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Determinants on firm survival in Chile: Evidence from cohort 2010 for the period 2011-2015[1]

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[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

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Abstract

In this paper we present evidence on the probability of firm survival in Chile for the period 2011-2015. Using information from the Chilean IRS we investigate the impact of financial variables on firms' survival. We first calculate the number of firms that "were born" in 2010 and follow them throughout the entire period of time and then we estimate the determinants of firm survival using the proportional hazard model. We find a positive and strong relationship between efficiency, leverage and profitability and the firms´ survival. Furthermore, we find that probability of survival has an inverted-U shape, which is in line with current literature.

Keywords: firms´ survival, proportional hazard model, economic industries

(*) Disclaimer: This document was first presented at the IFC *Satellite Seminar on Big data* that took place in Bali, Indonesia in March, 2017. The views, thoughts, and opinions expressed in the text belong solely to the authors, and do not reflect the view of the Central Bank of Chile. Any errors or omissions are our own. E-mail**:** dlopez@bcentral.cl, dofarril@bcentral.cl, jnperezt@bcentral.cl, bvelasqu@bcentral.cl.

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1. INTRODUCTION

The process of entry and exit of firms is determinant in the corporate structure in a country and it must be understood as a core element for describing and comprehending the economic growth. This process allows us to go beyond the traditional view of economy since is based on the measure of the added value from those industries participant in the productive process.

In this context the policies to promote the creation of firms are focused on establishing the conditions to improve innovation, competitiveness, the use of technology and employment generation. In this sense, it is relevant to examine the performance of firms in terms of markets, size, leverage, age, assets, liabilities, etc.

The studies on business demography offer statistical information about the population of firms in national borders. In general, these studies rely on a set of indicators that represent the transformations suffered by firms over a time span. The performance of these indicators over time might be indicative of the evolution of more aggregated variables such as employment, capital stock and economic growth.

In developing this kind of studies a dataset that covers a period of at least five years is necessary. Also, it is required the information available to be as much detailed as possible at the firm level in both qualitatively and quantitatively terms. In the case of Chile the Central Bank receives information from the Chilean Internal Revenue Service (IRS, Servicio de Impuestos Internos) on a regularly basis. In this paper we work with the IRS' anonymized administrative records data base that gathers information on annual income taxes.

The main objective of this paper is to characterize the survival of firms created in 2010 in Chile for the period 2011-2015; in order to do the latter we estimate the proportional hazard model using partial information from the firm´s financial statements. In general, we want to add new insights to the comprehension of firms´ dynamics in terms of their survival and "destruction".

We find a positive and strong relationship between profitability, leverage and efficiency and the firms´ survival. In particular, we find a statistical significant difference between "survivor" and "non-survivor" firms regarding these indicators. These results remain stables even after being controlled by other variables. Additionally, we find that the probability of survival has an inverted-U shape, which is in line with most of the literature on this subject. This study complement the results from Pérez and Suazo (2014) in two directions: a) we offer new insights on the dynamic of firms´ survival in Chile and b) we estimate a survival model to predict the viability of a business initiative based on indicators of economic activity, leverage and profitability.

The rest of the paper is organized as follows: Section two describes the literature review regarding the determinants of firms´ survival. Section three briefly explains the empirical methodology we use to address the problem of this research. In Section four the data is described and the relationship between "survivors" and "non-survivors" regarding our main variables is addressed. Section six reports the main results. Section seven concludes.

2. LITERATURE REVIEW

There is a wide-range of literature analyzing the demography of firms and its determinants as well. For instance, OCDE (2014) finds that the probability that firms in specific markets survive beyond two years goes from 60% to 80%. In other words, the probability of "fail" (firm exit) in *t+2* for firms created in *t* is in the range of 20% to 40%. Even more, only 40% to 50% of firms that were born in the same year survive beyond the seventh year.

López-García and Puente (2006) study the determinants of firm exit in Spain. They conclude that the bankruptcy rate for Spanish firms is lower than that of firms from similar countries like Italy, Germany and the United Kingdom. This finding is confirmed over time, even after being controlled by industries, with the main exception of financial services, insurance, real states and wholesale and retail where firms showed entry and exit patterns similar to those found in neighbor countries. These authors also find that the bankruptcy risk-function has an inverted-U shape, reaching a maximum in the fourth year of activity, which is confirmed for all industries in the economy.

Other studies (see below) reach the same conclusions using a different set of information; thus it is possible to safely rule out the effects of sample bias on these results. Both the survival rate and the inverted-U risk-function might be relevant for explaining the employment evolution and productivity growth, not only in Spain but also in other countries, which is why it is important to consider them in future analysis.

Audretsch, Santarelli and Vivarelli (1999) estimate an unconditional risk-function for manufacturing firms in Italy. They conclude this function increases up to two years and then falls down thereafter. Bhattacharjee (2005) estimates both a conditional and an unconditional risk-function in modelling the probability of survival of those firms traded on the London Stock Exchange. He gets to the conclusion that these firms survive up to three years after their stock exchange opening and exit the market afterwards. Wagner (1994) analyzes the demography of firms in Germany. He finds firms survive up to a maximum of three years before exiting the market. Bartelsman et al. (2003) also find an inverted-U risk-function for the United Kingdom, Italy and the United States using a different information set.

Ericson and Pakes (1998) and Bhattacharjee (2005) argue that an inverted-U risk-function is consistent with the theoretical models of active and passive learning since firms need time to learn about their efficiency. Brüderl and Schüssler (1990) and Fichman y Levinthal (1991) explain that new firms often possess a stock of initial resources that help them "to survive" for a while, a period in which firms can establish new operational structures. Those initial operations might explain why firms take time to comprehend they are not as efficient as they supposed to and, as a result, they must exit the market. The latter is even more evident when firms face high fixed costs in order to initiate their operations. In those cases, firms try to stay in business as much as their initial resources allow them to before taking the decision of shutting down.

Finally, there are studies on firms' demography and survival probabilities that use specific variables for each firm, including industry-specific characteristics. The choice of these variables depends on the economic theory and previous empirical analysis.[1] First, the initial investment of firms and their financial conditions at the time of "birth", or even one year later, are taken into account. For instance, the main findings point out to the existence of a non-lineal relationship between indebtedness and the survival of firms. The sign of such a relationship changes accordingly to the firms´ initial level of indebtedness: if the firm is not highly indebted increasing the level of indebtedness is favorable for the firm survival; on the contrary, increasing the level of debt when the firm is already highly indebted increases the probability of fail.

In what follows, we describe the empirical methodology we use in this paper to address the determinants of firm survival in Chile.

3. EMPIRICAL METHODOLOGY

Our empirical study is based on survival analysis using binary choice models and the Cox´s proportional hazard model for Chilean firms during the period 2011-2015. We first document the determinants of firm survival per each cohort using a probit model of all firms and not only the ones that were born in 2010 and then estimate the proportional hazard model over the entire period using only the sample of firms that were created in 2010. In doing the latter we document the firm survival on a yearly basis and show a more robust method in estimating the survival of firms when there are censored observations in the data.

3.1. Discrete choice models

In the literature is common to answer the dichotomy questions using the probability linear model.[2] However, it is well known that this model poses two important challenges to researchers: a) since the dependent variable is not bounded between 0 and 1, predictions in terms of probability are not useful and

[1] See, for instance, Mata, Portugal and Guimaraes (1995), Geroski, Mata and Portugal (2003), Stiglitz and Weiss (1981), Evans and Jovanovic (1989), Blanchflower and Oswald (1998), Holtz-Eakin, Joulfaian and Rosen (1994), Robert Cressy (1996), Audretsch, Houwelling and Thurik (1997), Weiss (1976).

[2] Wooldridge (2010) shows a complete guide of studies using the probability linear model to answer this kind of questions.

b) linearity does not make much sense conceptually. To walk around those challenges, non-lineal type models are considered. The Probit and Logit setups are two well-known examples.

Consider the following model:

$$\Pr(y = 1|x) = G(\beta_1 + \beta_2 x_2 + \cdots + \beta_k x_k \quad (1)$$

$$\Pr(y = 1|x) = G(\boldsymbol{x\beta})$$

where *G* is a function taking values strictly between 0 and 1: 0<*G(z)*<1, for all real numbers z. *G* is the cumulative density function and is monotonous increasing in index z with

$\Pr(y = 1|x) \rightarrow 1$ **when** $\boldsymbol{x\beta} \rightarrow \infty$

$\Pr(y = 1|x) \rightarrow 0$ **when** $\boldsymbol{x\beta} \rightarrow -\infty$

G can be approximated using the logistic distribution, which supports the Logit model, or the normal standard distribution, which supports the probit model. For the Logit model

$G(\boldsymbol{x\beta}) = \frac{\boldsymbol{exp(x\beta)}}{\boldsymbol{1+exp(x\beta)}} = \boldsymbol{\Lambda(x\beta)},$

which is between 0 y 1 for all values of $\boldsymbol{x\beta}$**.** This constitutes the cumulative function for the logistic variable. For Probit, *G* is the normal standard *cdf* expressed as an integral

$G(\boldsymbol{x\beta}) = \Phi(\boldsymbol{x\beta}) = \int_{-\infty}^{x\beta} \phi(v)dv$ **,**

where

$\phi(v) = \frac{1}{\sqrt{2\pi}} \exp(-\frac{v^2}{2}),$

is the standard normal density. Writing *G* in this way makes sure that the probability of success be strictly between 0 y 1 for all values of parameters and regressors.

