A Bad Time or a Bad Business? Identification of Profitable Firms with Short Run Problems

Diego Escobar
Juan Ignacio Vila

June 12^{th}, 2019

1 Problem Definition

Several small businesses fail to persist in the long run due to lack of access to resources, or to the high dependence on the availability of their owners to dedicate large amounts of time to them. Economically, it is efficient for some of these businesses to close, and some interventions could be designed to help the owners and workers of these small enterprises to overcome the problems arising from this through alternative mechanisms. However, numerous firms are forced to close due to the lack of access to credit and the low capacity to respond to events occurring in the life of their owners. This is particularly the case for small businesses, where the firms are highly dependent on their owners' work and resources.

As in any other area, local governments are faced with resources constraints and must thus prioritize where to assign their limited resources if they want to aid these firms. Consequently, accurately identifying firms that may suffer financial stress in the short run, but which are nonetheless viable in the medium and long run, can help to provide income stability to businesses' owners and their workers. Specifically, correctly classifying firms that may benefit from short-term aid, such as access to credit or business managing training, may help them to deal with short run liquidity difficulties. Unlike solvency problems, liquidity constraints could thus force firms to close that would have otherwise been productive in the long run. Hence, improving local governments resources' allocation could enhance the overall economic activity by ameliorating firms capacity to deal with problems in the short run (i.e. similar to what a financial institution would perform, but from a public institution, providing funding to firms that would likely be denied credit in the private sector).

2 Problem Relevance

Correctly classifying businesses depending on their long run profitability corresponds to a crucial part of determining what kind of assistance they may need to consolidate. Given the limited resources, however, it is not only relevant to find out what businesses would be profitable in the long run. In order to maximize impact, we should aim to focus the resources on companies that would otherwise not survive in the long due to short and medium run liquidity problems.

In particular we can broadly sort firms into the groups presented in Table 1. Following this scheme, even if we assume that the availability of public assistance was crucial for firms survival, only firms of type D would actually be impacted in the long run.

Table 1: Businesses Classification

	Economical Feasibility		
Type	Short Run	Long Run	Required Assistance?
A	Yes	Yes	No help required
B	Yes	No	Let them close and/or offer different programs
C	No	No	Let them close and/or offer different programs
D	No	Yes	**Relevant cases**

Suppose then, for instance, that we instead focused on providing funding, or access to credit, to firms that would face economic stress in the short run, as in groups C and D, independently of their long run profitability. Since firms in group C are not profitable in the long run, those resources would not induce higher firms survival –although it may extend the time until their closure, it could not do so indefinitely unless resources are constantly injected.

More generally we can think of cases where the probability of surviving is more highly affected for firms in group A than in group D, as opposed to a case where exclusively type D firms are benefited. The share of firms surviving can then be though of as

$$Prop.\ \ Firms\ \ Surviving = \sum_{g\in\{A,B,C,D\}} \omega_g \big[P_g(Survival|T=1) - P_g(Survival|T=0)\big] \tag{1}$$

Where ω_g is the proportion of firms of each type and $P_g(Survival|T = i)$ is the probability that a firm in group g will survive given treatment assignment i. This thus allows us to breakdown the effectiveness of the policy into two separate categories. First, whether granting access to credit or not has any impact on business survival, this is, whether the probability of surviving increases as when the treatment is offered (i.e., $P_g(Survival|T = 1) > P_g(Survival|T = 0)$. And secondly, whether we can target the intervention to groups where the impact of the evaluation would be the highest (i.e. assigning as much of the shares ω_g to the groups where the increase in the survival probability is higher).

Moreover, although business survival may constitute a goal by itself, it is also worth noting that there are several other policy dimensions that can be affected through this policy. The main underlying reason for supporting these firms is to increase the welfare of inhabitants of the city, either though business profits to their owners, jobs creation, positive externalities over the neighborhoods, and so on. Unfortunately we do not have access to information about all of these outcomes, so we use business survival as a first proxy for them. Depending on data availability, we also consider expanding the scope of the outcomes analyzed. This could translate into either by taking a composite index as our policy objective, or simply as the combination of different outcomes.

