 was collected from SAERG. This dataset includes information such as the distance-by-car to the closest store with a wide assortment of groceries. Additionally, it includes details about the sum applied for, the sum received, the municipality where each store was located, the region where the decision was made and the month when the decision was finalized. Economic data (i.e., turnover, number of employees, investments) for grocery stores was collected from Statistics Sweden for the years 2008-2018. Data was extracted from three databases: the statistical business register (FDB), the structural business statistics (FEK) and the geographic database (GDB). Firm data is organised according to the Swedish Standard Industrial Classification (SNI) and our data is for SNI 47: Retail except motor vehicles and motorcycles. The FDB was used to define all workplaces with activity in SNI 47. Thus, if a firm had more than one workplace, it will appear more than once in this dataset. FDB data was merged with FEK data that contain information about i.e., net turnover, productive value, value added, staff costs and the average number of employees in each year for each workplace. Furthermore, the FEK data also include information regarding activities in other sectors.

We focus on the effects of the operating support given in 2016. Most stores that received support in 2016 also received support in 2017, but there are 12 stores that received support in 2016 but not in the following year. These 12 stores are left in the sample. We use control stores from two sources. First, we use stores that did not receive the operating support in 2016 but received it in 2018. These stores are a suitable control group since they fulfil all the requirements (providing a basic type of service, open all year around, having a diverse selection of groceries and having a turnover that did not exceed 11 million SEK.) just like the stores receiving support in 2016. Note that the only prerequisite that changed in 2018 was the distance to another store. We find 57 stores that received support in 2018, which we use in our analysis. To increase the sample and to be able to investigate survival, we add stores that did not receive the support in the investigated period (2016-2018) using FEK data. The procedure for finding these stores is described in the following.

We start by selecting workplaces from the FEK-data where the main activity was reported to be in SNI sub code 47.112: Food retail with wide assortment. Large department stores or supermarkets (sub code 47.111) are not eligible for the support, but they are selected, not as controls, but for the purpose of measuring distances between stores. Next, we remove stores located less than within a five-kilometre radius from another grocery store, stores with missing coordinates (10.3 percent) and six stores on islands. We also exclude stores that had a turnover less than 0.5 and more than 11 million SEK from sales of groceries, as these stores were not eligible for the support. The distance between workplaces in sub code 47.112 to other workplaces in this sub code and sub code 47.111 is then calculated as the distances-by-car using Google maps.

After merging SAERG data with economic data, we find that there are 59 stores that received support but had no registered activity in 47.112. Since it is unclear if these stores are comparable to the control stores, we chose to remove them. Many of these stores report that they sell petrol. The final sample consist of 314 stores, 121 that are "treated" with the support and 193 that are used as controls.

Figure 1 shows how treated and control stores are dispersed geographically. It is evident that treated stores are more common in the less densely populated areas in the north of Sweden. Many control stores are located further south, but are still located in relatively sparsely populated areas, and many of them became eligible for the support in 2018.

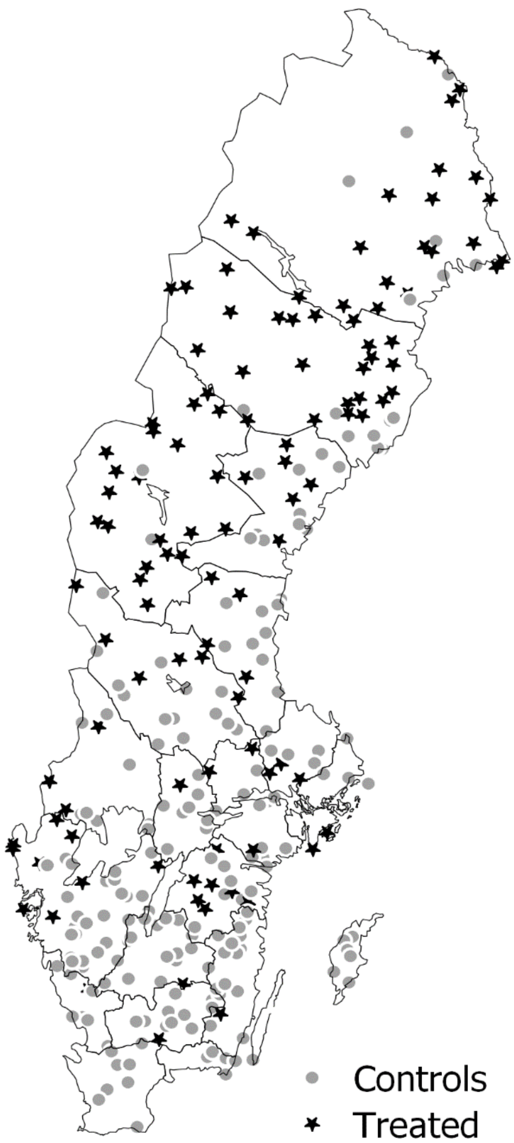

Figure 1. Map of Sweden with county borders, control stores, and treated stores.

Figure 2 shows grocery stores that received the operating support in 2016 and the distance to the closest grocery store. For illustrative purposes, stores that are further than 20 kilometres from another store are not shown. There is a clear break at 14 kilometres suggesting that distances have been rounded up when assessing the applications. A closer look reveals that there are seven stores that are between 14.5 kilometres and 15 kilometres to another store and 13 stores that are even closer to another store but still receive the operating support. The SAERG writes that when there are “special reasons” it is not necessary to fulfil the requirements about the distance (SAERG, 2017). We get back to this possible threat to the identification strategy later and show that there are reasons to consider these 13 stores as eligible in the analysis.