3.2. The proportional hazard model

Modelling firm exit (survival) using OLS provokes a sampling bias since in this case some firms are more likely to stay in business than others. It is possible to perform a logit or probit analysis on firm survival, but one would need to observe all firms from entry to exit. This generates an addition problem since the sample period ends before most of the firms leave the market. As a result, a censored data problem emerges and we need other methods to tackle it.

The issue when performing survival analysis is the use of the information on survivor firms. A widespread approach uses the proportional hazard model to perform event history analysis. This analysis allows us to study what happens over a time span before some event takes place; in this study, the event is the firm exit. A key process of event history analysis is the specification of the survival function which describes the probability of firms´ survival until a certain time has elapsed.

The survival function is presented as follows

$$S(t) = \Pr(T \geq t) \quad (2)$$

where *T* is the duration of survival of a firm and *t* is a certain time point. In particular, the function shows the probability of survival at time *t* as a function of *t*. Other important concept is that of the hazard function: it describes the probability of the risk of some event happening. If we denote the probability density function of event occurrence as $f(t)$, then the hazard function can be written in this way

$$\lambda(t) = \frac{f(t)}{s(t)} \tag{3}$$

The hazard function calculates the probability that some event occur (exit) in a lapse of time, conditional on no occurrence of the event until time *t*, which in our case means, conditional on firm survival until time *t*. An important issue to take into account is the specification of the probability distribution of firms' exit. It is not possible to know, *ex ante*, such a distribution, which make problematic to empirically specify the functional form for the hazard function.

Cox (1972, 1975) uses the hazard function to investigate the relationship between the probability that some event happens and several regressors. Under the condition of "hazard proportionality", which defines that the proportion of two kinds of hazard keeps constant over time, the analysis of regressors is developed without specifying a hazard function.

In the proportional hazard model, each sample´s rate $\lambda_i(t)$ is a function of a group of regressors. Conceptually, a) there is a baseline hazard $\lambda_0(t)$ that does not depend on any regressors and b) the proportion of $\lambda_i(t)$ and $\lambda_0(t)$ is constant. The latter is based on the assumption of hazard proportionality. As a result, the proportion of hazards is analyzed as a function of regressors.

Consider the vector of regressors as $\boldsymbol{x_k}$. We can write the proportional hazard model as follows

$$\frac{\lambda_i(t)}{\lambda_0(t)} = \exp(\boldsymbol{\beta x_k}) \tag{4}$$

or

$$\lambda_i(t) = \lambda_0(t)\exp(\boldsymbol{\beta x_k}) \tag{5}$$

Taking logarithm of both sides in (5) we obtain

$$\log\lambda_i(t) = \log\lambda_0(t) + \boldsymbol{\beta x_k} \tag{6}$$

In this set up we analyze the factors that influence the height of hazard rates. A negative regressor coefficient is correlated with a higher probability of survival. On the contrary, a positive regressor coefficient is correlated with a lower probability of survival.

Since we do not know the distribution of the hazard, the baseline hazard is estimated after a regression with all samples. With this information one can estimate the baseline survival function $S_0(t)$ using the following

$$S_0(t) = \exp\{-\Gamma_0(t)\} \tag{7}$$

where $\Gamma_0(t)$ is the cumulative function of the baseline hazard $\lambda_o(t)$. The relationship between $S_0(t)$ and $\lambda_o(t)$ is calculated from equation (3) as $\lambda_o(t) = -\frac{d(\log(S(t))}{dt}$. In this paper, the baseline survival function shows the survival pattern of firms when regressors do not impact their survival. According to (7), the probability of exit is higher in early stages before regressors are considered. Thus, regressors explain the deviations of actual hazard from baseline hazard $\lambda_o(t)$.

4. CONCEPTS AND DATA

Our main source of information is the Internal Revenue Service's anonymized administrative records data base (Annual Income Tax Return) from the Chilean IRS (Servicios de Impuestos Internos). It groups a wide range of information on legal entities (corporations, partnerships, sole proprietors and among others) from all industries in Chile that pay the capital gain tax.

The Central Bank of Chile has been receiving this information since the end of 90s. From 2007 to 2015 we have gathered roughly 25 million of administrative records. In this paper we focus our analysis on the information that covers the period 2010 to 2015. This data base has many potential uses being one of them the computation of a set of indicators related to business dynamics, firm entry and exit and survival patterns. The definitions below are the main concepts we use throughout this paper:

- Firm stock: Number of entities that have remained in business during part or whole year. Firms remaining active at the end of the period and those who shut their operations down during that period are also considered as part of the firm stock.
- Firm birth: Set of entities that have created a combination of new production factors within a year. There is not relationship between these set of new entities and previous existent ones or whatsoever. We say that the firm was born in period *t* if and only if we do not observe it in *t-j*.
- Firm survival: It is the set of entities that keep in business five years after the time of birth.

Furthermore, we can build some useful definitions from the concept above. In this regard we have:

Birth rate: $$\frac{\sum N^{ti}}{\sum T^{t}_{i}} \quad \frac{\text{Enterprise births in the sector i, at the year t}}{\text{Stock of enterprises in the sector i, at the year t}}$$

Survival rate: $$\frac{\sum S^{t+k}}{\sum T^{t}_{i}} \quad \frac{\text{Enterprise survivals in the sector i, year t+ k= 1,..., 5}}{\text{Stock of enterprises in the sector i, at the year t}}$$

Also, we consider total assets, total liabilities, turnover and total costs to build a set of economic activity (Gross margin), leverage (Indebtedness), which also can be understood as a measure of access to credit, and profitability (Return on Assets) ratios we later use in our estimation. Gross margin is a firm's total sales revenue minus its cost of goods sold divided by total sales revenue, expressed as a percentage. Indebtedness is the difference between total assets and firm equity divided by total assets. Finally, the Return on Assets is the ratio of profits to total assets. We also use the Inventory turnover ratio. It is an efficiency calculation used to control and manage turns by comparing cost of goods sold and average inventory.

Just like any other administrative register data, the information we use is affected by different types of errors. Most frequently are records with very high or low values and presence of missing information. As a first step we use a statistical procedure to detect the outliers in our data and then we run an imputation method to fill the missing records.[3]

In order to have a better comprehension of survival of firms we grouped them in our sample using both an industry and a size classification. At the industry level we create five groups: Agriculture-fishing, Mining-manufacturing-utilities[4] (MMU), Construction, Wholesale and retail trade-repair of motor vehicles and motorcycles-accommodation and food service activities (Trade) and Services[5]; at the size level we use two groups of firms: micro-small and medium-large.[6] We later control for the effects of both classification groups in the probability of firm survival.

Table 1 below summarizes the information on the number of firms from 2010 to 2015 by industry and size. First, notice we work with more than 600 thousands firms per year on average. Most of them are "Trade" and "Services" firms, which together represent almost an 80% of the entire sample. Also, it is important to notice how "Services" has been increasing its importance overall whereas "Trade" has been reducing it: in 2015 the proportion of "Trade" and "Services" was the inverse of that of 2010. Furthermore, around 20% of firms are producers of good, with almost 50% of them being part of MMU.

With respect to firm demography, 91 thousand firms were created in Chile in 2010, which accounts for a 14.1% of total stock of firms in that year. By industries, "Services" show the higher creation rate with a 15.7% whereas "Trade" shows the lower creation rate, accounting for a 12.6%. The left side of Table 1 shows the survival rates over the time span. The first year (2011), the survival rate reached 80.4% with slightly differences between industries. In the second year, 62,567 from a total of 91,067 firms "survived", which represents a 68.7%. Again, the differences between industries are not relevant; however there is a marginal difference between those firms that produce goods and those producers of services.

Overall, five years after the entry of a firm, the survival rates are almost 46%. This number is slightly larger for "MMU" (48.4%) and slightly smaller for "Construction" and "Trade" (44.9% and 44.7% respectively). These rates are located at the bottom of the statistical distribution showed by Eurostat (2007) and are consistent with the statistical fact that producers of services are more dynamic than producers of goods.

[3] We cluster the data using a defined classification by industry and size and detect the outliers using the Tukey´s (1972) method and impute the missing information using a median within each group of firms.

[4] By "Utilities" we mean electricity, gas, steam and air conditioning supply and water supply, sewerage, waste management and remediation activities.

[5] "Services" include transportation and storage, information and communication, financial and insurance activities, real estate activities, professional, scientific and technical activities and administrative and support service activities.

[6] Our definition of "size" is based on firm's level of turnover, in contrast to other studies that use firms' number of workers instead. This is mainly due to the lack of information on numbers of workers at the firm level. In this sense we define micro-small as those firms with level of turnover<1000.000 of USD and medium-large as those firms with level of turnover>=1000.000 USD in 2010 figures.

Table 1 Number of firms, Cohort 2010 and Survival by Industry

Number of Firms by Broad Economic Sectors: 2010-2015						Birth Rate (% total)	% of survival				
	2011	2012	2013	2014	2015	2010	2011	2012	2013	2014	2015
Agriculture & Fishin	30.087	30.603	30.782	30.976	32.862	13,8	78,1	68,7	60,1	52,3	45,5
MMU	60.366	62.298	62.951	65.201	69.170	14,7	82,2	71,4	62,6	55,0	48,4
Construction	39.059	40.708	43.162	45.814	48.603	14,7	82,1	70,3	60,4	52,3	44,9
Trade	272.565	272.945	274.075	272.866	289.478	12,6	81,4	68,4	59,1	51,4	44,7
Services	255.155	277.098	294.376	304.134	322.650	15,7	79,1	68,1	59,6	52,4	45,6
Total	657.232	683.652	705.346	718.991	762.763	14,1	80,4	68,7	59,8	52,2	45,5

Source: own calculations

The analysis by firms' size shows interesting results too. Table 2 below encompasses this information. For instance, Micro-Small firms represent a 95% of total stock of firms for the entire period. In 2010, 14.4% of total "births" corresponded to Micro-Small firms and only a 7.6% fraction to Medium-Large ones. Nevertheless, the latter group shows the higher rates of survival; certainly, after five years of creation, 84.6% of medium-large firms were still in the market, which represents almost twice the percentage showed by micro-small firms. Thus the size is relevant when explaining the patterns of firms´ survival.