3 Existing Interventions

Several interventions aim to help starting businesses to growth through their initial stages. For the purpose of this analysis we will focus in financial aid, but the scope of the analysis is not limited to that. In particular, we identify firms that are likely to require assistance but we cannot assert what are they lacking to sustain their growth. Specifically, for some of them offering access to credit for investments could be the most effective intervention, while for others helping them to enhance their business practices could be more productive.

There exist two major grants for supporting business in the local government. First, the Small Business Financial Improvement Funds (SBIF) which is a program created by the local government.

From the open data portal of Chicago we see that it covers only 2,000 firms.

Also, there exist other programs as the Industrial Retention Initiative (LIRI) program. LIRI agencies provide assistance to industrial businesses, primarily in the city's Industrial Corridors, with the purpose of retaining those businesses in the City and supporting the Industrial Corridors. LIRI agencies assess businesses, identify needed resources, provide project support, and act as counselors and ombudsmen to resolve a variety business issues.

These programs intervene in different ways. The SBIF program gives grants that offer limited possible expenditures, and the program participants can receive grants to cover between 25 percent and 75 percent of the cost of infrastructure remodeling, with a maximum grant of $100,000 for commercial properties and $150,000 for industrial properties.

The LIRI program intervene in completed projects, job retention and creation, leveraging public and private financing, and neighborhood development. Examples of how agencies help businesses include: identifying and securing funding for property, business and workforce development; finding the right location and filling key property vacancies; attaining permits and business licenses and acting as a liaison with City departments; helping find resources to grow businesses such as expanding sales both locally and internationally; and providing guidance on City and policy issues that impact industrial companies.

Moreover, there are other programs that concentrate in giving loans with low interest to a small firms. Nevertheless, there is limited information about these programs, since they are administrated through non-profits that do not provide information of how many business they effect in the Chicago area.

4 Data

The overall sample consist in 900,000 licenses, from the years 2008 until 2019. We convert this sample into unique business histories using the account number to identify them. Doing this, we manage to obtain around 149,889 unique licenses for this period. We further reduce the sample to select businesses that started in the period of analysis (i.e. avoiding licenses that already existed in the data from previous years). This is, we retain only licenses issued in a particular year. Additionally, we drop the observations that have less than 10 days to avoid retaining temporal licenses.

Table 2: Data Sources

Data	**Description**	**Time available**
Business Licenses	Data base with characteristics of the licenses	1998-2019
Chicago crime data	Data base with the reported crime data	2001-2019
Transit data	Transit data of Chicago	2006-2019
Chicago Boundaries	Chicago boundaries for geo-merging	N/A

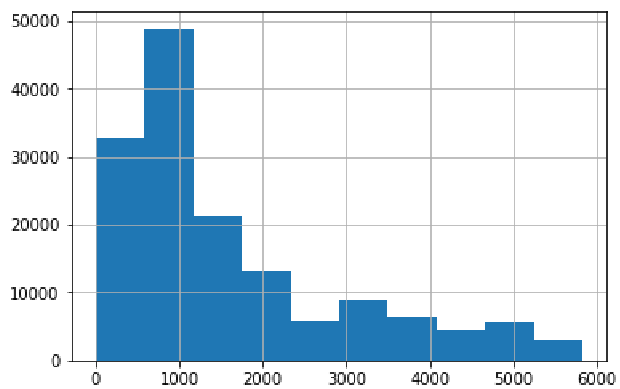
We believe these two filters to be a very relevant distinction for the following reasons: i) survival is much easier to predict for firms that have been operating for a larger time span, but aiding this firms is less relevant for the purpose of a project that aims to help new firms; and ii) temporal licenses are generally issued for different types of business activities. We expect these two changes to have negative impact in the precision of our models, since we are dropping from our sample many firms whose survival would have been relatively easier to predict. However, we think this distinction is relevant to implement the best resources allocation and to identify our intervention population.