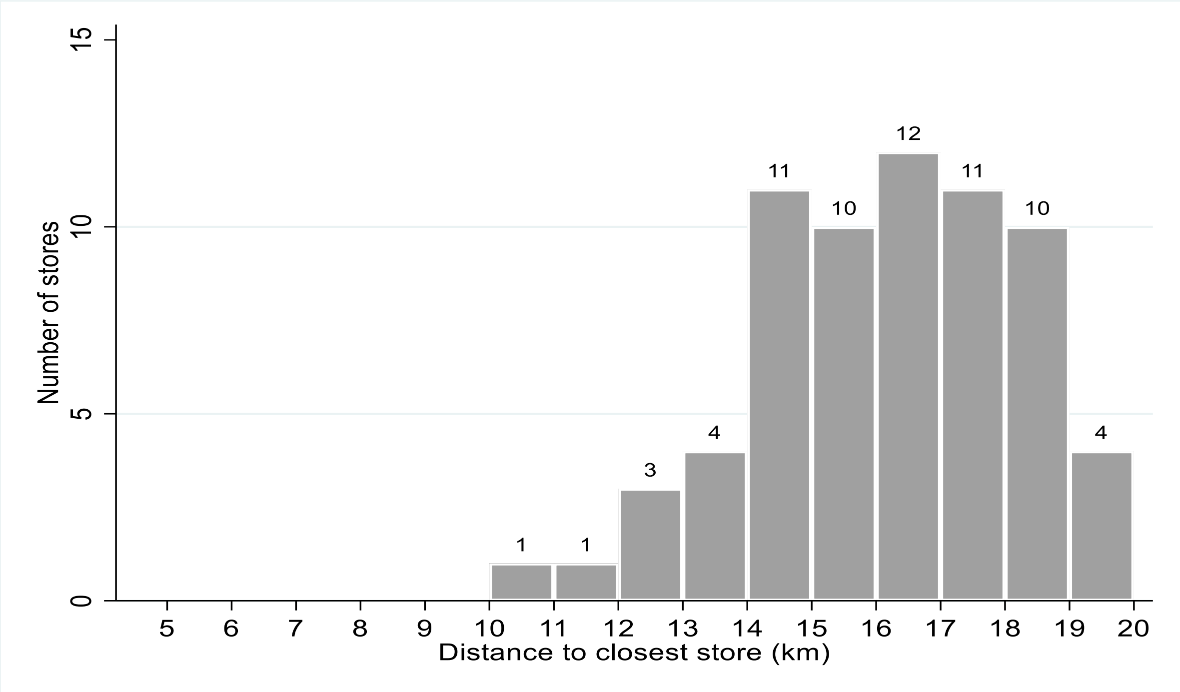

Figure 2. Distance to the closest grocery store for grocery stores receiving operating support in 2016.

Note: Grocery stores (n=54) further than 20 kilometres from another store are omitted for illustrative purposes.

Table 1 shows summary statistics for control and treated grocery stores in the pre-treatment period 2014-2015 and the post-treatment period 2016-2017. Survival is defined as a dummy variable equal to one if the store had a total turnover larger than 0.5 million SEK in 2018 and zero otherwise. Although it would be possible to use a strict definition of survival (i.e., zero turnover in 2018) we choose to allow for some turnover during the year as we believe that a sharp drop in turnover signals that the store was closed during the year or the following year. Seven stores out of eight with non-zero turnover in 2018 had a drop in turnover exceeding 75 percent compared to the turnover in 2016 and were classified as non-survivors. Employment is the average number of full-time employees in a year and turnover is defined as income (in SEK) from sales of goods and services excluding taxes (note that the operating support is not part of turnover).

Investments are measured at the company level rather than at the workplace level and thus there are stores that are owned by larger companies that also own other stores or other enterprises. We find 10 such stores in our data and we are thus unable to use these stores in the analysis of investments.

Table 1. Summary statistics of treated and control stores (averages and standard deviations in brackets).

	Treated	Control
Survival	0.96	0.85
	(0.20)	*(0.35)*
Number of employees 2014-2015	2.23	2.23
	(1.53)	*(1.82)*
Number of employees 2016-2017	2.36	2.40
	(1.62)	(1.86)
Turnover (million SEK) 2014-2015	5.18	4.90
	(2.76)	*(3.27)*
Turnover (million SEK) 2016-2017	5.06	5.00
	(2.89)	*(3.24)*
Investments (thousands SEK) 2014-2015	42.10	63.99
	(67.87)	*(165.49)*
Investments (thousands SEK) 2016-2017	81.07	48.26
	(161.80)	*(101.21)*

Table 1 shows that most of the treated stores survived until 2018, while a notable proportion of the control stores closed down (the difference is eleven percentage points). The number of employees and turnover pre-treatment does not seem to differ much between control and treated stores. This is good news as it suggests that control stores are similar to treated stores in these aspects. The similarities in the number of employees and turnover does not seem to change after the implementation of the operating support, i.e., there is generally no indication that treated stores employ more people or increase their turnover when studying averages. Investments are higher in control stores in the pre-treatment period suggesting that control stores and treated stores have somewhat different investment patterns. Average investments are higher for treated than for control stores after the implementation of the support. Testing the differences in means between the two groups confirm that the differences in post-treatment survival and investments are significant (p-values of 0.002 and 0.041) whereas the differences in post-treatment employment and turnover are insignificant.

Comparing means will however not isolate the effect of receiving the operating support on outcomes. Stores that are closer to cities will operate under different conditions than stores in very remote rural areas. For example, stores closer to cities face greater competition from other stores while stores in the most rural areas may have very little demand linked to low population density. In the next section we describe the Regression Discontinuity Design (RDD) that will overcome problems such as these.

5. Method

RDD use arbitrary rules that determine treatment. In our case the 15-kilometre distance rule is arbitrary chosen by the legislator. Around this cut-off grocery stores are assumed to resemble each other on both sides of the cut-off, and in the post-treatment period only the operating support is supposed to generate differences in outcomes around the cut-off. In other words, differences in the likelihood of survival and the change in turnover, employees and investments around the cut-off can only be explained by the operating support.

Figure 2 shows that the true cut-off is lower than 15 kilometres in 2016. There is a tendency to round off close to the cut-off and our interpretation is that stores that are between 14.5 and 15 kilometres are fulfilling the distance rule. For this reason, we use 14.5 kilometres as our cut-off point.

For the RDD to work it is important that treatment is exogenous to outcomes given a running variable determining treatment. In our case the running value is the distance to the nearest grocery store. It is unlikely that specific grocery stores could influence the choice of cut-off since it was suggested by the investigation (Swedish government, 2015) and decided by the government. But it may be possible to influence how the distance is measured by choosing different routes on the map or making different assessments about which store is the closest store. But the grocery stores do not have control over these measurements. SAERG measures distances between grocery stores and regional authorities use this data to make decisions about which stores receive support. In most cases, stores identified by the SAERG align with the ones ultimately receiving the support. However, the regulation allowed for exceptions in special circumstances and in some cases regional authorities could suggest a few more stores (personal communication, Pär-Ove Bergquist, SAERG, 2021-12-09). The motivations for making exceptions varied (examples involve stores situated in areas with low population density or long commuting distances or stores in tourist destinations). But even in such instances, exceptions from the established cut-off point had to be convincingly justified and made in dialogue with SAERG; the message from SAERG was to be restrictive with exceptions (Pär-Ove Bergquist, SAERG, 2023-08-16). Thus, store managers could not manipulate the cut-off. Also, the SAERG or the regional authorities had no clear incentives to manipulate the cut-off or the selection of grocery stores.