Table 2 Number of firms, Cohort 2010 and Survival by Size

Number of Firms by Size: 2010-2015						Birth Rate (% total)	% of survival				
	2011	2012	2013	2014	2015	2010	2011	2012	2013	2014	2015
Micro & Small	625.166	197.436	669.837	682.441	725.175	14,4	79,9	52,6	46,1	51,3	44,5
Medium & Large	32.066	34.164	35.509	36.550	37.588	7,6	98,5	95,5	9,2	88,5	84,6
Total	657.232	231.600	705.346	718.991	762.763	14,1	80,4	53,6	45,2	52,2	45,5

Source: own calculations

4.1. DETERMINANTS OF FIRM SURVIVAL IN CHILE

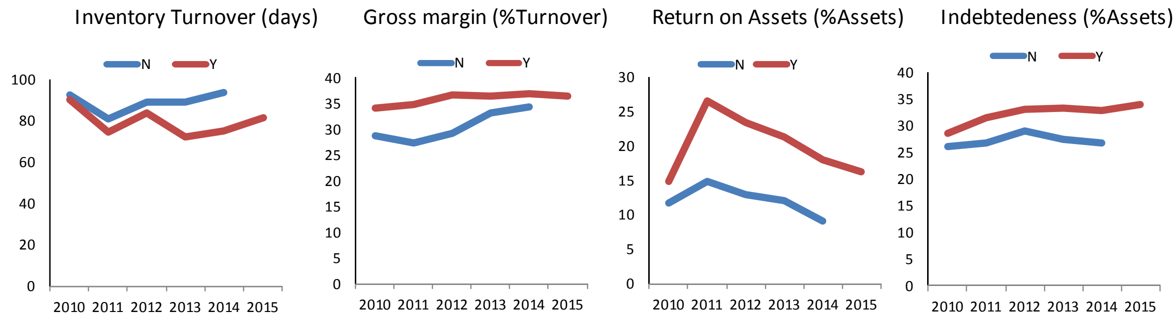
Here we show the pattern of firm survival by broader economic industries and size. Just to clear the things up: in all graphs below the "N (blue line)" refers to "non-survivor" firms whereas the "Y (red line)" refers to "survivor" firms.

4.1.1. Descriptive

In general those firms that survive show a lower Inventory turnover, higher leverage rates, higher Gross margin and higher profitability. The latter is highly significant. Notice that the difference between "survivors" and "non-survivors" increases over the years for all variables considered with the only exception of Gross margin (See Graph 1 below).

Graph 1 Economic activity, financing and profitability 2010-2015: All

(Cohort 2010, median)



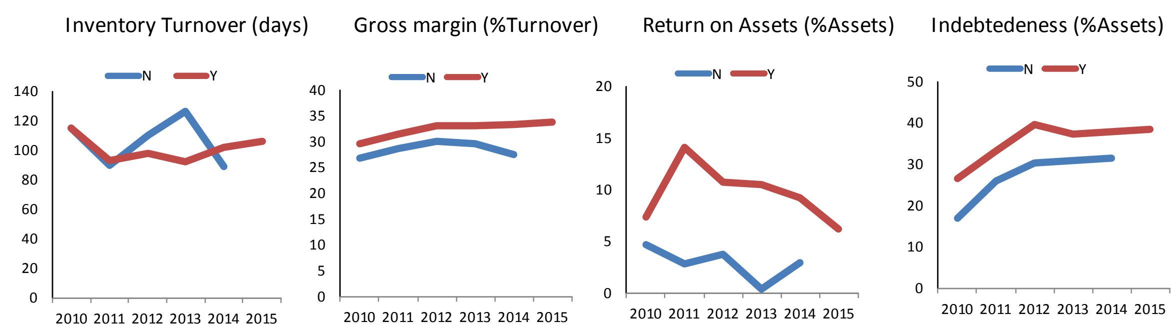
The results above are general in that they consider the whole group of firms. A more interesting issue is to disentangle the dynamics of survival by industry and size. After all, we expect relevant differences to emerge between firms of different size or pertaining to different industries.

4.1.1.1. By industry

In Agriculture-fishing we observe that "non-survivor" firms have lower leverage rates compared to that of "survivors". They also enjoy a relatively lower Gross margin, lower rate of profitability and higher Inventory turnover rates. The latter is less conclusive; in 2010, 2011 and 2014 the Inventory turnover is the same for "survivor" and "non-survivor" firms.

Graph 2 Economic activity, financing and profitability 2010-2015: Agriculture-fishing

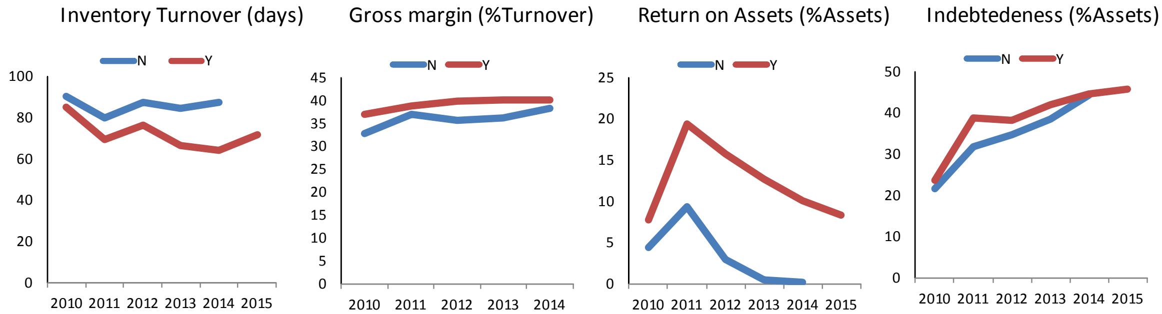
(Cohort 2010, median)



Within MMU (Mining, Manufacturing-Utilities) the firms that survive are characterized by lower rates of Inventory turnover, significant differences in profitability, higher Gross margin and higher leverage. Yet, the differences in the degree of indebtedness seem to be inconclusive, or at least not highly significant, for the entire period of analysis (See Graph 3).

Graph 3 Economic activity, financing and profitability 2010-2015: MMU

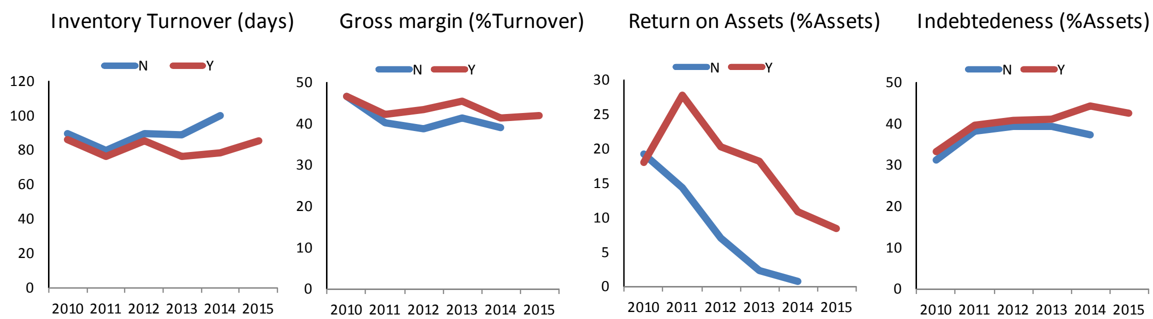
(Cohort 2010, median)



For Construction it is important to notice how the level of profitability of those firms that do not survive rapidly falls after the first year. Actually it falls for both groups of firms but in the case "survivors" the falling starts after the second year. Notice also, the huge differences in levels for this variable. As for the rest of the indicators, Gross margin is higher for "survivors" and so it is the leverage rate, whereas the Inventory turnover remains the same for both groups until 2012 and then a gap emerges afterwards (Graph 4 below).

Graph 4 Economic activity, financing and profitability 2010-2015: Construction

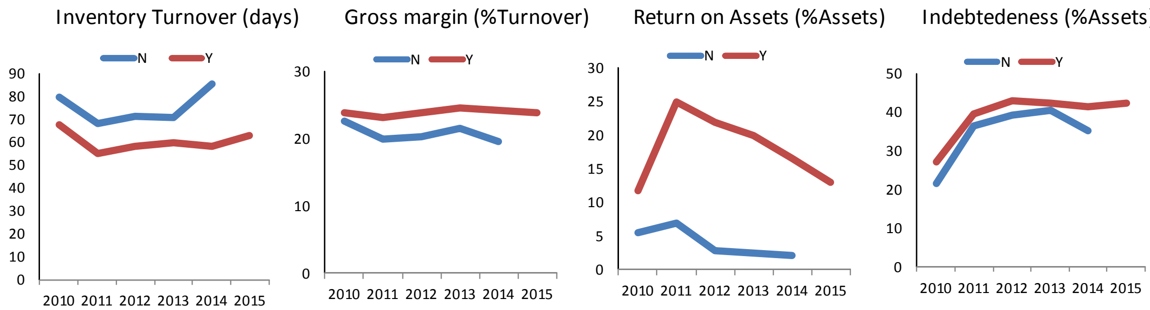
(Cohort 2010, median)



The "survivor" firms within Trade show lower rates of Inventory turnover rate, higher Gross margin and profitability. There is, however, a close relationship between "survivors" and "non-survivors" regarding their leverage until 2013; although, the firms that survive clearly show higher rates of indebtedness.