Table 3: Descriptive Statistics

Statistic	Duration (days) Full Sample	10+ Days Sample
Mean	1,547	1,691
St. Dev.	1,419	1,399
Min	1	10
25%	699	737
50%	879	1,156
75%	2,208	2,307
Max	5,827	5,827
Observations	149,889	137,062

Overall, the whole data set have 150,470 unique business. Additionally, we use other sources as the Chicago Crime Data and the transit data. We can see that the average duration of the licenses included in our sample is 1,691 days and median is 1,156 days (see Table 3).

Figure 1: Business Survival



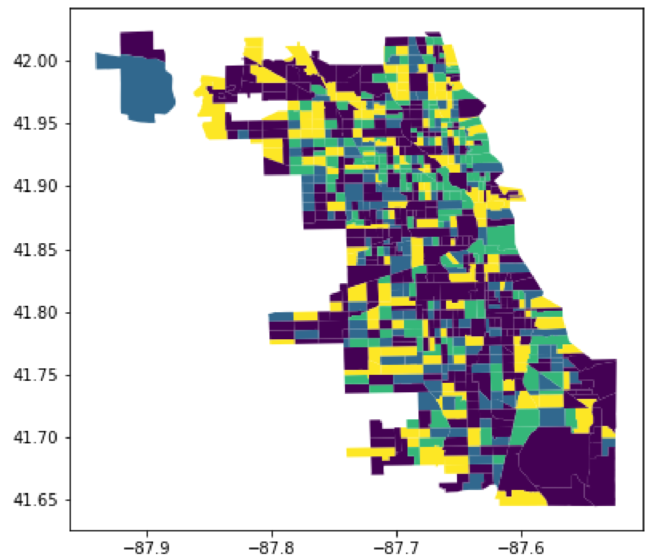
As explained above, the objective of this project is to compare probability of failure of business in time spans of one-year vs three years. We thus need to construct the duration. We first calculate the duration of the businesses survival, displayed in Figure 1. We do this by computing the time since the first license request to open a business until the time when the licenses expire, or the first year in the date where there is no renovation of them. We see that most of the businesses duration is concentrated in the less of 1,000 days. Precisely, 46% of the cases have duration over 3 years. On other hand, only 16% have a duration less than a year, and this changes drastically between years. Finally, we have that 38% of business last between one year and two years.

The duration of the businesses also varies geographically. Figure 2 displays the quintiles of the distribution of duration throughout the city (lighter colors represent larger duration quintiles). We observe that there is a high degree of dispersion of the duration throughout the city.

5 Analysis

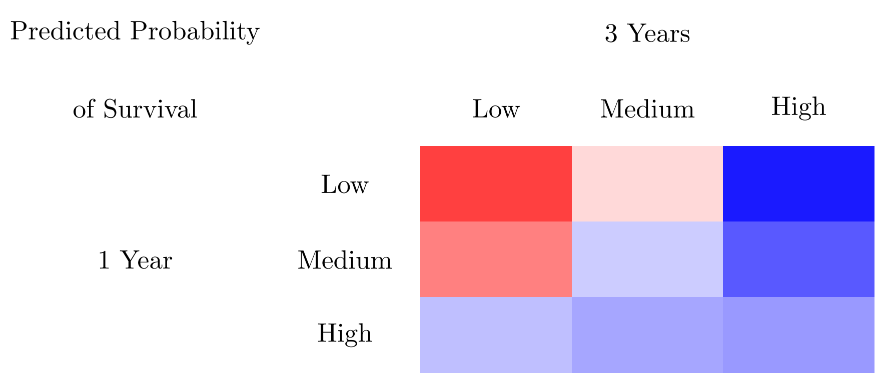
As stated above, the main objective of this analysis is to identify firms that may be profitable in the long but that may suffer from short-term constraints that could provoke their closure. In order to identify them we use firms survival over different time horizons as a proxy for firm profitability.