Based on this reasoning, we consider the 13 stores that received the operating support and are below the 14.5 cut-off as eligible in our regression analysis since it is unlikely that there has been systematic manipulation to become eligible for the support. An inspection of the geographic locations of the 13 stores using google maps reveal that the closest store often is another rural store and that the stores are placed in remote locations were travel to the closest community often takes more than an hour. Although we include the 13 treated stores below the cut-off in our estimations – a violation of the strict approach – we show later that it has no major impact on the results.

Moreover, to be eligible for the support is not the same as receiving treatment, i.e., not all eligible stores will apply for the operating support. Thus, since assignment is imperfect, we will use two different approaches. In the first approach we use a sharp RDD, where we exclude non-compliers, i.e., stores that were above the cut-off but did not receive the operating support (24 stores). The reason for these stores not receiving support could be that they were different in ways that we have not been able to measure, it may e.g., be that they did not fulfil the requirement of supplying another kind of service. If this is the case these stores are not suitable for the control group. Second, we will work with a fuzzy RDD where the probability of receiving treatment changes discontinuously at the cut-off. Here we assume that non-compliers are suitable to use in the control group. In the fuzzy RDD the probability of receiving support is estimated in the first step and the effect of the predicted treatment is estimated in the second step. Table 2 summarizes the number of observations (stores) that we use in the sharp and fuzzy regression designs.

Table 2. Number of observations (stores) in sharp and fuzzy designs

	Sharp	Fuzzy
Treated	121	121
Controls	169	169
Non-compliers		24
Total	290	314

We focus on four outcomes of the stores: survival, employment, turnover and investments. Survival is defined as above (i.e. a dummy variable equal to one if turnover is larger than 500 000 SEK in 2018). Employment, turnover and investments are measured as changes before and after the implementation of the support. The decision to set aside money for the support was taken in december 2015 and decisions for stores that applied were taken continuously during 2016 with the first decisions made in April 2016. Thus, our pre-treatment period is 2014-2015 and our post-treatment period is 2016-2017. The change in employment is measured as the difference between the average number of employees in the post- and pre-treatment periods. The percentage change in turnover is measured as the difference between turnover in the post-treatment period and the pre-treatment period divided by turnover in the pre-treatment period.

6. Results

We begin by checking the density of the running variable and examine whether predetermined variables are affected by treatment status. First, we perform a density test (as proposed by Cattaneo, Jansson and Ma, 2018) to examine whether we observe a similar number of observations on each side close to the cut-off. The null hypothesis is that there is no manipulation of the densitiy of the running variable around the cut-off. The results are shown in Table 3. Using a bandwidth of five kilometres on either side of the cut-off and a uniform kernel (i.e. all observations have equal weight) we fail to reject the null hyptheses, i.e. there is no evidence of manipulation near the cut-off. Using a triangular kernel or a bandwidth of -5 and 10 or -5 and 20 km does not change this conclusion.

Table 3. Manipulation test using local polynomial density estimation

	Density1	Density2	Density3	Density4
T	1.62	1.11	1.26	0.58
P-value	0.11	0.27	0.21	0.56
Polynomial	2	2	2	2
Bandwidth	-5, 5	-5, 5	-5, 10	-5, 20
Kernel	Uniform	Triangular	Uniform	Uniform
Efficient number of observations on each side of the cut-off	108, 67	108, 67	108, 92	108, 117

Note: The rddensity package in Stata is used.

If grocery stores (or their managers) are unable to influence their treatment status there should be no systematic differences between stores near the cut-off. Except for treatment status, stores should be similar in ways that are not affected by treatment. A common RD falscification test is to check if placebo outcomes are affected by treatment. However, we have not been able to find any suitable placebo outcomes in our case but are able to check if diffferent pre-determined variables differ below and above the cut-off. Treatment should not have an effect on pre-determined variables.

First, we use data on side activities of the grocery stores. We find that 77 stores report some type of side activity in addition to sales of groceries (i.e. activity in SNI sub code 47.112) in 2015. The most common side activities are restaurants (16 stores) and petrol stations (15 stores). Being treated with the support should not affect whether the store had a side activity in 2015. Having a side activity could affect survival as well as economic outcomes but it is unlilkely that there are systematic differences depending on treatment status. Hence, side activity is the dependent variable affected by treatment, and linear trends (a single polynomial) of the running variable is included on each side of the cut-off. Three different bandwidths are used here and throughout the paper. The first allows the use of all available observations and these are found in a span that reaches 10 kilometres below the cut-off and 75 kilometres above the cut-off. The second bandwidth is narrowed down to five kilometres to the left and ten kilometres to the right of the cut-off. We allow for longer distances to the right of the cut-off for this bandwidth to consider that we have a longer span here. Finally, equal bandwidths of five kilometres on each side of the cut-off are used. Results (see Table A1-A3) support that there are no effects on the likelihood of having a restaurant, petrol station or any side activity of being treated with the operating support (see appendix). The postive effect of having a petrol station or any side activity when all observations are used disappears when the bandwidth is narrowed down.

Next we check if economic variables (average employment, turnover and investments) prior to the implementation of the support (2014-2015) differ between treated and control stores. As before, treatment and linear trends of the running variable are used as explanatory variables. There is no indication that there are systematic differences in these variables for treated and control stores (see Table A4-A6).

6.1 Survival

We start by investigating the effects on survival of the operating support by plotting binned outcome means for survival against the distance variable (Figure 3). We use only stores that are treated and found above the cut-off and stores that are not treated and found below the cut-off. The observations are distributed evenly into ten bins on either side of the cut-off, ensuring an equal number of observations in each bin to the best extent possible. On each side of the cut-off a line is fitted to the original number of observations.

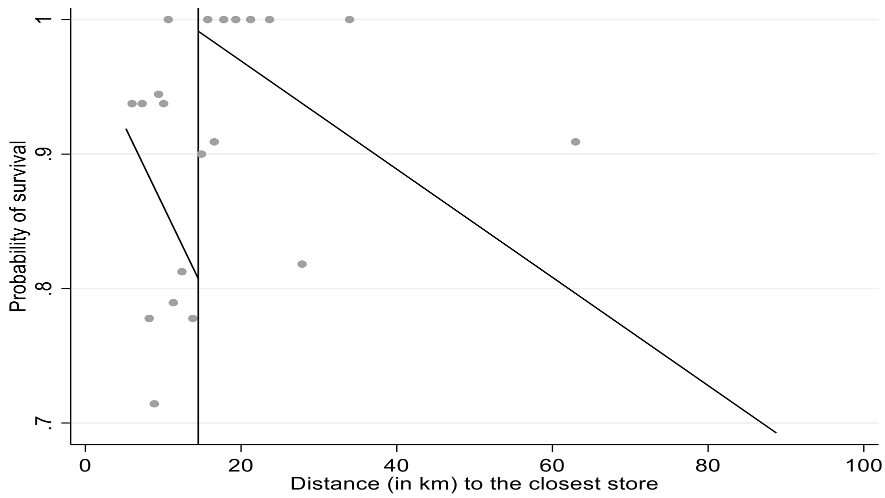

Figure 3. Plot of binned outcome means for survival.