Graph 5 Economic activity, financing and profitability 2010-2015: Trade

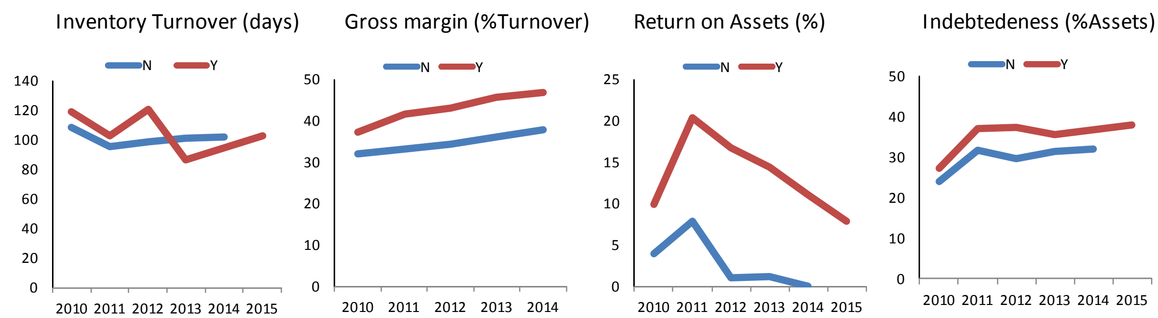
(Cohort 2010, median)



Finally, in Services "survivors" enjoy higher leverage rates than "non-survivors" and a higher Gross margin rate, particularly toward the final periods. The result from Inventory turnover is not informative. Also the level of profitability looks rare in this case. All in all, profitability is higher for those firms that survive.

Graph 6 Economic activity, financing and profitability 2010-2015: Services

(Cohort 2010, median)

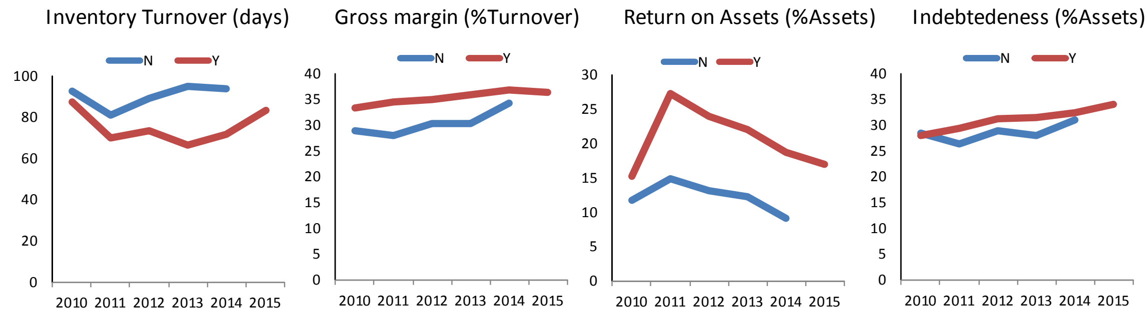


To sum up, there are noticeable differences between the set of "survivors" and "non-survivors" in all variables considered. In general, those firms that survive show higher rates of Gross margin, a higher access to credit markets and profitability is also higher. The Inventory ratio is not statically significant in some cases and in others is not informative at all.

4.1.1.2. By size

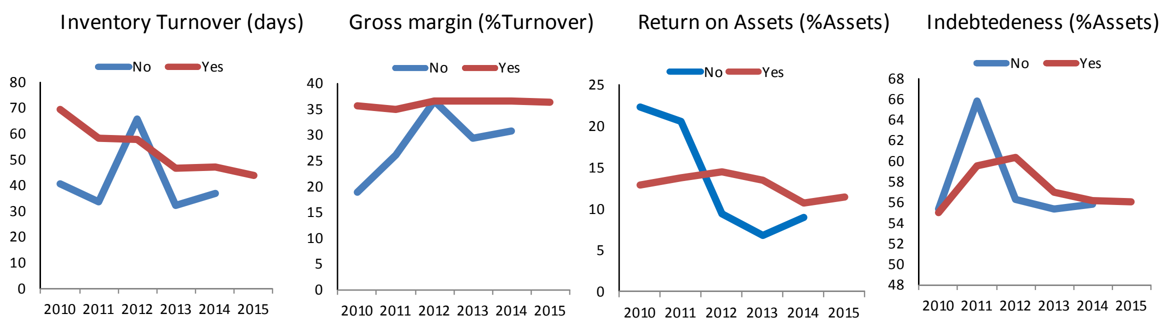
The analysis above is also interesting when looking at the differences between "survivors" and "non-survivors" by size. As it can see in Graph 7 micro-small "survivors" show higher results in terms of economic activity, leverage and profitability when compared to "non-survivors". The latter is highly significant for the entire period of analysis.

Graph 7 Economic activity, financing and profitability 2010-2015: Micro-Small (Cohort 2010, median)



On the other hand, the medium-large firms that remain in business are characterized by higher rates of Gross margin; notice the those firms show a lower level of indebtedness during the first two years and then the relation with "non-survivors" changes afterwards. This is interesting: it seems like those firms that have a low level of indebtedness at first are more likely to survive than those who were highly indebted at the same moment. The profitability ratio starts lower for "survivors" but after 2011 it remains higher. The result for Inventory turnover is odd. Probably, the low numbers of firms in this group is provoking this kind of result.

Graph 8 Economic activity, financing and profitability 2010-2015: Medium-Large (Cohort 2010, median)



5. MAIN RESULTS

In this section we present the main results obtained from the estimation of our proportional hazard model and discuss their implications. For comparative reasons, we estimate the probability of firm survival for the entire stock of firms using a probit model.

5.1. Probit estimates

In general, the results provided are stable and deliver evidence of our intuition. Table 3, 4 and 5 below shows the estimates from the probit model. We estimate the probability of survival overall and for each year in the sample. The Model 1 is the "basic model" since we use only four regressands in the estimation. The signs of the coefficients are as expected, with the only exception of the Inventory turnover ratio. The latter might be explained, first, by the fact we do not control for firm entry in our model and second, by the fact that Inventory turnover is not an efficiency proxy for some activities, like agriculture and fishing, where business are affected by seasonality factors.

Table 3 Probit estimates: overall

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Gross margin	-0.367***	-0.375***	-0.355***	-0.399***	-0.346***	-0.385***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)
Return on Assets	-0.172***	-0.166***	-0.179***	-0.174***	-0.185***	-0.191***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Indebetedeness	-0.116***	-0.117***	-0.080***	-0.121***	-0.078***	-0.083***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Inventory turnover	-0.000***			-0.000***	-0.000***	-0.000***
	(0.000)			(0.000)	(0.000)	(0.000)
Industry1*Inventory turnover		-0.000***	-0.000***			
		(0.000)	(0.000)			
Industry2*Inventory turnover		0.001***	0.000***			
		(0.000)	(0.000)			
Industry3*Inventory turnover		0.001***	0.001***			
		(0.000)	(0.000)			
Industry4*Inventory turnover		0.000***	0.000***			
		(0.000)	(0.000)			
Industry5*Inventory turnover		-0.000***	-0.000***			
		(0.000)	(0.000)			
Size(Medium-Large)			-0.621***		-0.628***	-0.636***
			(0.007)		(0.007)	(0.007)
Agriculture-fishing(Industry1)				-0.197***		-0.187***
				(0.008)		(0.008)
Trade(Industry4)				-0.045***		-0.056***
				(0.003)		(0.003)
Construction(Industry3)				0.117***		0.127***
				(0.005)		(0.005)
MMU(Industry2)				-0.050***		-0.036***
				(0.005)		(0.005)
GDP gap						-0.131***
						(0.001)
Constant	-1.275***	-1.305***	-1.282***	-1.239***	-1.255***	-1.242***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)
Log-likelihood	-531,338	-530,259	-525,255	-530,555	-526,201	-520,570
Obs	2,166,862	2,166,858	2,166,858	2,166,858	2,166,862	2,166,858

** p<0.05, ** p<0.01, *** p<0.001*

Source: own calculations

In the Model 2 we add interactions of the Inventory turnover ratio and each industry dummy. Notice that in the case of Agriculture-fishing the sign of the coefficient is negative, this is also true for Services. For

MMU, Construction and Trade the sign is positive. In general, in Agriculture-fishing and Services the more time firms spend in selling their inventories the higher their probability of survival overall. Nevertheless, the value of the coefficients is rather low for all interactions and even for Inventory turnover itself. As a result, we drop this variable from the rest of our estimations.

Additionally, we include a variable of size and the GDP gap for the period under analysis (Model 3 to Model 5) together with dummies for each industry. The coefficients of Gross margin, indebtedness and profitability remain stable. Additionally a larger size of firms is associated to a higher probability of survival. Other things being equal, firms are more likely to survive in Agriculture-fishing, MMU and Trade industries compared to Services. The contrary is true for Construction. These results are strongly significant at a 95% level of statistical significance.