Figure 2: Duration Quintiles: Spatial Distribution



We estimate models for business survival for 1 and 3+ years. We are interested in crossing the prediction of each model, as depicted in Figure 3. We also considered using the expected survival time as a continuous variable (i.e. number of days) but for most firms the data only identifies closure in a yearly basis.

Figure 3: Businesses Predicted Survival Rate by Year



In this figure, more intense red areas represent firms that according to our model should not be prioritized for aid, since are not likely to be profitable in the long run even though they would probably benefit highly from credit access or funding in the short run (the colors intensities are referential at this point but do not imply actual magnitudes). On the other hand, the more intense blue areas represent firms that according to our model are highly likely to close in the short run but that have potential to be profitable over a longer time span, and thus constitute the ideal target of the policy.

It is worth noting at this point that the scope of this project is to improve the allocation of the resources among groups that i) have heterogeneous impacts of the policies themselves and that ii) may have fundamentally different outcomes in the absence of the policy. However, it is beyond of the scope of this project to directly evaluate what is the impact of any particular policy that could plausibly be implemented by the Chicago local government.

5.1 Validation

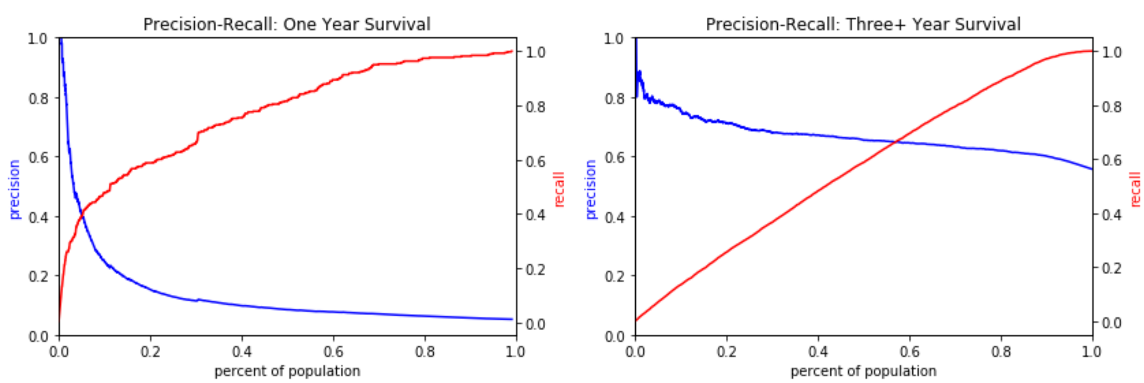
For the purpose of model selection we will use precision as our comparison metric. This is the proportion of the predicted positives that were correctly classified as such. In this context then, precision will be measuring what proportion of the businesses forecast to shut down their businesses in a given term actually do close. We select precision as our metric since capacity limitations usually force local governments to focus exclusively in firms that are highly likely to be benefited from the program.

Following this metric we then choose the best model separately for each outcome variable and each period. In order to evaluate the precision of the models we use temporal holdouts of the data, using the first x years of the data to train the model, and setting the years between $x+1$ and $x+t$ as test data. Moreover, we sequentially use information of more recent years to perform the same procedure.

5.2 Models

We deploy several machine learning algorithms to predict firm survival and test several combination of hyper-parameter for each one of these. In particular, we are interested in the crossing of the predictions of survival models over different time spans, ranging from 1 to 3 years. For this we will fit the following models: Random Forest, Decision Tree, Logistic Regression. [1] Once we take into account the different parameters specification for each model we estimate and compare a total of 21 models hyper-parameters for each year and each outcome.