Note: There are ten bins at each side of the cut-off noted by the horizontal line (at 14.5 km). Each point represents the average of the observations in the bins. On each side of the cut-off each bin contains the same number of observations (quantile-spaced bins). The lines are fitted on each side of the cut-off based on the individual observations and not the bin values.

The figure illustrates several interesting points. First, it shows that there are relatively few observations as the distance increases above 40 kilometres and more observations close to the cut-off, something that is expected. Second, when examining bins close to the cut-off (e.g., between 10 and 20 km) it is evident that survival is on average higher to the right of the cut-off. Finally, the slopes indicate that survival is decreasing with distance and the jump in the fitted lines at the cut-off suggest that there is an increase in survival at the cut-off that is equal to approximately 18 percent. Overall, the figure supports that the operating support has increased the survival rate of grocery stores.

We will now use RDD regression analysis to see if we can confirm the results found in Figure 4. Table 4 presents results when estimating the sharp version of the RDD (using OLS). In all models we estimate different trends on each side of the cut-off. Three different bandwidths as described above are used together with first-order polynomials (Model 1, 2 and 3) and second-order polynomials of the running variable (Model 4, 5 and 6).

Table 4. Impact of operating support on grocery stores on survival – sharp model

	(1)	(2)	(3)	(4)	(5)	(6)
Bandwidth	-10, 75	-5, 10	-5, 5	-10, 75	-5, 10	-5, 5
Polynomial	1	1	1	2	2	2
Coefficient on treated	0.184**	0.181**	0.176**	0.151**	0.153**	0.165**
Robust standard error	(0.07)	(0.08)	(0.07)	(0.08)	(0.07)	(0.06)
Number of observations	290	180	158	290	180	158

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Results for constant and running variable (km) are not shown.

The results confirm the picture in Figure 4. The treatment effect is significant and ranges between 15 and 18 percent. The estimates do not change much as the bandwidth is narrowed down or when the second order polynomials are used for the running variable. In Table 5 model 7-12 present the results when using the fuzzy RDD design, i.e., the probability of treatment is regressed on eligibility in the first step and predicted values are used in the second step when the effects of treatment on survival are estimated. The bandwidths and polynomials are the same as for the sharp models.

Table 5. Impact of operating support on grocery stores survival – fuzzy model

	(7)	(8)	(9)	(10)	(11)	(12)
Bandwidth	-10, 75	-5, 10	-5, 5	-10, 75	-5, 10	-5, 5
Polynomial	1	1	1	2	2	2
Coefficient on treated	0.191**	0.202**	0.187**	0.163*	0.155**	0.177**
Robust standard error	(0.08)	(0.09)	(0.09)	(0.09)	(0.08)	(0.07)
Number of observations	314	198	173	314	198	173

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Results for constant and running variable (km) are not shown. The fuzzy model estimates treatment as a function of eligibility in a first step (not shown).

Again, the results confirm that there is a positive effect on survival of the operating support. The fuzzy regressions indicate that the effect on survival is slightly larger than was indicated by the sharp model, but the difference is not large. There is not much difference between estimates when different bandwidths are used or when the second order polynomials are added to the fuzzy models.

As the number of observations is limited, we opted for a uniform kernel in the estimations above (all observations are equally weighted). However, it is common to give higher weights to observations closer to the cut-off as these are assumed to be more important. If the weights are maximized at the cut-off and declines linearly as the value of the running variable gets further from the cut-off the kernel is triangular. In this and the following analysis, we use first order polynomials only (i.e., linear trends on each side of the cut-off). Using triangular kernels does not change the results much compared to the main analysis in Tables 4 and 5 (see Table 6).

Table 6. Impact of operating support on grocery stores survival – triangular kernels

	kernel1	kernel2	kernel3	kernel4	kernel5	kernel6
Bandwidth	-10, 75	-5, 10	-5, 5	-10, 75	-5, 10	-5, 5
Method	sharp	sharp	sharp	fuzzy	fuzzy	fuzzy
Coefficient on treated	0.158**	0.159*	0.168**	0.172*	0.177	0.183*
Robust standard error	(0.07)	(0.09)	(0.08)	(0.09)	(0.11)	(0.11)
Number of observations	290	180	158	314	198	173

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Results for constant and running variable (km) are not shown. The fuzzy model estimates treatment as a function of eligibility in a first step (not shown).

Next, we investigate how sensitive our results are to the survival share of stores that are close to the cut-off. If there has been systematic manipulation when measuring the distance between stores it can be assumed that it is the stores closest to the cut-off that engaged in manipulation. Thus, we exclude stores that are very close to the cut-off (so called donut approach). Table 7 shows the case where we exclude observations that are within a two-kilometre radius around the cut-off. A one-kilometre radius around the cut-off is also tested and produces very similar results (provided upon request).

Table 7. Impact of operating support on grocery store survival – donut approach

	donut1	donut2	donut3	donut4	donut5	donut6
Bandwidth	-10, 75	-5, 10	-5, 5	-10, 75	-5, 10	-5, 5
Method	sharp	sharp	sharp	fuzzy	fuzzy	fuzzy
Coefficient on treated	0.216***	0.237**	0.221***	0.225**	0.265**	0.232**
Robust standard error	(0.08)	(0.09)	(0.08)	(0.09)	(0.11)	(0.10)
Number of observations	265	155	133	283	167	142

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Results for constant and running variable (kilometre) are not shown. The fuzzy model estimates treatment as a function of eligibility in a first step (not shown).

If treatment is exogenous there is theoretically no need for control variables other than the running variable. Nevertheless, we test if our results are sensitive to the inclusion of regional fixed effects. In Sweden there are 25 counties and the grocery stores in our sample are represented in 21 of them. The results (Table 8) do not seem to be affected much by the inclusion of regional fixed effects. The likelihood of survival for treated stores is estimated to be between 16 and 22 percentage points higher than for non-treated.

Table 8. Impact of operating support on grocery store survival – with regional fixed effects

	fe1	fe2	fe3	fe4	fe5	fe6
Bandwidth	-10, 75	-5, 10	-5, 5	-10, 75	-5, 10	-5, 5
Method	sharp	sharp	sharp	fuzzy	fuzzy	fuzzy
Coefficient on treated	0.158**	0.174**	0.155*	0.200**	0.221**	0.182*
Robust standard error	(0.08)	(0.09)	(0.09)	(0.10)	(0.11)	(0.11)
Number of observations	290	180	158	314	198	173

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Results for constant, running variable (kilometres) or fixed effects are not shown. The fuzzy model estimates treatment as a function of eligibility in a first step (not shown).