Table 4 Probit estimates: 2011-2014

	Model 7	Model 8	Model 9	Model 10
Gross margin	-0.324***	-0.368***	-0.333***	-0.319***
	(-0.012)	(-0.011)	(-0.011)	(-0.01)
Return on Assets	-0.195***	-0.197***	-0.203***	-0.188***
	(-0.006)	(-0.006)	(-0.006)	(-0.006)
Indebetedeness	-0.078***	-0.089***	-0.112***	-0.066***
	(-0.008)	(-0.008)	(-0.008)	(-0.008)
Size(Medium-Large)	-0.721***	-0.709***	-0.631***	-0.649***
	(-0.018)	(-0.017)	(-0.015)	(-0.014)
Agriculture-fishing(Industry1)	-0.196***	-0.199***	-0.188***	-0.159***
	(-0.018)	(-0.017)	(-0.017)	(-0.016)
Trade(Industry4)	0.005	-0.026***	-0.025***	-0.019**
	(-0.007)	(-0.007)	(-0.007)	(-0.006)
Construction(Industry3)	0.153***	0.154***	0.135***	0.175***
	(-0.012)	(-0.012)	(-0.011)	(-0.01)
MMU(Industry2)	-0.012	0.015	-0.025*	0.020*
	(-0.011)	(-0.01)	(-0.01)	(-0.01)
Constant	-1.215***	-1.137***	-1.098***	-1.065***
	(-0.008)	(-0.008)	(-0.007)	(-0.007)
Log-likelihood	-105,998	-114,919	-123,321	-133,091
Obs	405,037	416,729	425,293	422,862

** p<0.05, ** p<0.01, *** p<0.001*

Source: own calculations

On a yearly basis (See Model 7 to Model 14) the results above remain stable. We remove the GDP gap from the estimations since the effect is irrelevant in this particular set up. Again, the coefficient signs from Gross margin, indebtedness and profitability are in line with our intuition and are highly significant. Finally, Construction is the only industry where firms have a lower probability of survival compare to Services.

Table 5 Probit estimates: 2011-2014

	Model 11	Model 12	Model 13	Model 14
Gross margin	-0.325***	-0.370***	-0.336***	-0.320***
	(-0.012)	(-0.011)	(-0.011)	(-0.01)
Return on Assets	-0.188***	-0.187***	-0.194***	-0.180***
	(-0.006)	(-0.006)	(-0.006)	(-0.006)
Indebetedeness	-0.115***	-0.127***	-0.148***	-0.105***
	(-0.008)	(-0.008)	(-0.008)	(-0.008)
Agriculture-fishing(Industry1)	-0.205***	-0.210***	-0.202***	-0.175***
	(-0.018)	(-0.017)	(-0.017)	(-0.016)
Trade(Industry4)	0.014*	-0.018**	-0.018**	-0.013*
	(-0.007)	(-0.007)	(-0.007)	(-0.006)
Construction(Industry3)	0.139***	0.136***	0.122***	0.165***
	(-0.012)	(-0.012)	(-0.011)	(-0.01)
MMU(Industry2)	-0.032**	-0.005	-0.043***	0.003
	(-0.011)	(-0.01)	(-0.01)	(-0.01)
Constant	-1.238***	-1.161***	-1.121***	-1.089***
	(-0.008)	(-0.008)	(-0.007)	(-0.007)
Log-likehood	-107,110	-116,155	-124,468	-134,442
Obs	405,037	416,729	425,293	422,862

** p<0.05, ** p<0.01, *** p<0.001*

Source: own calculations

5.2. Proportional hazard estimates

The results related in Table 6 are consistent with the ones obtained in Table 3, 4 and 5. The main difference here is we address the probability of survival using the proportional hazard model and focus on the set of firms that were born in 2010.

First, the signs of our main variables remain strong. A higher Gross margin, for instance, is related with a higher probability of survival. This is intuitive; a Gross margin can be used as a measure of firm efficiency; as a result, the more efficient is the firm the higher its probability of remaining in business, *ceteris paribus*. Notice that the sign of the Gross margin coefficient remains strong in each of the five models considered; which means that, regardless the industry and the size of the firm, a higher Gross margin is always a good new for enhancing the probability of survival.

Table 6 Proportional hazard model estimates

	Model 1	Model 2	Model 3	Model 4	Model 5
Gross margin	-0.708***	-0.715***	-0.685***	-0.710***	-0.681***
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Return on Assets	-0.347***	-0.340***	-0.346***	-0.341***	-0.346***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Indebtedeness	-0.528***	-0.524***	-0.528***	-0.472***	-0.476***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
GDP gap		0.093***	0.092***	0.097***	0.096***
		(0.007)	(0.007)	(0.007)	(0.007)
Agriculture-fishing			-0.420***		-0.433***
			(0.046)		(0.046)
Trade			-0.095***		-0.117***
			(0.027)		(0.027)
MMU			-0.203***		-0.204***
			(0.033)		(0.033)
Construction			-0.190***		-0.214***
			(0.027)		(0.027)
Size(Medium-Large)				-1.478***	-1.481***
				(0.061)	(0.061)
Obs	206192	206192	206192	206192	206192

**** p< 0.05, ** p< 0.01, *** p< 0.001***

Source: own calculations

Second, firms with a higher degree of profitability are more likely to remain in business than firms with a lower degree of profitability. Truly, the Return on Assets coefficient is negative and highly significant at a 95% level of significance. This result remains stable after being controlled by other variables.

Third, the probability of survival is positive related to a higher degree of indebtedness. Say it differently, higher indebted firms are more likely to remain in business than lower indebted ones. According to the financial theory a highly leveraged firm is the one who enjoys tax deduction benefits and also is able to send a good signal into financial markets; putting all these together results in a higher value firm which means the probability of survival is higher.

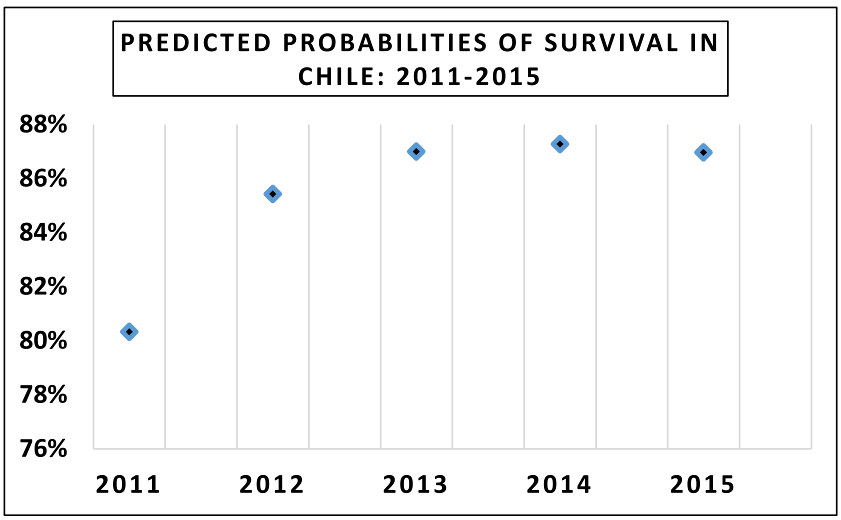
Fourth, larger firms are more likely to survive than smaller ones. Notice, also, that the coefficient on Gross margin is reduced when controlling by size. This is not surprising since we build the size of firms using turnover, which is also the same variable we employed to calculate the Gross margin.

In general a higher GDP gap is correlated with a lower probability of survival. The coefficient remains the same in all of the five models presented. A higher GDP gap (negative or positive) suggest that the economy is working inefficiently. Accordingly, there might be a negative effect on firm survival since economics conditions are adverse.

Trade is the more dynamic industry and Agriculture-fishing is the less dynamic one when comparing to Services. The probabilities of survival for both industries are 0.11% and 0.43% respectively. Construction and MMU, on the other hand, show probabilities of survival of 0.2% approximately.

Finally, we can see in Graph 9 and 10 the shape of our predicted probabilities. Overall, the predicted probability of survival is almost 80% in the first year; it reaches its peak in 2014, four years after the "birth" of the firms, and then falls afterwards (See Graph 9).