Figure 4: Precision-Recall



(a) One Year Survival

(b) 3+ Years Survival

Figure 4 shows the precision and recall for different threshold for our best model for the 2014 prediction. We use this year to allow for at least 3 full years of data in our most recent follow up, in 2018. In this case best model is defined as the one with the highest precision level at 5 percent.

[1]Taking more models into account is extremely simple but very time consuming, so we could not run the whole set of results using more models. However, precision and recall did not change significantly when testing other models.

We use this value of the precision because in this particular year 5.2 percent and 54 percent of the firms closed in one and three years for our reference year, respectively. In panel (a) we observe that precision sharply drops as we increase the threshold, but that is simply mechanical since only 5 percent of the firms actually close. On the other hand, we observe in panel (b) that we achieve a relatively high precision sorting firms that will close in the longer run.

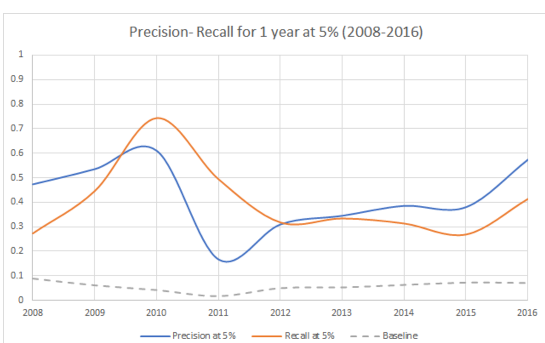
Table 4 shows the validation measurements of the best parameters combination for each algorithm, for each of the outcome variables. Since we focus in precision at the 5 percent for the one year model we then choose the random forest for this particular year. Similarly, we also choose random forest when focusing in precision at the 50 percent for survival for more than 3 years.

Table 4: Models Fitted: Best Parameters

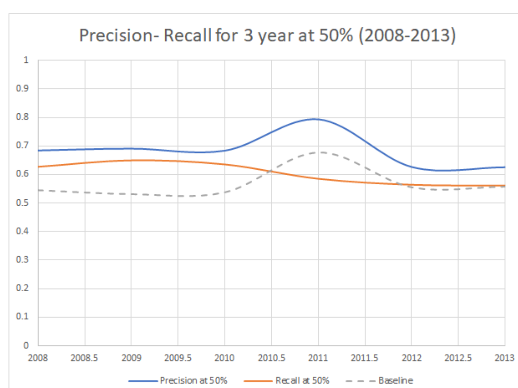
1 Year Closure						**Precision**				
Model	**AUC_ROC**	**1**	**2**	**5**	**10**	**20**	**30**	**50**	**70**	**100**
DT	0.69	37.0%	41.1%	34.0%	20.9%	12.6%	9.9%	7.6%	6.3%	5.2%
LR	0.65	27.4%	30.1%	21.9%	14.1%	9.7%	7.9%	7.0%	6.4%	5.2%
RF	0.71	84.9%	63.0%	34.5%	19.8%	12.1%	9.6%	7.3%	6.6%	5.2%
						Recall				
		1	**2**	**5**	**10**	**20**	**30**	**50**	**70**	**100**
DT		7.1%	15.8%	32.7%	40.4%	48.5%	57.3%	73.1%	85.2%	100.0%
LR		5.3%	11.6%	21.1%	27.2%	37.5%	45.6%	67.5%	86.0%	100.0%
RF		16.4%	24.3%	33.2%	38.3%	46.7%	55.4%	70.2%	88.7%	100.0%
3+ Years Closure						**Precision**				
Model	**AUC_ROC**	**1**	**2**	**5**	**10**	**20**	**30**	**50**	**70**	**100**
DT	0.57	63.0%	65.8%	66.0%	62.4%	62.4%	62.3%	61.0%	58.9%	55.7%
LR	0.57	94.5%	94.5%	77.8%	68.1%	65.2%	62.7%	60.6%	58.8%	55.7%
RF	0.60	86.3%	80.1%	74.8%	72.4%	67.5%	65.5%	62.6%	60.1%	55.7%
						Recall				
		1	**2**	**5**	**10**	**20**	**30**	**50**	**70**	**100**
DT		1.1%	2.4%	5.9%	11.2%	22.4%	33.5%	54.8%	74.0%	100.0%
LR		1.7%	3.4%	7.0%	12.2%	23.4%	33.8%	54.4%	73.8%	100.0%
RF		1.5%	2.9%	6.7%	13.0%	24.2%	35.2%	56.1%	75.5%	100.0%