Next, we check how sensitive our results are to the choice of cut-off. Without treatment there should be no abrupt changes at the cut-off for stores below and above the cut-off. This should also be true if we choose a different cut-off than the actual one assuming that there are no other explanations for a sudden change in the survival rate at these levels. We use two placebo cut-offs to see if there are different effects on survival of stores above and below these cut-offs. First, we use a placebo cut-off at 12.5 kilometres (i.e., 2 kilometres below the actual cut-off) and then we use a placebo-cut-off at 16.5 kilometres (i.e., two kilometres above the actual cut-off). Since we have a limited number of observations, we do not want to restrict the sample too much. We therefore choose to stay relatively close to the original cut-off and use the same bandwidths as in the original analysis. The results are presented in Table 9.

Table 9. Impact of operating support on grocery stores survival – placebo cut-offs

	p1	p2	p3	p4	p5	p6
Bandwidth	-10, 75	-5, 10	-5, 5	-10, 75	-5, 10	-5, 5
Placebo cut-off	16.5	16.5	16.5	12.5	12.5	12.5
Coefficient on placebo treated	0.094	-0.047	-0.107	0.082	-0.043	-0.078
Robust standard error	(0.06)	(0.08)	(0.10)	(0.07)	(0.09)	(0.11)
Number of observations	290	128	107	290	219	190

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Results for constant and running variable (km) are not shown.

The results show that using a placebo cut-off at 16.5- or 12.5-kilometres does not affect survival as the coefficients are small and insignificant. This is the case regardless of the choice of bandwidth.

As we have discussed above, we assume that stores that are treated but are below the cut-off are eligible for the operating support for reasons pointed out above. However, it may be of interest to see how the results change if treated stores below the cut-off are omitted from the analysis (sharp version) or when these stores are treated as non-eligible and used in the analysis (fuzzy version). Table 10 shows the results.

Table 10. Impact of operating support on grocery stores survival – assuming treated stores below the cut-off are non-eligible.

	s1	s2	s3	s4	s5	s6
Bandwidth	-10, 75	-5, 10	-5, 5	-10, 75	-5, 10	-5, 5
Polynomial	sharp	sharp	sharp	fuzzy	fuzzy	fuzzy
Coefficient on treated	0.189**	0.186*	0.172	0.208*	0.253	0.192
Robust standard error	(0.07)	(0.11)	(0.11)	(0.12)	(0.24)	(0.29)
Number of observations	277	167	145	314	198	173

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Results for constant and running variable (kilometres) are not shown. The fuzzy model estimates treatment as a function of eligibility in a first step (not shown).

Although the results do not change drastically, they do become less significant as the bandwidth is narrowed down. Thus, fewer observations mainly affect the standard errors and not the size of the point estimates. We conclude that these stores should be regarded as eligible for the support as they have been evaluated by the regional authorities and assigned to treatment.

6.2 Economic outcomes

Next, we investigate the impact of the operating support on the number of employees, turnover and investments of surviving stores. According to the SAERG survey (SAERG, 2018), the support was used to increase the number of employees, to offer a wider assortment of groceries, to extend opening hours, and for investments. Investments was the most common use according to the survey (SAREG, 2018). Plots of binned means of the economic variables against the running variable are shown in the Appendix (Figure A1) together with fitted lines. It is difficult to discern any patterns of the binned means for employment although the fitted lines suggest that the increase in employment is smaller for grocery stores that receive the support. The percentage change in turnover does not display any particular pattern. Finally, investment changes are positive for most bins to the right of the cut-off whereas the picture is more mixed to the left of the cut-off. Also, the gap between the fitted lines suggest that stores that received the support invested more than stores that did not receive the support.

Next, the economic outcomes are analysed using RDD regression analysis. First, we estimate the effects of treatment on the change in employment between 2014-2015 and 2016-2017. The results (Table 11) support the findings in Figure A1 there is a negative employment effect for stores that received the support. The models (sharp and fuzzy) with a bandwidth of -5 and 10 imply that treated stores used approx.. 50 percent less of a full-time employee compared to control stores. This is a large effect on employment, considering that the stores on average have two employees.

Table 11. Impact of the operating support on employment

	emp1	emp2	emp3	emp4	emp5	emp6
Bandwidth	-10, 75	-5, 10	-5, 5	-10, 75	-5, 10	-5, 5
Model	sharp	sharp	sharp	fuzzy	fuzzy	fuzzy
Coefficient on treated	-0.199	-0.480**	-0.427*	-0.215	-0.517*	-0.441
Robust standard error	(0.18)	(0.24)	(0.25)	(0.22)	(0.30)	(0.31)
Number of observations	247	148	127	268	164	141

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Results for constant and running variable (km) are not shown. The IV-model estimates treatment as a function of eligibility in a first step (not shown).

Alternative specifications are presented in Table A7 and A8, using second order polynomials of the running varibale, triangular kernels, the donut approach, and a specification where treated stores below the cut-off are omitted. Using second order polynomials produce results that are very similar to the once presented in Table 11. Other specifications, however, produce insignificant results although the employment effect is still negative.

We proceed to estimate the effects of the percentage change of turnover (Table 12). As was indicated in figure A1 in the appendix there is no evidence of an effect of the support on turnover. The results from the regression analysis support this finding.

Table 12. Impact of operating support on turnover

	turn1	turn2	turn3	turn4	turn5	turn6
Bandwidth	-10, 75	-5, 10	-5, 5	-10, 75	-5, 10	-5, 5
Model	sharp	sharp	sharp	fuzzy	fuzzy	fuzzy
Coefficient on treated	-0.109	-0.071	-0.073	-0.104	-0.023	-0.007
Robust standard error	(0.07)	(0.06)	(0.07)	(0.09)	(0.09)	(0.09)
Number of observations	246	148	127	267	164	141

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Results for constant and running variable (km) are not shown. The IV-model estimates treatment as a function of eligibility in a first step (not shown).

Alternative specifications do not provide any evidence that contradict the conclusion that the support had no effect on turnover in general (see Table A9 and Table A10 in the appendix).

Finally, we estimate the effects on changes in investments (Table 12). Although there is a significant effect in the model with the largest bandwidth (-10, 75) the coefficients on investments are not significant in the models with shorter bandwidths, due to large standard errors. Still, it is evident that investments are higher on average in the post-treatment period for treated stores as indicated by the positive and large numbers. For example, the sharp model with a bandwidth of -5 and 5 indicates that the investments were approximately 111 000 SEK higher in the post-treatment period for treated stores. This can be compared to the average amount of the support that was 179 000 SEK.