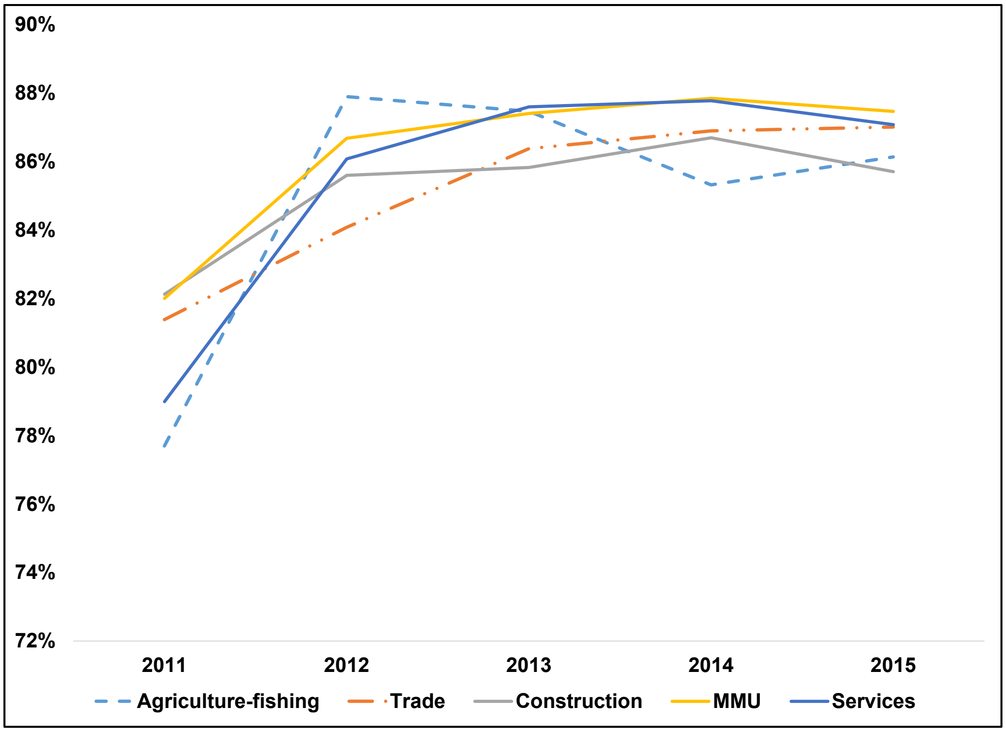
Graph 9 Inverted-U shape survivals



Source: own calculations

Looking at the probability of survival at the industry level the results are diverse. For Agriculture-fishing the peak is reached two years after the "birth", falling immediately afterwards. The same seems to be true for Construction, although in this case the tendency is not clear. In Trade and Services the survival rate reaches its peak in 2014, four years after the firms´ "birth"; the latter is also true for MMU. In conclusion Trade, Service and MMU seems to be leading the dynamic in terms of firm survival overall (See Graph 10).

Graph 10 Inverted-U shape survivals by industry



Source: own calculations

6. CONCLUSION

In this paper we analyze the survival of Chilean firms using information from the Chilean IRS for the period 2010-2015. The importance of this analysis relies on the fact that we take a sample of firms that were born in the same year, share similar characteristics and yet show a different pattern of survival over time.

The results confirm our intuition regarding the impact of firms´ economic and financial variables in their probability of survival. First, firms are more likely to stay in business the higher their Gross margin, the higher their level of indebtedness and the higher their profitability level. This is confirmed in both the probit and the proportional hazard model. All results are highly significant at 95% level of statistical significance.

In the case of Return on Assets and Gross margin, the correlation is very intuitive; after all, both variables are indicators of firm´s efficiency and profitability respectively. For Indebtedness the result seems to be odd at a first sight, however, this goes in line with the financial theory related to the effect of leverage on economic performance of firms. All results remain stable after being controlled by other variables.

Second, the probability of survival increases with the firm size: larger firms are more likely to survive than smaller ones. This finding is similar to others using a different set of information. Notice also this result remains stable for the entire period 2011-2015 and on a yearly basis as well.

At the industry level firms face higher probability of survival in Agriculture-fishing than that in Trade. Furthermore, comparative speaking, there is not difference in being part of Services or MMU regarding the survival of firms. Both industries show similar probabilities of survival.

Finally, the pattern of survival of Chilean firms is similar to that in other countries. Overall, the survival rate is 80% in the first year after the firm "birth" and reaches its peak in the fourth year. At the industry level the results are mainly different; however some similarities between industries emerge. The survival in Trade, Services and MMU reaches its maximum point in the fourth year, whereas in Agriculture-fishing the maximum point is in the second year.

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BANK FOR INTERNATIONAL SETTLEMENTS

IFC-Bank Indonesia Satellite Seminar on *"Big Data"* at the ISI Regional Statistics Conference 2017

Bali, Indonesia, 21 March 2017

Determinants of business demography in Chile over the 2010-15 period[1]

Beatriz Velasquez,

Central Bank of Chile

1 This presentation was prepared for the meeting. The views expressed are those of the author and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Determinants of business demography in Chile over the 2010 – 2015 period

Central Bank of Chile – Statistics Division

Diana López
Daymler O’Farril
Josué Pérez
Beatriz Velasquez

Outline of the presentation

- Motivation
- Background
- Data
- Preliminary Findings

Motivation

- Using Big Data to exploit the potential of the Internal Revenue Service's anonymized administrative records data base.

- Using Big Data to find evidence on the probability of survival of non-financial enterprises in Chile by analyzing the reasons behind their definitive closure.

Background

- The Central Bank has been receiving the tax records data base from the Chilean IRS by way of special orders since 2010 and only since 2015 through a formal agreement.

- This formalization has allowed the creation of an historical data base of roughly 25 million administrative registers from the year 2007 to 2015. The software that managed this DB was also acquired in 2015, and it is SAS.

- This data base has many potential uses, being one of them, computing a set of indicators related to business dynamics, describing births, deaths and survival patterns of companies.

- In 2014 Suazo and Pérez presented the first paper of Chilean business demography, based on this data.

Data

- Annual income tax returns (anonymized) filed by individuals and corporations from the calendars years 2007 to 2015. Source: Chilean Internal Revenue Service (IRS).

- Around 25 million of registers including individuals and firms, of which, approximately 7 million correspond to enterprises.

- Corporations fill a balance sheet reduced version too. Decision rule: Corporate tax $\neq 0$.

- Issues in use of this administrative data: lack of quality control over the data and missing items or missing records

Data: Imputation Process

1. Append to the corporate tax record data base the economic sector according to National Accounts & size stratum.
2. Calculus of 15 financial ratios with two pivots: Total assets, sales income. These ratios are standardized and clustered by economic sector (80), business structure (10) and size stratum (4).
3. Extreme values deletion by cluster. Threshold +/-2.5 standard deviation.
4. Compute the M-Estimator for the 15 financial ratios within each cluster.
5. Ratio imputation of missing values in levels.

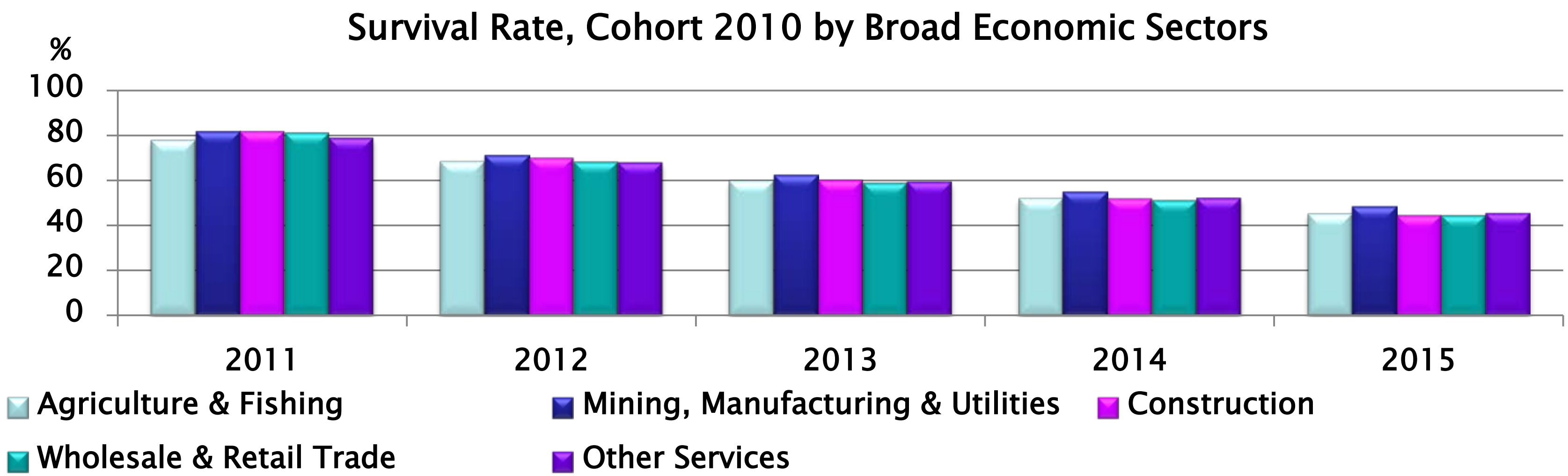
Definitions

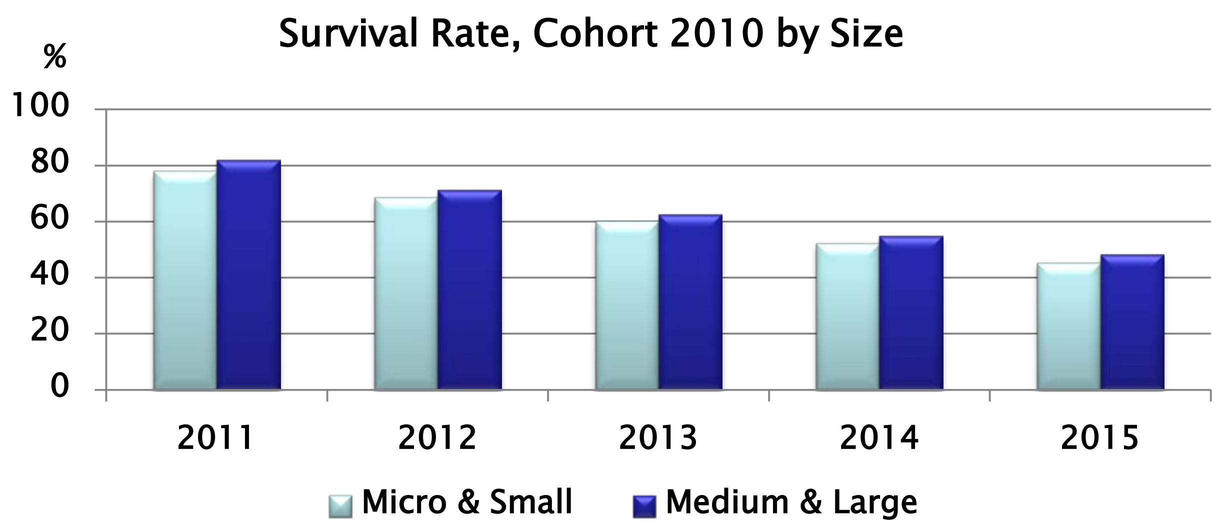
- Birth rate: $\frac{\Sigma N^{ti}}{\Sigma T^{t}_{i}}$ Enterprise births in the sector i, at the year t / Stock of enterprises in the sector i, at the year t