Finally, Figure 5 depicts the precision and recall for the best model for each individual year, as well as the baseline level for each variable.

Figure 5: Precision-Recall Over Time



(a) One Year Survival



(b) 3+ Years Survival

Finally, Table 5 shows the sensitivity of the results for different threshold levels. As we previously explained, our baseline case is a 5% threshold for the one year outcome and 50% for the over-three-years outcome. For this base case we get a total 2.8% classified as having low probability of surviving in the long run but high probability in the longer run (i.e. predicted to close in 1 year but to remain in 3 years).

As we variate the threshold for one year, moving horizontally along a row, we see that the number of firms that the model allocates in the intersection that we analyze increase very fast. For example, in the case if we increase the threshold for one year from 5% to 20% the firms identified in our group of interest increase almost four times, form 4.1% to 16%. Instead, we see that the changes in the threshold for the three years model affect the margin less drastically. For instance, moving from 20% to 50% we see that the selected firms diminish from 4.1% to 2.8%.

5.3 Caveats

The main limitations in our analysis can be broadly categorized into the following:

- Survival data is a proxy for the outcomes of interest.
- We do not have accurate estimations of the treatment effects in the intervened businesses.
- Structural changes are likely to occur in longer periods, which would make out estimations less precise.
- Data availability.

First, we are using survival data as a proxy for our policy goal, which may not necessarily be completely reflected by this. Specifically, business survival does not necessarily translate into businesses profitability, employment creation, or in general positive spillovers over the neighborhoods where they operate.

Second, we do not have accurate estimations of the treatment effects (e.g. changes in surviving probabilities) due to the intervening or aiding the selected firms. Our analysis is thus intended to identify the firms that potentially need assistance in order to survive short term fluctuations, but does not signal what kind of intervention should be carried out to do so. An ideal measurement would thus quantify $P_g(Survival|Treated) - P_g(Survival|Control)$, where the treatment would correspond to the assistance offered by local government to the identified firms.

One way to complement this would be to compute a matching estimator using propensity score for the treatment effects. This estimator of the treatment effect is however biased, since we do not have experimental variation to measure the impact. To account for this, we can analyze our allocation mechanism under different assumptions for the bias to perform a sensitivity analysis of

Table 5: Crossing: Close-in-one-year and Survive-in-three-years

		1 Year			
	Threshold	5%	10%	15%	20%
3 years	10%	4.5%	8.9%	13.3%	17.8%
	20.0%	4.1%	8.0%	11.9%	16.0%
	30.0%	3.8%	7.2%	10.7%	14.4%
	40.0%	3.3%	6.3%	9.4%	12.5%
	50.0%	2.8%	5.3%	7.8%	10.3%