Table 13. Impact of operating support on investments.

	inv1	inv2	inv3	inv4	inv5	inv6
Bandwidth	-10, 75	-5, 10	-5, 5	-10, 75	-5, 10	-5, 5
Model	sharp	sharp	sharp	fuzzy	fuzzy	fuzzy
Coefficient on treated	173.389**	118.708	110.764	194.612**	125.470	111.593
Robust standard error	(71.02)	(79.82)	(77.42)	(84.76)	(94.58)	(92.07)
N	247	147	126	270	164	141

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Results for constant and running variable (km) are not shown. The IV-model estimates treatment as a function of eligibility in a first step (not shown).

Most of the alternative specifications (see Table A11 and Table A12) confirm the patterns found in Table 13. The support only has significant effects on investment changes if all observations are used, i.e., the broadest available bandwidth. But the positive effect on investment changes is apparent in all specifications. Large standard errors are perhaps expected since not all stores invest in the short study period and hence the variation in investments is large. Interestingly, the investment changes become significant for shorter bandwidths when using the donut approach. Here, we do not interpret this as a sign of manipulation around the cut-off, rather we believe that this is re-affirming the notion that investment patterns are highly varying between stores.

Lastly, we investigate differences between large and small stores. The SAERG survey (SAERG, 2018) suggests that effects of the support may vary with store size. For instance, managers of larger stores report that they often use the support for hiring staff (SAERG, 2018). Median turnover in 2016 is used to split the observations into large or small stores and a dummy variable is created, assigning a value of one to large stores and zero to small stores. Median turnover was approximately 4.4 million SEK in 2016, which was below the required level (5 million SEK) for receiving the highest amount of support. The dummy variable is interacted with being treated.

We do not find differences in survival rates for large and small stores. However, among surviving stores the employment effect is stronger for small stores (see Table A13), i.e., the support is related to hiring fewer employees especially for small stores. The percentage change in turnover is slightly lower for small stores (between 11 and 14 percentage points) whereas there is no effect on turnover for large stores, consistent with the original model (Table A14). Further, the investment effect is strongest for small stores, although the effects are still not significant as the bandwidth decreases (Table A14). Overall, economic effects are more apparent for small stores. This might be expected since smaller stores are more likely to be affected by the support and since the support gradually reduces as store turnover exceeds 7 million SEK.

7. Concluding discussion

Forty percent of store managers, according to the survey conducted by the SAERG in 2018, reported that they did not believe their stores would have survived without the special operating support (SAERG, 2018). Our findings partially support these claims, as they suggest that the support led to a 15-20 percent increase in the survival rate. This result holds across different specifications and is surprisingly robust despite the small sample size.

For surviving stores, the effect on employment is negative, stores that received support did not increase their number of employees to the same extent as stores that did not receive the support. This effect is especially pronounced for smaller stores. However, investments appear to be larger for stores that received the support. A plausible interpretation is that the support has caused labour to be replaced by capital investments.

While the SAERG survey reports that stores were able to maintain a wider assortment of groceries and increase their opening hours (SAERG, 2018), we did not investigate these variables directly. There may however be a link between having a wider assortment, longer opening hours, and increased turnover: but we do not find that the support increased store turnover.

The period for investigating survival is short although the intention of policy makers is that the support should be long-term. There is no reason to believe that the support would not have similar long-term effects as the short-term effects estimated in our study. With more data becoming available in the future, it would be possible to examine the long-term effects of the support. It would also be possible to investigate the impacts of the support for stores that became eligible in 2018 when the minimum required distance between stores was reduced to ten kilometres. Hence, we believe that these results are valuable for decision-making regarding measures aimed at preventing grocery store closures and maintaining other commercial services in rural areas as part of regional policy objectives. Additionally, policymakers can utilize these results when considering potential changes to the special operating support program.

Our results are also in line with results from previous studies where regional support has shown to have positive effects investments (Cerqua and Pellegrini, 2014; Decramer and Vanormelingen, 2016). Many previous studies have however, contrary to our results, found positive effects on employment of regional support (Cerqua and Pellegrini, 2014; Decramer and Vanormelingen, 2016; Cerqua and Pellegrini, 2022). The specific contextual factors will play a role, as demonstrated in our study where effects differ between small and large firms. External validity is often a concern when using RDD analysis because the estimated effect is local around the cutoff. However, our results remain relatively robust as we move further away from the cutoff.

Some studies point out that the positive effects found in RDD analysis from regional support to firms in supported regions may come at the expense of negative effects on firms in other regions (Einiö and Overman, 2016; Ehrlich and Seidel, 2018). This is especially problematic if adjacent regions are used in the comparison. In case of the operational support, it is a minor problem since the support is conditional on the distance to other grocery stores.

The aims of place-based firm support often extend beyond its immediate impact on the supported firms. Previous studies using RDD have evaluated broader regional policies where support is aimed generally at firms in regions that fall below a cut-off of a composite running variable (often based on indicators aimed at measuring structural weakness) (e.g., Cerqua and Pellegrini, 2014; Decramer and Vanormelingen, 2016; Einiö and Overman, 2016 and Brachert et al., 2019). We evaluate a support that is specifically tailored and aimed at grocery stores in remote areas in Sweden. We do not know if the support has facilitated the establishment of new stores or if it has affected variables such as migration, business growth or tourism, in the local areas. These aspects remain subjects for future research.

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Appendix

Table A1. The probability of having a restaurant as dependent variable.

	1	2	3	4	5	6
Bandwidth	-10, 75	-5, 10	-5, 5	-10, 75	-5, 10	-5, 5
Model	sharp	sharp	sharp	fuzzy	fuzzy	fuzzy
Coefficient on treated	0.015	0.054	0.030	0.013	0.078	0.059
Robust standard error	(0.04)	(0.06)	(0.06)	(0.05)	(0.08)	(0.08)
Number of observations	298	168	146	298	185	161

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Results for constant and running variable (km) are not shown. The IV-model estimates treatment as a function of eligibility in a first step (not shown).

Table A2. The probability of having a petrol station as dependent variable.

	1	2	3	4	5	6
Bandwidth	-10, 75	-5, 10	-5, 5	-10, 75	-5, 10	-5, 5
Model	sharp	sharp	sharp	fuzzy	fuzzy	fuzzy
Coefficient on treated	0.086***	0.025	0.036	0.074*	0.018	0.033
Robust standard error	(0.03)	(0.04)	(0.05)	(0.04)	(0.05)	(0.05)
Number of observations	298	168	146	298	185	161

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Results for constant and running variable (km) are not shown. The IV-model estimates treatment as a function of eligibility in a first step (not shown).