- Survival rate: $\frac{\Sigma S^{t+k}}{\Sigma T^{t}_{i}}$ Enterprise survivals in the sector i, year t+ k=1,…, 5 / Stock of enterprises in the sector i, at the year t

- Death rate: $\frac{\Sigma M^{ti}}{\Sigma T^{t}_{i}}$ Enterprise deaths in the sector i, at the year t / Stock of enterprises in the sector i, at the year t

Preliminary Findings: Survival Rates

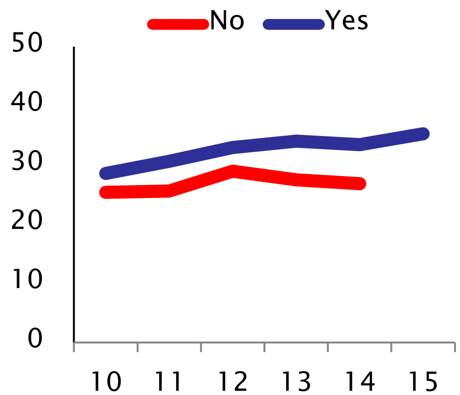


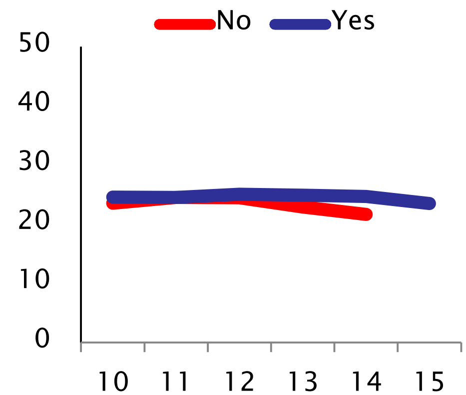


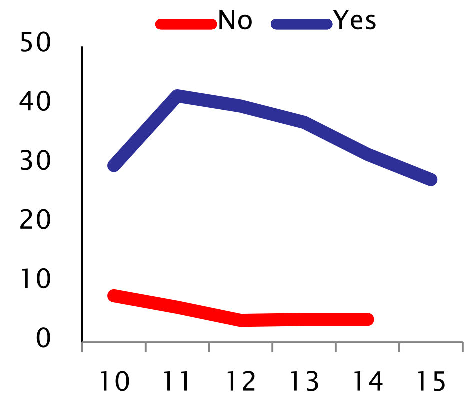
Preliminary Findings: Financial Indicators, cohort 2010 over the 2010 – 2015 period

$\frac{\textbf{Total Debt}}{\textbf{Total Assets}}$ $\frac{\textbf{(Revenue – Cost of goods Sold)}}{\textbf{Revenue}}$ $\frac{\textbf{Net Income}}{\textbf{Shareholder's Equity}}$

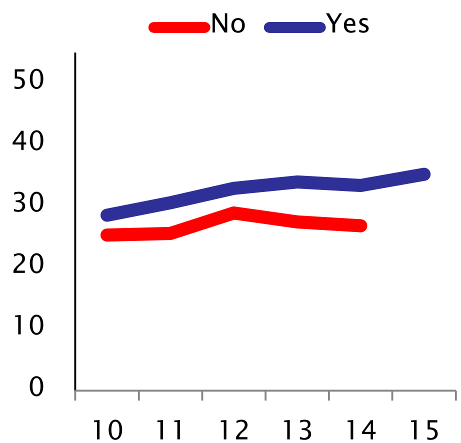
Agriculture & Fishing

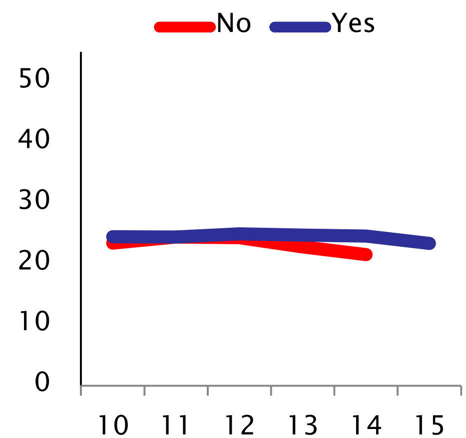


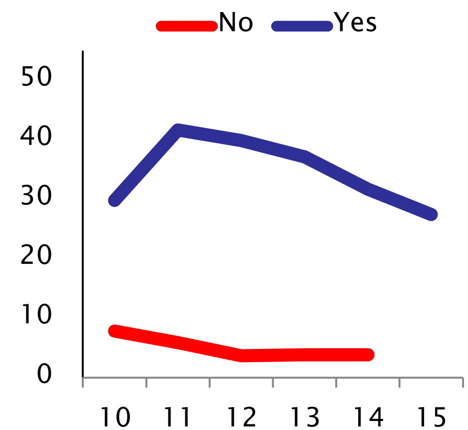




Construction



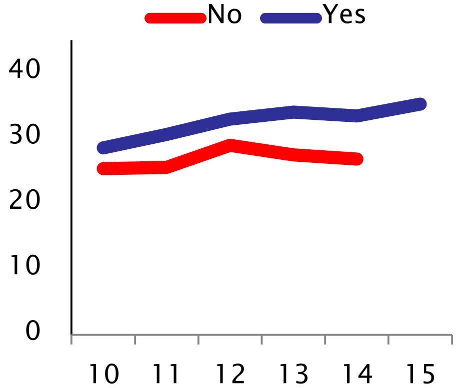


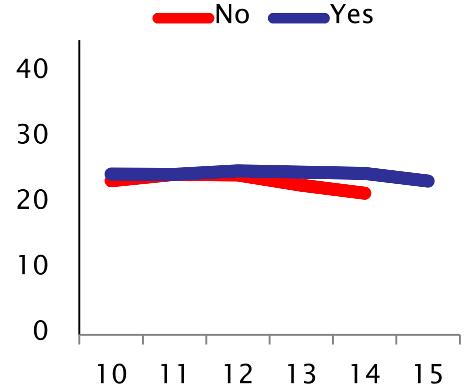


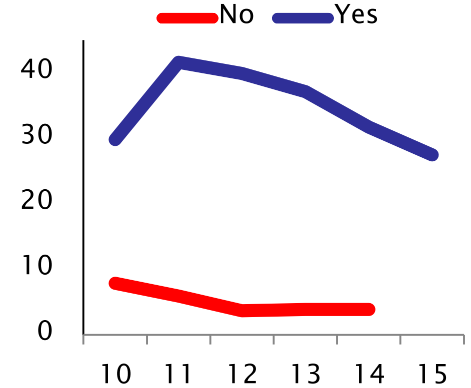
Preliminary Findings: Financial Indicators, cohort 2010 over the 2010 – 2015 period

$$\frac{\textbf{Total Debt}}{\textbf{Total Assets}} \qquad \frac{(\textbf{Revenue} - \textbf{Cost of goods Sold})}{\textbf{Revenue}} \qquad \frac{\textbf{Net Income}}{\textbf{Shareholder's Equity}}$$