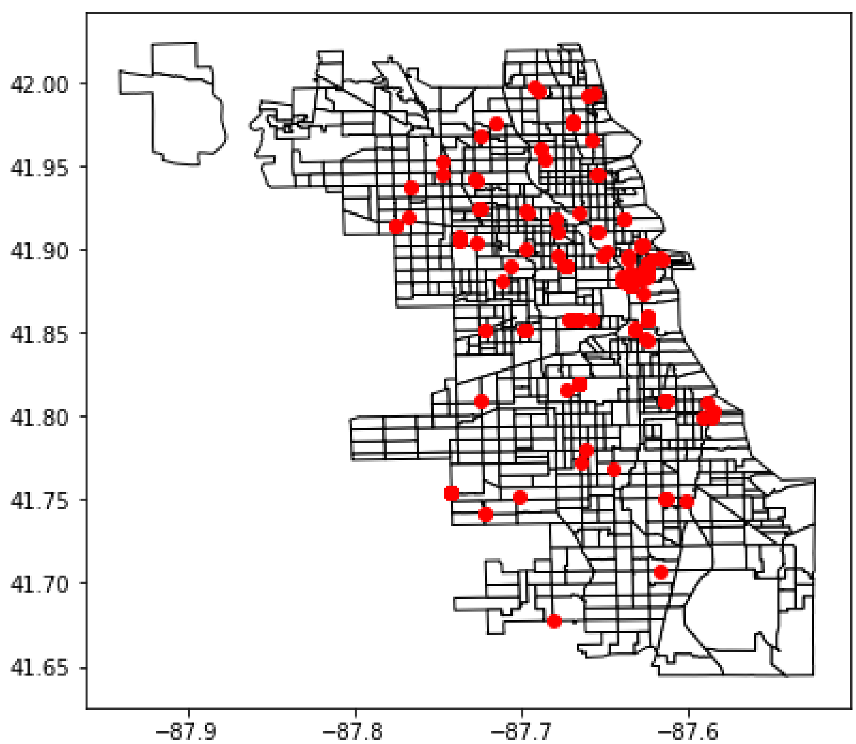
our results. Moreover, we could look for evidence of similar programs that have been evaluated in the country using experimental or quasi-experimental methods to have a comparison point.

Since we are interested in medium and short term business survival, one limitation is the availability of data over a longer time horizon. In particular, although our outcome is interest is available for a large period, many feature that we could have included for longer time span are not available for older years. We prefer to maintain a larger time frame rather than a shorter period analysis because this larger frame is more appropriate to analyze the occurrence of structural changes. Furthermore, another data limitation is the lack of financial information from the firms. This data would be crucial towards better predicting the firms that are more likely to close. Moreover, in a real environment where businesses may be applying for funds that information could be matched from administrative records or gathered by the local government, thus allowing for more accurate predictions.

6 Bias and Fairness

Since one of the main interest of the city of Chicago when aiding firms is to improve the neighborhoods where they operate, we concentrate in the spatial analysis of the firms. In particular, we focus in the location of the firms pointed as relevant. Figure 6 shows the distribution of the firms we obtain after crossing the predictions of both models. As expected, we observe a higher concentration of businesses in the downtown, given the higher number of businesses. In general, however, we observe that the selected firms to intervene are spread around the city.

Figure 6: Geographical Distribution



7 Policy Recommendations

Based on our classification of firms depending on their expected profitability over the short and long run, we identify a group of firms that survive over three years but they do not last one year.

From our selected group of firms we observe that 73 percent of them are not in special service areas. This imply that there exist a possibility to extend SSA areas to incorporate information about other factors such as business survival in order to enhance the effects of the program. In particular, allocating more resources to these businesses could potentially increase the impact of the local government funds, thus complementing the SSA program. However, we acknowledge that this program takes several factors other than business profitability into account when deciding these areas.

A relevant feature of this analysis is that some of the public programs currently implemented in Chicago to aid firms are aimed to to improve the appearance of the neighborhoods. Although this can help to improve the likelihood of non closure of firms, it is not the primary goal of these policies. However, simply remodeling building appearances may be an extremely ineffective policy if there is a high business turnover. It would thus be critical to analyze whether such policies turn to be effective in the middle and long run in this context, but this goes beyond the scope of our project.

Moreover, as mentioned above, a more exhaustive examination of the treatment effect would further enhance the utility of this project. Taking this into consideration, we consider that an adequate evaluation of the impact of this type of policies would strongly complement this analysis, allowing us to tune the resources allocations to achieve a maximum impact from the government program and funds.