Table A3. The probability of having any side activity as dependent variable.

	1	2	3	4	5	6
Bandwidth	-10, 75	-5, 10	-5, 5	-10, 75	-5, 10	-5, 5
Model	sharp	sharp	sharp	fuzzy	fuzzy	fuzzy
Coefficient on treated	0.124*	0.096	0.111	0.128	0.099	0.082
Robust standard error	(0.07)	(0.12)	(0.13)	(0.11)	(0.15)	(0.16)
Number of observations	298	168	146	298	185	161

Note: * p < 0.10, ** p < 0.05, *** p < 0.01. Results for constant and running variable (km) are not shown. The IV-model estimates treatment as a function of eligibility in a first step (not shown).

Table A4. Employment before treatment (average 2014-2015)

	1	2	3	4	5	6
Bandwidth	-10, 75	-5, 10	-5, 5	-10, 75	-5, 10	-5, 5
Model	sharp	sharp	sharp	fuzzy	fuzzy	fuzzy
Coefficient on treated	-0.047	0.311	0.035	0.271	0.631	0.415
Robust standard error	(0.33)	(0.52)	(0.54)	(0.46)	(0.71)	(0.74)
Number of observations	280	155	134	280	172	149

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Results for constant and running variable (km) are not shown. The IV-model estimates treatment as a function of eligibility in a first step (not shown).

Table A5. Turnover before treatment (average 2014-2015)

	1	2	3	4	5	6
Bandwidth	-10, 75	-5, 10	-5, 5	-10, 75	-5, 10	-5, 5
Model	sharp	sharp	sharp	fuzzy	fuzzy	fuzzy
Coefficient on treated	510,540	271,148	391,860	193,591	534,264	666,481
Robust standard error	(538,366)	(1,004,310)	(1,076,556)	(892,781)	(1,333,171)	(1,399,760)
Number of observations	280	155	134	280	172	149

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Results for constant and running variable (km) are not shown. The IV-model estimates treatment as a function of eligibility in a first step (not shown).

Table A6. Investments before treatment (average 2014-2015)

	1	2	3	4	5	6
Bandwidth	-10, 75	-5, 10	-5, 5	-10, 75	-5, 10	-5, 5
Model	sharp	sharp	sharp	fuzzy	fuzzy	fuzzy
Coefficient on treated	-28,721	-37,243	-39,742	-61,460	-33,991	-32,491
Robust standard error	(21,560)	(39,872)	(40,247)	(40,523)	(56,356)	(56,802)
Number of observations	278	152	131	278	169	146

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Results for constant and running variable (km) are not shown. The IV-model estimates treatment as a function of eligibility in a first step (not shown).

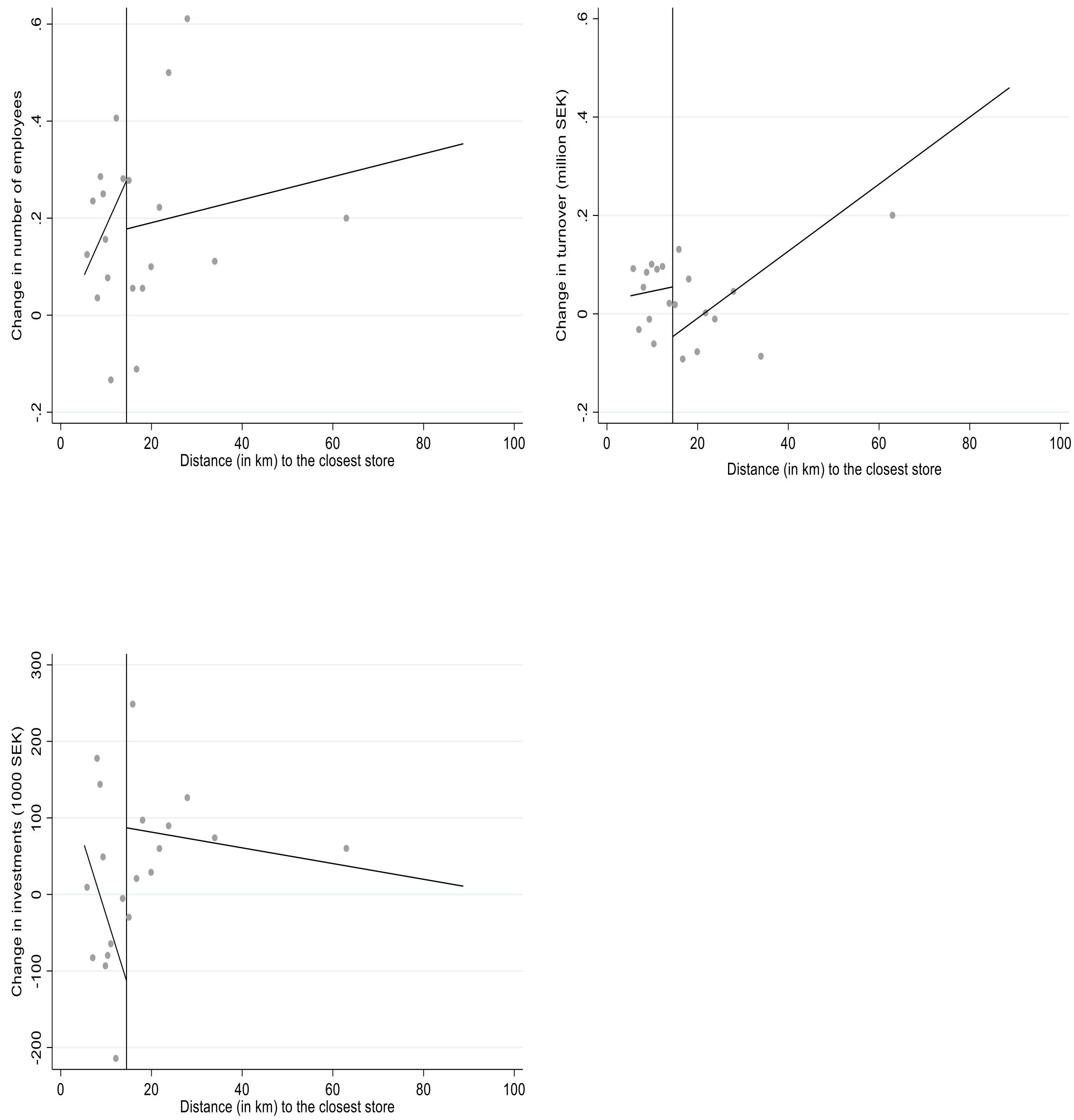

Figure A1. Plot of binned outcome means for employment, turnover and investments.