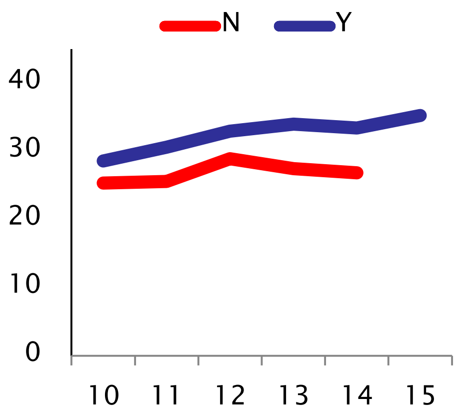
Mining, Manufacturing & Utilities

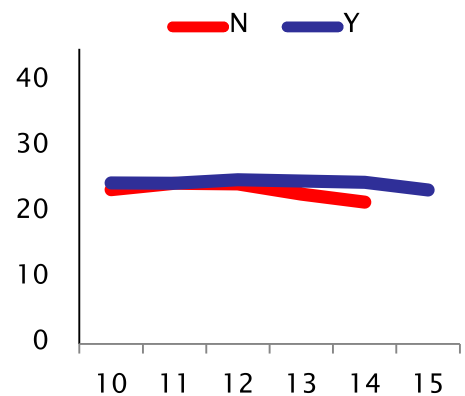


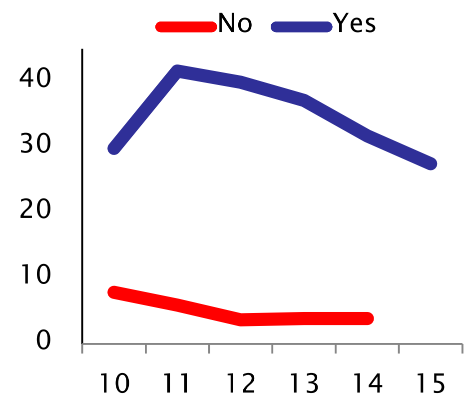




Wholesale & Retail Trade



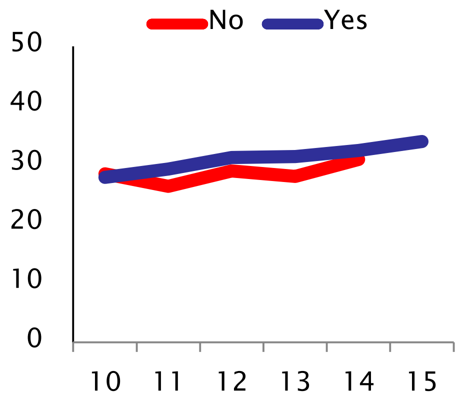


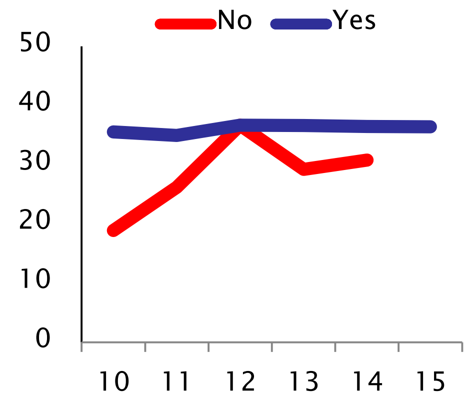


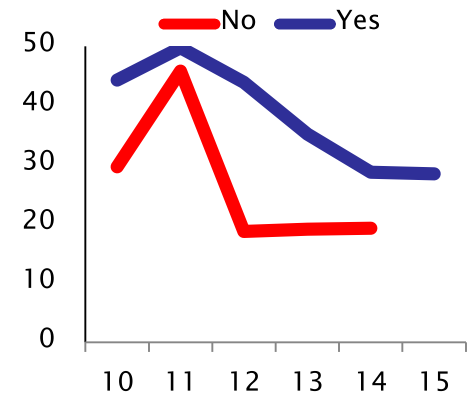
Preliminary Findings: Financial Indicators, cohort 2010 over the 2010 – 2015 period

$$\frac{\textbf{Total Debt}}{\textbf{Total Assets}} \qquad \frac{\textbf{(Revenue − Cost of goods Sold)}}{\textbf{Revenue}} \qquad \frac{\textbf{Net Income}}{\textbf{Shareholder's Equity}}$$

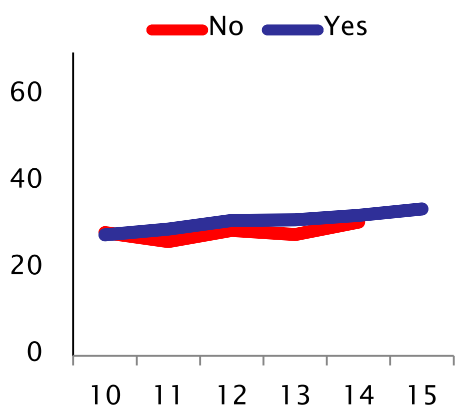
Micro & Small

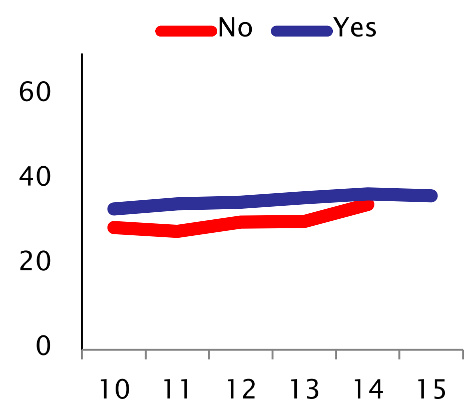


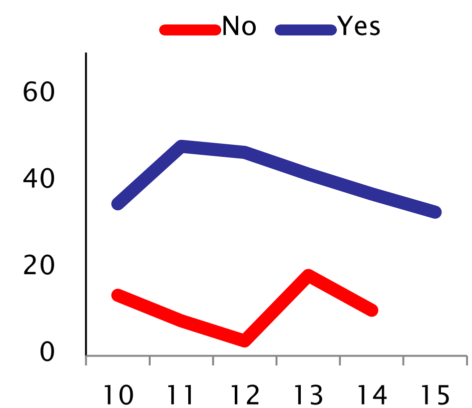




Medium & Large







Preliminary Findings: A Probit model (work in progress…)

- Consider the model below:

$$\Pr(\text{Survival}_{it}|\text{x}_{it-1}) = G(\beta_1 + \beta_2\text{Leverage}_{it-1} + \beta_3\text{MP}_{it-1} + \beta_4\text{ROE}_{it-1} + \beta_5\text{IT}_{it-1})$$

- where:
  - $\Pr(\text{Survival}_{it}|\text{x}_{it-1})$: Survival probability for the firm "i" in the period "t" conditional on its financial performance at the period "t-1".
  - Leverage_{it-1}: Debt to assets ratio for the firm "i" in the period "t-1".
  - MP_{it-1} : Margin price ratio for the firm "i" in the period "t-1".
  - ROE_{it-1} : Return on equity ratio for the firm "i" in the period "t-1".
  - IT_{it-1} : Inventory turnover ratio for the firm "i" in the period "t-1".

Preliminary Findings: A Probit model (work in progress…)

Table 1 Probit Estimates

	2010	2011	2012	2013	2014
Intercept	0.6141***	0.7191***	0.8100***	0.7765***	0.7795***
	(0.0141)	(0.0178)	(0.0204)	(0.0221)	(0.0236)
Leverage	1.1720***	0.7903***	0.6539***	0.7316***	0.7857***
	(0.0399)	(0.0363)	(0.0388)	(0.0418)	(0.0443)
Margin Price	0.1900***	0.4138***	0.3595***	0.3664***	0.2425***
	(0.0325)	(0.0380)	(0.0421)	(0.0446)	(0.0476)
Return on Equity	0.3754***	0.1748***	0.2910***	0.4190***	0.5504***
	(0.0191)	(0.0167)	(0.0222)	(0.0279)	(0.0342)
Inventory Turnover	−0.0000	−0.0002	−0.0006***	−0.0004**	−0.0002
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)

Note: The dependent variable is a dummy equal to one if the firm "i" survives in year t, and zero otherwise. Robust White Standard Errors are presented in the parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

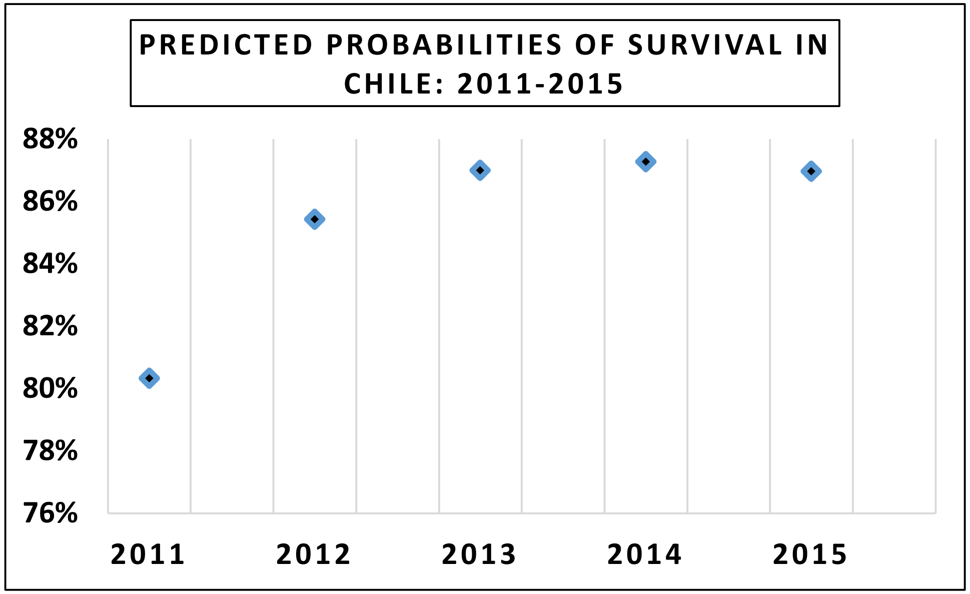
Table 2 Linear Hypothesis Tests

	Wald Chi-square				
	2010	2011	2012	2013	2014
Leverage=0	861.94	472.77	284.55	306.39	315.22
Margin Price=0	341.17	118.87	73.04	67.44	25.96
Return on Equity=0	387.98	108.93	171.73	226.18	259.72
Inventory Turnover=0	0.16	1.53	8.94	2.98	0.99
All four covariates are equal	1717.63	974.76	775.63	886.40	908.45

Preliminary Findings: A Probit model (work in progress…)

Table 3 Clasification table

	2011		2012		2013		2014		2015	
Y/N	N	Y	N	Y	N	Y	N	Y	N	Y
Correct	4	73147	1	62550	0	54435	9	47517	15	41355
Total		**91057**		**73221**		**62567**		**54452**		**47567**
Survival Probabilities	***80.34%***		***85.43%***		***87.00%***		***87.28%***		***86.97%***	



Thank you!