Note: There are ten bins at each side of the cut-off that is noted by the horizontal line (at 14.5 km). Each point represents the average of the observations in the bins. On each side of the cut-off each bin contains the same number of observations (quantile-spaced bins). The lines are fitted on each side of the cut-off based on the original number of observations.

Table A7. Impact of the operating support on employment – polynomial and triangular models

	emp7	emp8	emp9	emp10	emp11	emp12
Bandwidth	-10, 75	-5, 10	-5, 5	-10, 75	-5, 10	-5, 5
Model	polynomial	polynomial	polynomial	triangular	triangular	triangular
Coefficient on treated	-0.489**	-0.502*	-0.474*	-0.226	-0.415	-0.253
Robust standard error	(0.25)	(0.26)	(0.27)	(0.20)	(0.27)	(0.28)
N	247	148	127	237	138	117

Note: All models are sharp. Running variable is not shown. “Polynomial” means that the running variable is modelled as a second order polynomial on both sides of the cut-off. Triangular means that observations are weighted with a triangular kernel.

Table A8. Impact of the operating support on employment – donut and no-cross models

	emp13	emp14	emp15	emp16	emp17	emp18
Bandwidth	-10, 75	-5, 10	-5, 5	-10, 75	-5, 10	-5, 5
Model	donut	donut	donut	no cross	no cross	no cross
Coefficient on treated	-0.109	-0.468	-0.453	-0.100	-0.384	-0.246
Robust standard error	(0.21)	(0.32)	(0.35)	(0.18)	(0.27)	(0.29)
N	227	128	107	237	138	117

Note: All models are sharp. Running variable is not shown. "Donut" means that observations within a one kilometre from the cut-off have been omitted. "No cross" means that treated observations to the left of the cut-off (cross-overs) have been omitted.

Table A9. Impact of the operating support on turnover – polynomial and triangular models

	turn7	turn8	turn9	turn10	turn11	turn12
Bandwidth	-10, 75	-5, 10	-5, 5	-10, 75	-5, 10	-5, 5
Model	polynomial	polynomial	polynomial	triangular	triangular	triangular
Coefficient on treated	-0.096	-0.085	-0.099*	-0.085	-0.049	-0.077
Robust standard error	(0.06)	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)
N	246	148	127	246	148	127

Note: All models are sharp. Running variable is not shown. "Polynomial" means that the running variable is modelled as a second order polynomial on both sides of the cut-off. Triangular means that observations are weighted with a triangular kernel.

Table A10. Impact of the operating support on turnover – donut and no-cross models

	turn13	turn14	turn15	turn16	turn17	turn18
Bandwidth	-10, 75	-5, 10	-5, 5	-10, 75	-5, 10	-5, 5
Model	donut	donut	donut	no cross	no cross	no cross
Coefficient on treated	-0.117	-0.060	-0.040	-0.101	-0.014	0.014
Robust standard error	(0.09)	(0.09)	(0.09)	(0.08)	(0.08)	(0.09)
N	226	128	107	236	138	117

Note: All models are sharp. Running variable is not shown. "Donut" means that observations within a one kilometre from the cut-off have been omitted. "No cross" means that treated observations to the left of the cut-off (cross-overs) have been omitted.

Table A11. Impact of the operating support on investments – polynomial and triangular models

	inv7	inv8	inv9	inv10	inv11	inv12
Bandwidth	-10, 75	-5, 10	-5, 5	-10, 75	-5, 10	-5, 5
Model	polynomial	polynomial	polynomial	triangular	triangular	triangular
Coefficient on treated	171.072**	75.129	49.118	193.547**	88.574	57.745
Robust standard error	(70.33)	(53.09)	(48.95)	(77.14)	(77.03)	(60.43)
N	247	147	126	247	147	126

Note: All models are sharp. Running variable is not shown. "Polynomial" means that the running variable is modelled as a second order polynomial on both sides of the cut-off. Triangular means that observations are weighted with a triangular kernel.

Table A12: Impact of the operating support on investments – donut and no-cross models

	inv13	inv14	inv15	inv16	inv17	inv18
Bandwidth	-10, 75	-5, 10	-5, 5	-10, 75	-5, 10	-5, 5
Model	donut	donut	donut	no cross	no cross	no cross
Coefficient on treated	228.893**	205.599*	223.706*	199.804**	140.429	134.813
Robust standard error	(88.78)	(120.88)	(131.62)	(81.69)	(127.17)	(143.22)
N	227	127	106	237	137	116

Note: All models are sharp. Running variable is not shown. "Donut" means that observations within a one kilometre from the cut-off have been omitted. "No cross" means that treated observations to the left of the cut-off (cross-overs) have been omitted.

Table A13: Impact of operating support on survival and employment for small and big stores.

	survive1	survive2	survive3	emp19	emp20	emp21
Bandwidth	-10, 75	-5, 10	-5, 5	-10, 75	-5, 10	-5, 5
T=0, B=1	0.050	0.038	0.038	0.041	-0.123	-0.123
	(0.05)	(0.07)	(0.07)	(0.13)	(0.19)	(0.19)
T=1, B=0	0.202***	0.199**	0.192**	-0.291	-0.608**	-0.595**
	(0.08)	(0.09)	(0.08)	(0.20)	(0.28)	(0.29)
T=1, B=1	0.221***	0.201**	0.198**	-0.060	-0.441	-0.347
	(0.07)	(0.09)	(0.09)	(0.20)	(0.28)	(0.27)
	290	180	158	247	148	127

Note: T= Treated, B=Big. First order polynomials of the running variable on each side of the cut-off are used in all models. All models are sharp. Running variable is not shown. Robust standard errors in brackets.

Table A14: Impact of operating support on turnover and investments for large and small stores.

	turn19	turn20	turn21	inv19	inv20	inv21
Bandwidth	-10, 75	-5, 10	-5, 5	-10, 75	-5, 10	-5, 5
T=0, B=1	0.029	-0.016	-0.017	25.533	37.154	35.168
	(0.06)	(0.08)	(0.08)	(58.16)	(78.52)	(78.64)
T=1, B=0	-0.114*	-0.131*	-0.143*	185.289**	132.543	116.933
	(0.07)	(0.07)	(0.07)	(84.18)	(82.81)	(73.05)
T=1, B=1	0.034	-0.029	-0.041	181.418**	23.912	-32.598
	(0.08)	(0.07)	(0.08)	(73.24)	(69.46)	(95.18)
N	246	148	127	247	147	126

Note: T= Treated, B=Big. First order polynomials of the running variable on each side of the cut-off are used in all models. All models are sharp. Running variable is not shown. Robust standard errors in brackets.

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